



## Planning the Optimal 3D Quadcopter Trajectory Using a Delivery System-Based Hybrid Algorithm

Abbas A. Kareem<sup>1,2\*</sup> Bashra K. Olewi<sup>1</sup> Mohamed J. Mohamed<sup>1</sup>

<sup>1</sup> Control and Systems Department, University of Technology-Iraq, Baghdad, Iraq

<sup>2</sup> Technical Instructors Training Institute, Middle Technical University, Baghdad, Iraq

\* Corresponding author's Email: cse.21.16@grad.uotechnology.edu.iq

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**Abstract:** Path planning is one of the most crucial aspects of implementing unmanned aerial vehicle (UAV) missions. Therefore, it is essential to figure out the optimal path from the starting point to the target point in different scenarios. In this paper, we propose employing a hybrid algorithm, named FPA-GA, generated by combining the flower pollination algorithm (FPA) and genetic algorithm (GA), to find an optimum path in a real modern building's environment. In addition, a cubic polynomial algorithm via two points was proposed to make the route adequate and smooth. Because the GA has a good capability for exploring the search space, it is employed for exploration while the FPA and GA are employed to increase the exploitation capability in the proposed algorithm. Five different scenarios are utilized to evaluate FPA-GA's ability to find the optimal path in a variety of situations, and then the proposed algorithm's performance is compared with that of seven other algorithms: GA, FPA, bat algorithm (BA), particle swarm optimization (PSO), whale optimization algorithm (WOA), improved whale optimization algorithm (IWOA), and IWOA-PSO. The best path, the mean path length, the standard derivation, and the worst path length are the four parameters used to compress data. In all scenarios, the results demonstrate that FPA-GA is capable of locating the shortest and most collision-free paths, and the hybrid algorithm FPA-GA is always superior to other algorithms. The proposed algorithm provided the mean path length enhancement in all scenarios, where the maximum enhancement equals (33.6%), (23.1%), (55.5%), (29.8%), (50.5%), (53.9%), and (26.4%) compared with GA, FPA, BA, PSO, WOA, IWOA, and IWOA-PSO, respectively. On the other hand, the proposed algorithm is guaranteed to find the best path in all scenarios, where the standard deviation of FPA-GA is always less than that of other algorithms.

**Keywords:** Optimal 3D path planning, Quadcopter, Trajectory, UAVs, FPA, GA, Hybrid FPA-GA, Known realistic environment, Static obstacles, Off-line path planning.

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### 1. Introduction

One of the technologies that have become human-assisted is the robot, which is utilized in various industries, including the military, the civilian sector, the medical field, aerospace, and agriculture [1]. Unmanned aerial vehicles (UAVs) are the most widely utilized flying robots because of their cost-effectiveness, small size, lightweight, and portability [2]. Several companies around the world, including Amazon, Walmart, DHL, and Zookal, which invested in drone research for a variety of purposes, including freight and package delivery to consumers, have lately revealed the use of drones for commercial

purpose [3]. One of the primary aspects of the robot's transition from one location to another is to generate a path plan from the starting point to the target point and avoid collisions with obstacles [1-4]. The global path planner is one vehicle path planning system type, it uses a priori information from the road map to generate the optimal possible path from the starting point to the destination point [5-8].

Several studies investigated global path planning by using meta-heuristic algorithms and their variations to find the shortest flight path between the starting point and the destination point that doesn't cause any collisions including A\* and Dijkstra algorithms [1], particle swarm optimization (PSO) [9, 14], modification particle swarm optimization

(MPSO) [11], the genetic algorithm (GA) [10], improved artificial bee colony algorithm (ADL-ABC) [12], glow-worm swarm optimization (GSO) [13,14], improved grey wolf optimization algorithm (IGWO) [15], bat algorithm (BA) and improved bat algorithm (IBA) [16], flower pollination algorithm (FPA) [17], and improved flower pollination algorithm (IFPA) [18]. From the previous studies, the meta-heuristic algorithms and its improvement must have a perfect balance between exploring and exploiting operations to do both global and local searches well. As a result, many researchers proposed a hybrid algorithm that combines two or more algorithms to improve algorithm search and find optimal path planning with a speed up convergence rate.

In the reference [19], the researchers combined the third-order B-spline curve, ant colony optimization (ACO), and probabilistic roadmap (PRM) in a 2D environment. This approach can identify a straight smooth route, but this method's disadvantage is that the path's degree is dependent on the number of control points. Moreover, the PRM that produced random nodes, when evaluated in a complicated environment with a lot of obstacles, could not guarantee to find the route for a tiny area. While in [20], the researchers developed an offline route planning algorithm for the quadcopter by combining an enhanced artificial potential field (APF) method with a sampling-based bidirectional RRT algorithm. This method is a combination of two algorithms that were used to find the local path planning, so it cannot find the optimal path length between the starting and target points.

In reference [21], the authors suggest a novel hybrid algorithm called HSGWO-MSOS that combines a modified symbiotic organism search (MSOS) and a simplified grey wolf optimizer (SGWO). The proposed method did not balance the exploitation and exploration processes, and it has fallen into the local optimal. So, it failed to find the optimal path in 3D environments; it also has a high value for both the standard deviation and the worst path found. While a hybrid method known as (CPSOFFB) that combines the chaotic particle swarm optimization (CPSO), fire-fly (FF), and Bees (B) algorithms was proposed, the generated path was smoothed by using spline interpolation [22]. The suggested approach should be compared to other approaches. In this work, the comparison was solely done using CPSO, FF, and BA. These methods are the conventional ones that make up the suggested method. Furthermore, spline interpolation is used with the slope calculation to determine the smooth

route; however, it is ineffective at closed chosen locations.

The author of the reference [23] employed PSO and D\* algorithms to find the optimal smooth trajectory using a cubic polynomial equation. They discovered that the suggested algorithm performed well in determining the best path in complex 2D environments but lacked coverage in a 3D situation. While reference [24] suggests two hybrid algorithms: PSO with harmony search algorithm (PSO HSA) and PSO with GA (PSO GA) to find an optimal UAV path plan, although they enhanced the path length, the proposed algorithms are suggested to apply two meta-heuristic algorithms one at a time, which increased the computation processes.

A hybrid (HFAMCPSO) method that combines the modified chaotic particle swarm optimization (MCPSO) and firefly algorithm (FA) is suggested by the authors in reference [25]. The hybridization improved the variety of options and helped prevent stagnation. While the reference's author [26] suggested combining Improved Whale Optimization with particle swarm optimization (IWOA-PSO), they used PSO and IWOA to speed up convergence and then employed the crossover technique for information exchange after using an IWOA to stop the system from settling at the local optimum. In order to find an optimal route, the author did not consider the minimal path length, which result in significant energy consumption for the necessary operation.

These algorithms are capable of creating paths without collisions from start to finish. The problem with these approaches is that the ideal route they produce is still somewhat long, so a novel hybrid FPA-GA algorithm is proposed that is based on artificial pollination and is a combination of the Flower Pollinated algorithm (FPA) and the genetic algorithm (GA). The proposed combination algorithm is expected to solve the slow convergence and, additionally, use the variation to produce new offspring that prevents the algorithm to fall into local optimality. So that the proposed hybrid algorithm will be used to improve and accelerate the quadcopter path planning search.

The main contributions of this paper are:

- 1- A novel hybrid FPA-GA algorithm is proposed that is based on artificial pollination.
- 2- Creating realistic and well-known 3D environments from the real world and selecting the university of technology (UOT) in Baghdad, Iraq, to build the quickest, smoothest, and most collision-free route between its departments.

- 3- To smooth the path, cubic polynomial interpolation with three via points is proposed.
- 4- The performance of the hybrid FPA-GA algorithm is compared with that of the FPA [17], GA [10], BA [16], PSO [14], WOA [26], IWOA [26], and IWOA-PSO [26].

The structure of the paper is as follows: In Section two, the problem formulation of quadcopter path planning, the FPA, GA, and FPA-GA technique is detailed, mapping FPA-GA to the quadcopter path planning and the suggested environmental model's underlying principles. In Section three, several well-designed, similar simulation findings are presented and thoroughly explained. Then, a conclusion is reached in section four.

## 2. Methodology

This section will show how the path is made using a cubic polynomial and interpolation points that are chosen at random. Next, we will describe how the meta-heuristics cost function was created and how the FPA, GA, and FPA-GA algorithms are used in optimizing path planning. Finally, the designed environment will be demonstrated.

### 2.1 3D Polynomial path planning

A polynomial is the traditional way of describing the trajectory. The predicted trajectory is defined as a collection of position coordinates as functions of time. A smooth path can be described using a cubic polynomial with independent coefficients [5]. The initial and final time instants,  $t_i$  and  $t_f$ , as well as the conditions for location and velocity at  $t_i$  and  $t_f$ , are used to describe the motion [5, 12, 23]. In a 3D coordinate space, every point in the environment may be represented as an (x, y, z) coordinate. An algebraic cubic polynomial is used to define the trajectory between two points. They are represented as follows: [5,12,23]

$$x(t) = a_0 + a_1t + a_2t^2 + a_3t^3 \quad (1)$$

$$y(t) = b_0 + b_1t + b_2t^2 + b_3t^3 \quad (2)$$

$$z(t) = c_0 + c_1t + c_2t^2 + c_3t^3 \quad (3)$$

Where t is time, x is the position on the x-axis, y is the position on the y-axis, z is the position on the z-axis, and  $(a_0:a_3, b_0:b_3, c_0:c_3)$  are trajectory coefficients for each axis equation. These equations can be differentiated to compute velocity:

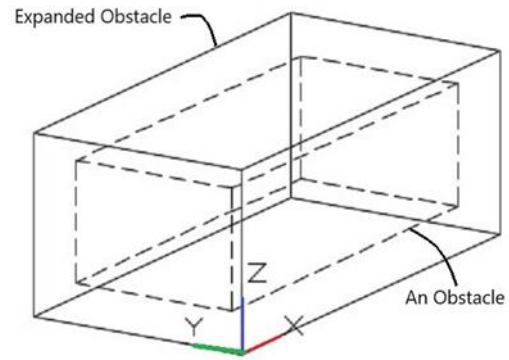


Figure. 1 Describe the 3D obstacles expanded

$$v_x(t) = a_1 + 2a_2t + 3a_3t^2 \quad (4)$$

$$v_y(t) = b_1 + 2b_2t + 3b_3t^2 \quad (5)$$

$$v_z(t) = c_1 + 2c_2t + 3c_3t^2 \quad (6)$$

Where  $v_x$ : is the velocity at the x-axis,  $v_y$ : is the velocity at the y-axis,  $v_z$ : is the velocity at the z-axis.

The optimal trajectory in a realistic trajectory planning issue is often complicated because of constraints and collision avoidance difficulties. So, to make the trajectory more flexible and give it the ability to avoid obstacles, a complicated trajectory is partitioned into four segments by three via points and connected to each segment with a polynomial curve.

Under the assumption that we have already pre-allocated the starting, via-points, and final path information with a time and velocity sequence, we calculate the trajectory parameters  $(a_0:a_3, b_0:b_3, c_0:c_3)$ . The cost function and limitations must be taken into account in order to create the shortest trajectory. On the other hand, the path will be separated into three sections in order to keep it safe and to ensure that its route won't collide with people, objects, automobiles, trees, parking lots, etc. Where the UAV doesn't fly horizontally till it reaches 5 meters of height above both the ground and obstacles, the first part is the UAV take-off; in this instance, the UAV will be raised 5 meters vertically toward the z-axis. The second part shows the 3D polynomial-based UAV path planning, and the last part shows the UAV landing; where at this moment the polynomial path stops 5 meters above the target point and the UAV will be moved down vertically into the target point. Also, in order to ensure safe navigation while traveling through the environment, all obstacles' dimensions must be expanded virtually by a ratio equal to the robot's radius. [11, 12], as illustrated in Fig. 1.

## 2.2 Cost function

The primary goal of the trajectory planning issue is to reduce the path length and time that UAVs need to travel from the start point to the target point. Numerous variables affect the possible solution. Path length, flight altitude, and collision avoidance impact the cost. The Euclidean distance, represented in Eq. 7, is used to define the path length [1].

$$L_p = \sum_{j=1}^{j=n} \sqrt{(x_{j+1} - x_j)^2 + (y_{j+1} - y_j)^2 + (z_{j+1} - z_j)^2} \quad (7)$$

Where:  $L_p$  is a path length,  $n$  is number of sampling points along the trajectory,  $j$  is a counter from one to  $n$ ,  $(x_j, y_j, z_j)$  are the coordinates of the current node, and  $(x_{j+1}, y_{j+1}, z_{j+1})$  are the coordinates of the next node.

To stay safe, the quadcopter's flight path must avoid collisions and stay above the ground. To do this, the cost function will punish the path by adding a lot of value ( $P_o$ ) to it if it goes through an obstacle or is below a certain height, as shown in the equation below [12]:

$$\text{Cost} = L_p + P_o \quad (8)$$

The minimum cost function value is achieved by applying the above equation, which guarantees the shortest path with constraint avoidance.

## 2.3 Overview of FPA

Xin-She Yang proposed a population-based method called the flower pollination algorithm (FPA) inspired by nature (2012). By surviving the best flowers among flower plants, flower pollination's main objective is to guarantee that plants reproduce as effectively as possible. A flower's basic task is to reproduce through pollination. Pollen transfer is commonly associated with flower pollination, and pollinators such as insects, birds, bats, and other animals are frequently involved [27].

Abiotic and biotic pollination are the two main types of pollination. Around 90% of flowering plants utilize biotic pollination, which means pollen is transferred by pollinators like insects and animals. Abiotic pollination, which does not require pollinators, accounts for around 10% of pollination.

Self-pollination and cross-pollination are two methods for pollination. Cross-pollination happens when pollen from a flower of a different plant is used to fertilize a single flower, whereas self-pollination

occurs when pollen from the same flower or different flowers of the same plant is used to fertilize a single flower [27,28].

The following guidelines were established by Yang [27] to model the FPA:

1. Biotic cross-pollination is a global pollination in which pollinators use Levy flights to transport pollen.
2. Abiotic self-pollination is regarded as a local pollination.
3. It is supposed that flower constancy is the reproduction probability.
4. To regulate the quantity of local and global pollination, a probability switch is suggested.

The global pollination process is start if  $R < \rho$ , and the new solution is made by a Lévy distribution as Eq. 9.

$$A_i^{T+1} = A_i^T + L(g^* - A_i^T) \quad (9)$$

Where  $A_i$  is the variables solution,  $g^*$  is the best solution,  $T$  is the iteration number,  $R$  is the random number,  $R \in [0,1]$ ,  $\rho$  is the probability switch, and  $L$  is a Lévy flight,  $L > 0$  and calculated as follow [27-29]:

$$L = \frac{\lambda \Gamma(\lambda) \times \sin(\frac{\pi \lambda}{2})}{\pi \times s^{1+\lambda}}, \quad (|s| \rightarrow \infty) \quad (10)$$

For large steps, this distribution is appropriate ( $s \gg s_0 > 0$ ). Where  $\Gamma(\lambda)$  is the standard gamma function and  $s_0$  is a minimum step,  $\lambda$ : is a scaling parameter used to regulate the step size, in this research will used  $\lambda = 1.5$  as Yang proposed [27],  $S$ : is a step length. If  $R \geq \rho$ , the local pollination starts with the generation of  $\epsilon$ , where  $\epsilon$  is a random number in  $[0,1]$  as follows [27].

$$A_i^{T+1} = A_i^T + \epsilon(A_j^T - A_k^T) \quad (11)$$

Where  $(A_i^T, A_k^T)$  are flowers (solutions) from the same plant species. If  $A_j^T, A_k^T$  comes from the same plant species (selected randomly from the same population), this becomes a local random walk. The population of solutions  $A_i^{T+1}$  was evaluated, and greedy selection was used to update the best solutions ( $g^*$ ).

## 2.4 Overview of GA

One of the most often used evolutionary algorithm techniques is the genetic algorithm (GA).

Holland was the first to develop it on a theoretical foundation. Based on the survival of the fittest concept, GA finds the best possible answer among all potential options for a population. The most appropriate individuals will probably live and reproduce. With the use of two operators, crossover and mutation, GA repeatedly creates new chromosomes. The procedure is continued until the necessary conditions, such as convergence, a certain amount of time, or a certain number of iterations, are satisfied [30]. The GA work may be summed up as follows [10,31]:

**Initial population.**

The algorithm created a random matrix at this stage. The number of chromosomes ( $N_{pop}$ )  $\times$  the number of variables ( $N_{var}$ ) makes up the dimension of the resulting matrix.

**Elitism (Natural selection).**

The algorithm chooses the best individual percent and moves it to the next generation in order to prevent the generation's best solution from being lost due to the mating process.

**Selection (Pairing).**

From the  $N_{keep}$  chromosomes' mating pool, two chromosomes are chosen to create two new offspring. The next generation comprises both the parents and their children. In this article, we decided to choose the patents using the roulette wheel approach. This method determines the probability based on the chromosome's rank,  $N_{pop}$ .

**Crossover.**

A crucial stage of the GA is crossover. In order to alter the genes, two parents are successfully merged in a number of ways, including one-point crossover, two-points crossover, and uniform crossover. The two-points crossover method is applied in this article as shown in Fig. 2.

**Mutations.**

The second method by which a GA explores a cost field is via mutation. It allows for the introduction of features that were not present in the initial population and prevents the GA from becoming convergent before sampling the whole cost field. From the total number of variables in the population matrix,  $N_{pop} \times N_{var}$ , random numbers are used to replace mutation points as shown in Fig. 3.

**2.5 The proposed Hybrid FPA-GA algorithm**

The fundamental concept of a hybrid FPA-GA algorithm is artificial pollination. There is another sort of pollination, known as artificial pollination, even though the pollination process is divided into

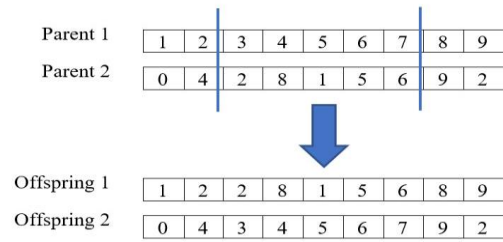


Figure. 2 The two-points crossover method

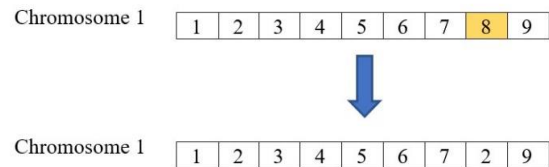


Figure. 3 The random mutation processes

biotic and abiotic pollination based on pollen transport. Artificial pollination is the use of extra, compatible pollen that has already been collected and put to use in a biological or mechanical way with human assistance [32]. When a person begins researching the desired flower for pollination, mechanical artificial pollination begins like palm pollination. Because of GA's superior exploratory capabilities [10], both the crossover and mutation approaches are used to guide the hybrid algorithm in exploration instead of the pollinator carrier. Once the pollinator carrier reaches the chosen flower, he starts to scatter the pollinators to complete the pollination process, but a small portion of the pollinators are transferred to another flower due to the wind. To represent this process, a large portion of the FPA local search is used to achieve the hybrid algorithm with an exploitation capability, and the remainder is used in a global search with Lévy distribution to represent pollinators transferred by the wind. This combination of FPA and GA will satisfy the balancing act between exploring and exploiting capabilities to find the optimal solution and not fall into the local solution. The hybrid FPA-GA algorithm is employed to find an optimal 3D path planning for a quadcopter based on a delivery system, as shown in Fig. 4.

**2.6 Environment design**

In order to find the best, shortest route from the starting point to the target point dependent on the delivery system, in a large and realistic environment, we chose to utilize the map of (the University of Technology-Iraq), Due to the variety of building structures and the densely populated modern setting

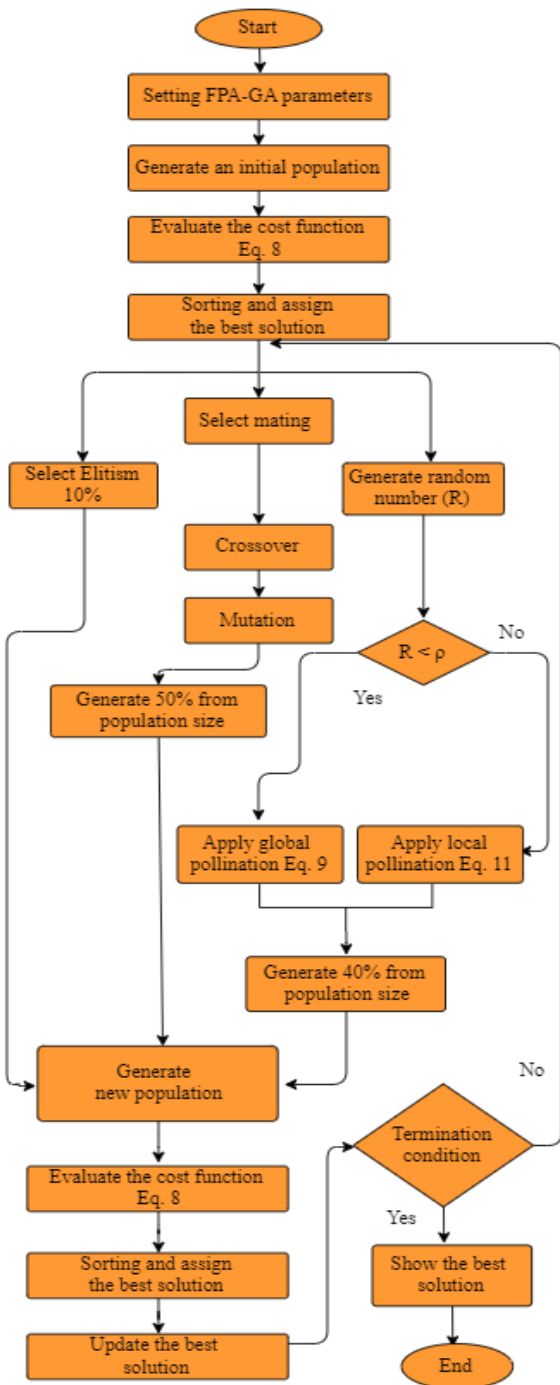
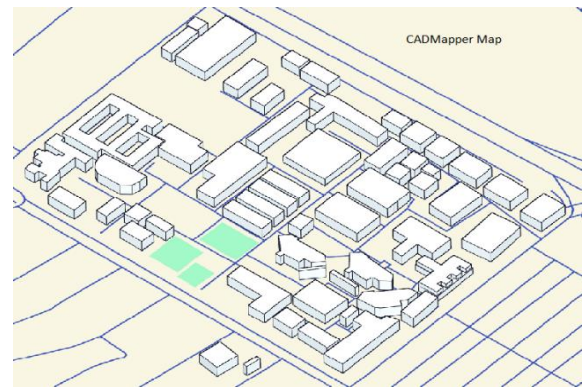
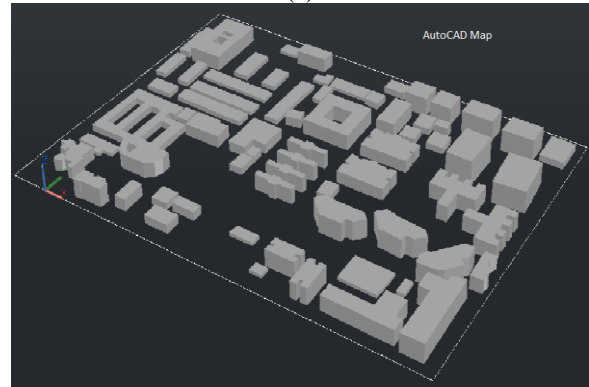


Figure. 4 The hybrid FPA-GA flow chart

in this research. Using the website (<https://cadmapper.com/>), which is a virtual 3D mapping library that was utilized as a platform for urban building and architectural activity, we got a map of the area of 560m x 410m (229600 m<sup>2</sup>). In combination with the 3D CAD program AutoCAD, as shown in Fig 5. The map is downloaded in DXF file format, which AutoCAD opens, and is then converted to STL file format so that it to be used with MATLAB [1]. In Fig. 5, the cad mapper did not



(a)



(b)

Figure. 5 The UOT map: (a) on CAD Mapper, and (b) on Auto CAD 2016.

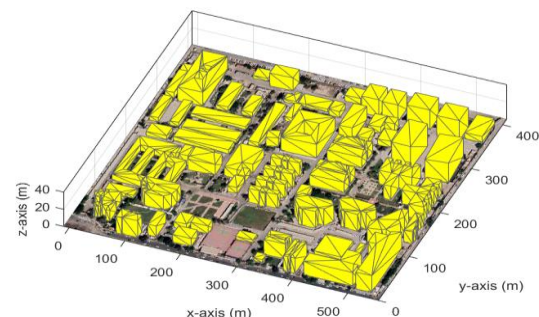


Figure. 6 Show the Google Earth image with the updated CAD Mapper map overlaid

support the 3D data of UOT buildings and missed some buildings. Due to these factors, the map was downloaded as a 2D map, the missing structures were added using AutoCAD, and the height of each building was manually determined by counting the number of stories in each building and assuming that each level had a height of 3.5 meters and the staircase 2 meters. The overall height of each building is shown in Table 1.

Fig. 6 shows how a 3D map is placed on top of a Google Earth image of the UOT. This is done to make the simulation more realistic and to see if any buildings are missing from the map.

Table 1. The total height of the university of technology's buildings

Building No.	Height (m)	Building No.	Height (m)	Building No.	Height (m)
1	3.5	23	5	45	16
2	9	24	3.5	46	16
3	7	25	15	47	12.5
4	9	26	5	48	16
5	12.5	27	10	49	10.5
6	19.5	28	16	50	7
7	12.5	29	16	51	7
8	3.5	30	16	52	7
9	7	31	16	53	12.5
10	16	32	16	54	7
11	12.5	33	3.5	55	19.5
12	7	34	5	56	19.5
13	7	35	3.5	57	19.5
14	7	36	3.5	58	14
15	10.5	37	7	59	19.5
16	5	38	19.5	60	3.5
17	3.5	39	19.5	61	16
18	3.5	40	23	62	3.5
19	16	41	23	63	17.5
20	7	42	26.5	64	17.5
21	3.5	43	23	65	3.5
22	5	44	7		

### 3. Simulation and results

The offline path planner has been tested between the starting and target points with three algorithms, then we will be comparing the performance of FPA-GA with that of FPA, GA, PSO, BA, WOA, IWOA, IWOA-PSO algorithms. The starting point, the via points, and the target point are all known for both velocity and time. The DJI Matrice 100 quadcopter is used in this paper, and the selected quadcopter's maximum speed is 5 m/s [33]. Five different scenarios will be investigated in the same realistic environment to cover all potential scenarios with various levels of complexity and assess the method's effectiveness in terms of path length. Because of the random nature of the meta-heuristic algorithms, ten runs are carried out for each situation to assess the technique's durability and its findings for path length. For all situations, the hybrid algorithms' parameters and via-point velocity are described in Table 2. The simulations are run in MATLAB (R2016a) on a Windows 10 computer with an Intel(R) Core (TM) i7-1165G7 @ 2.80 GHz and 8 GB RAM.

In the first scenario, the quadcopter will travel from the take-off point (110, 73, 0) to the landing point (340, 370, 19.5). The algorithm will be tested to find the shortest path with a few obstacles directly in the path, the take-off point is located on the ground, and the landing point is located on a building.

Table 2. FPA-GA algorithm parameter values and via points velocity.

No.	Parameter name	Values
1	Population size (N)	40
2	Number of generations (T)	200
3	Number of variables	9
4	Switch probability ( $\rho$ )	0.2
5	Mutation	0.4
6	Crossover	0.1
7	Lower band for (x, y) axis	0 m
8	Lower band for z-axis	5 m
9	Upper band for x-axis	560 m
10	Upper band for y-axis	410 m
11	Upper band for z-axis	40 m m
12	Velocity at each via point	3 m/s

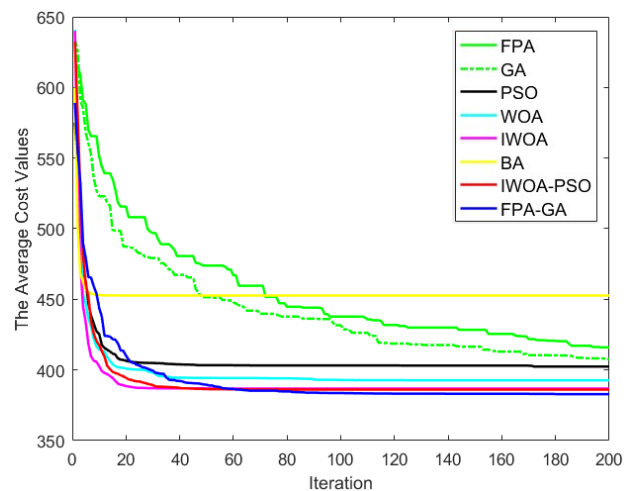


Figure. 7 The Average cost value performance for algorithms at first scenario

The FPA-GA algorithm's best-achieved distance is 381.350 m, with a mean value equal to 382.826 m and a 0.8744 standard deviation value. While the best value for each of the GA, FPA, BA, PSO, WOA, IWOA, and IWOA-PSO is 392.621, 397.831, 395.369, 385.816, 381.847, 381.833, and 381.914, respectively, as shown in Table 3. The proposed algorithm finds the shortest path length in the first scenario without collision and achieves the best performance for each best, mean, worst, and standard deviation value. Fig. 7 shows the convergence of the average cost value with iteration numbers, where the hybrid FPA-GA identified two polynomials via points, respectively, (134.406, 82.084, 7.701) and (238.715, 229.630, 24.229) that gave the shortest path length between the take-off and landing places with avoidance of collisions as shown in Fig. 8.

In the second scenario, the quadcopter's travel from the take-off point (110, 73, 0) to the landing point (495, 150, 0) will be examined. In this scenario, the algorithms will be tested to find the optimal path

Table 3. The simulation results for the first scenario.

Starting point	(110,73,0)			
Target point	(340, 370, 19.5)			
Items	Best	Mean	Std.	Worst
Algorithm				
GA	392.621	407.666	12.935	434.506
FPA	397.831	415.961	11.266	436.069
BA	395.369	452.699	35.736	523.486
PSO	385.816	402.397	12.255	423.750
WOA	381.847	392.706	16.708	438.789
IWOA	381.833	386.764	7.231	403.981
IWOA-PSO	381.914	386.068	8.462	409.612
FPA-GA	<b>381.350</b>	<b>382.826</b>	<b>0.8744</b>	<b>384.120</b>

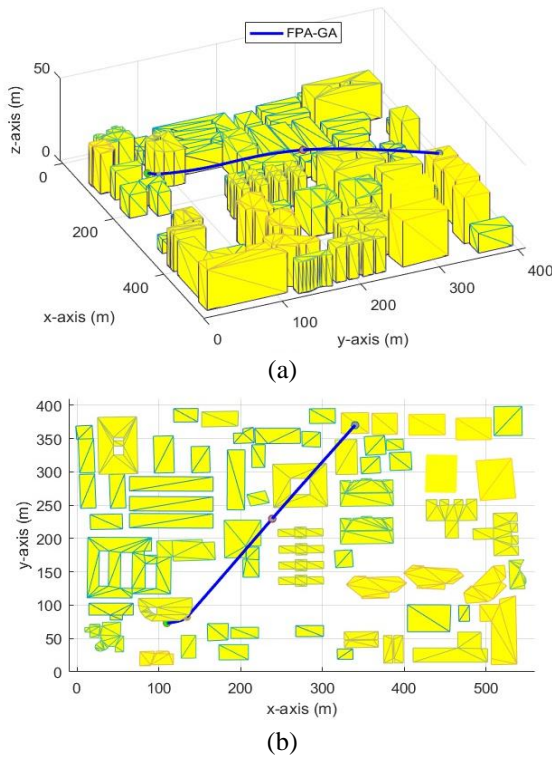


Figure 8 The best path planning of the quadcopter for the first scenario: (a) 3D view, and (b) Top view

with some obstacles directly in the path; and both the take-off and landing points will be located on the ground. As simulated in the second scenario shown in Fig. 9, the hybrid FPA-GA is finding the collision-free and shortest quadcopter path, which is defined by a sequence of polynomial via points (120.006, 74.532, 5.000) and (399.680, 106.091, 5.000) respectively, and the optimal path length is 397.349m, the mean value is 397.929, and the standard deviation value equal to 1.402 as explained in Table 4.

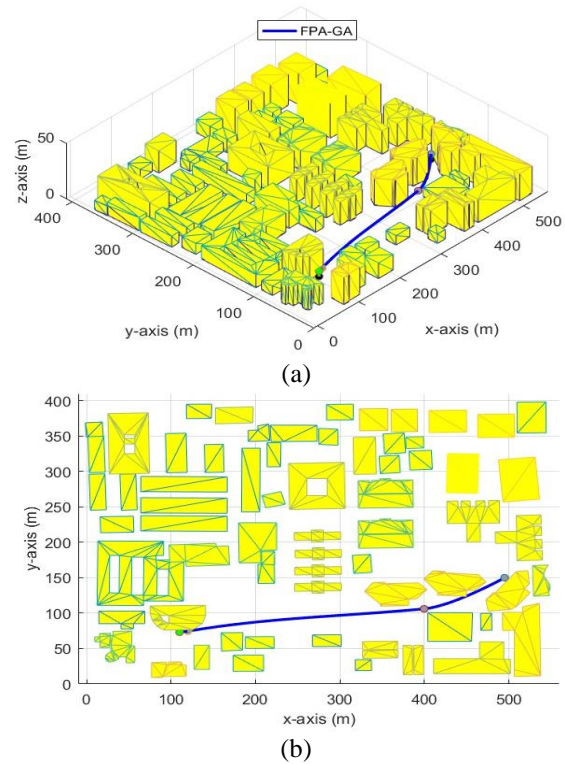


Figure 9 The path planning of the quadcopter for the second scenario: (a) 3D view, and (b) Top view

Table 4. The simulation results for the second scenario.

Starting point	(110,73,0)			
Target point	(495, 150, 0)			
Items	Best	Mean	Std.	Worst
Algorithm				
GA	399.085	407.509	5.613	414.606
FPA	401.617	414.769	8.680	427.392
BA	442.739	515.232	53.783	616.678
PSO	399.911	415.576	11.560	438.927
WOA	397.975	411.846	19.554	446.224
IWOA	397.763	415.353	16.790	452.902
IWOA-PSO	397.953	411.601	22.774	470.310
FPA-GA	<b>397.349</b>	<b>397.929</b>	<b>1.402</b>	<b>401.893</b>

In contrast to previous algorithms, the hybrid FPA-GA was able to find the shortest route with the fewest iterations, as seen in Fig. 10's convergence of the average cost value with iteration numbers.

The third scenario involves finding the optimal 3D path for a quadcopter with a take-off point at (50, 330, 0) and a landing point at (495, 150, 0). In this scenario, the simulation will test the algorithms' ability to find the shortest path that is collision-free when there are many direct obstacles between the take-off and landing points.



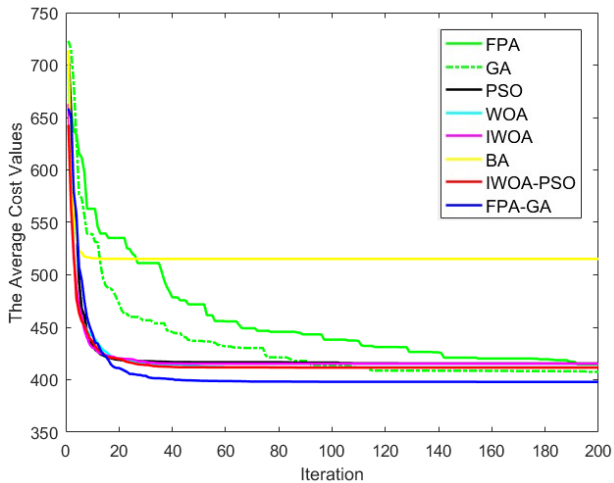


Figure. 10 The Average cost value performance for algorithms at second scenario

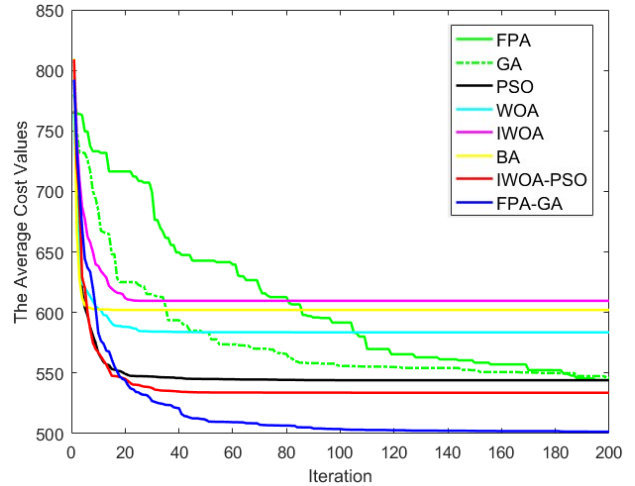


Figure. 12 The Average cost value performance for algorithms at third scenario

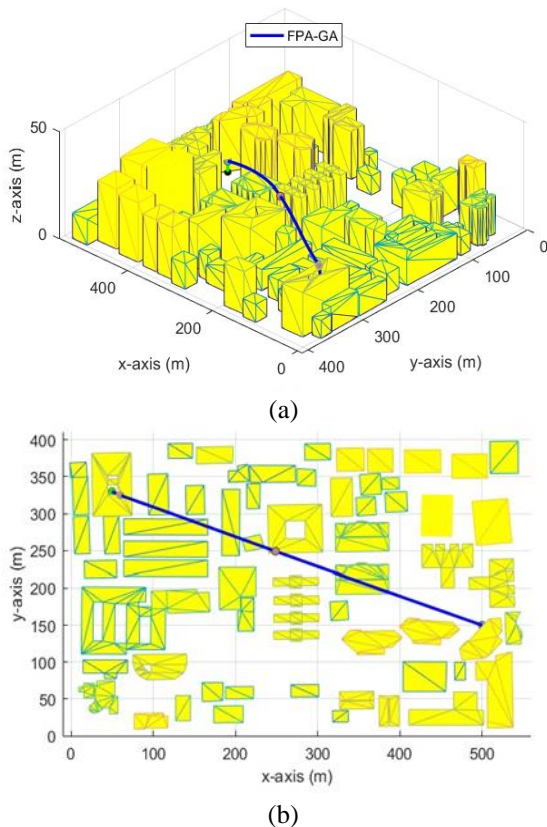


Figure. 11 The path planning of the quadcopter for the third scenario: (a) 3D view, and (b) Top view

The starting point is located on the ground and surrounded by obstacles from all directions, while the target point is also located on the ground. At the third scenario simulation, the hybrid FPA-GA found two via points that gave the shortest path (496.215m) with no collision; they are defined in sequence, respectively, as (60.089, 324.757, 22.394) and (248.948, 248.948, 26.671) as shown in Fig. 11 and

Table 5. The simulation results for the third scenario

Starting point	(50, 330, 0)			
Target point	(495, 150, 0)			
Items	Best	Mean	Std.	Worst
Algorithm				
GA	523.793	546.058	18.536	580.660
FPA	513.541	544.219	20.985	588.611
BA	553.403	602.094	36.382	665.597
PSO	496.585	544.052	31.899	594.325
WOA	499.706	583.590	51.981	665.477
IWOA	580.408	609.646	22.625	653.311
IWOA-PSO	502.483	533.750	23.451	571.217
FPA-GA	<b>496.215</b>	<b>501.485</b>	<b>4.376</b>	<b>508.598</b>

12. While the mean, standard deviation, and worst values are (501.485, 4.376, and 508.598) respectively, they are the best achieved values compared with other algorithms as shown in Table 5.

The proposed algorithm will be tested in the fourth scenario, where the quadcopter will move from the starting point (45,60,12.5) to the target point (272,278,0), which is on the ground and surrounded by obstacles on all sides. In this scenario, the start point is located on a building and the target point is on the ground. Table 6 shows that the suggested hybrid algorithm with length (321.998) achieves the best-formed route and that the founded polynomial midway points are (104.44, 116.947, 21.857) and (258.698, 264.171, 21.857), as shown in Figs. 13 and 14. Additionally, the suggested technique outperformed competing algorithms for mean, standard, and worst values in each case.

Finally, the proposed algorithm will be tested in the fifth scenario, which involves a quadcopter

Table 7. The simulation results for the fourth scenario

Starting point	(45,60,12.5)			
Target point	(272,278,0)			
Items	Best	Mean	Std.	Worst
Algorithm				
GA	336.546	358.447	23.760	418.607
FPA	332.926	362.948	19.535	403.213
BA	367.721	412.605	22.885	444.743
PSO	326.074	356.650	23.394	406.512
WOA	335.273	385.527	34.845	441.306
IWOA	352.539	390.395	20.765	413.766
IWOA-PSO	323.577	330.526	8.350	351.650
FPA-GA	<b>321.998</b>	<b>324.265</b>	<b>1.421</b>	<b>327.312</b>

Table 8. The simulation results for the fifth scenario

Starting point	(50,330,0)			
Target point	(272,278,0)			
Items	Best	Mean	Std.	Worst
Algorithm				
GA	286.274	349.061	48.126	447.963
FPA	284.698	321.000	20.790	351.730
BA	341.640	406.177	35.017	450.693
PSO	260.908	338.949	60.138	474.363
WOA	326.858	393.113	62.307	545.543
IWOA	337.474	402.209	56.977	523.746
IWOA-PSO	268.254	330.004	52.303	419.140
FPA-GA	<b>250.370</b>	<b>261.106</b>	<b>5.665</b>	<b>271.320</b>

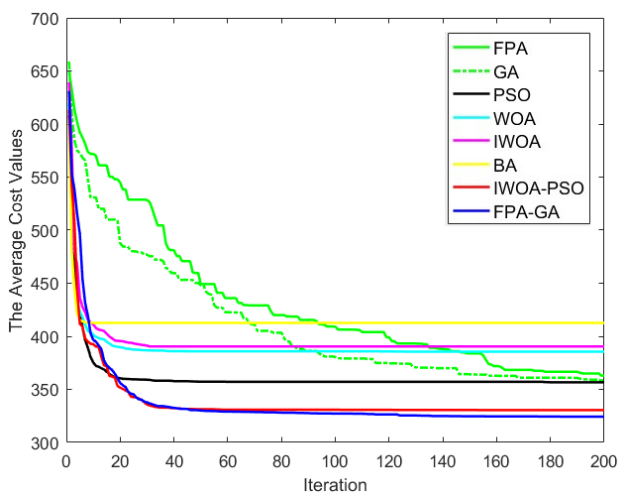


Figure. 13 The Average cost value performance for algorithms at fourth scenario

traveling from the starting point (50,330,0) to the target point (272,278,0). In this scenario, both the starting point and the target point are on the ground and are surrounded by obstacles on all sides. According to the findings in Table 8, even though the scenario is complex, the proposed hybrid FPA-GA algorithm outperformed all other algorithms and discovered the best path, measuring 250.370 m in length. The established polynomial midway points are (63.843, 325.199, 26.181) and (251.893, 284.309, 26.181), as shown in Figs. 15 and 16.

The results show that the suggested hybrid FPA-GA algorithm increased the quadcopter's effectiveness in path planning. The suggested hybrid algorithm is better than all other algorithms that were compared to it, as shown by the percentage of path mean value enhancement acquired in Table 9, and we observe that the improved values are raised in more difficult situations.

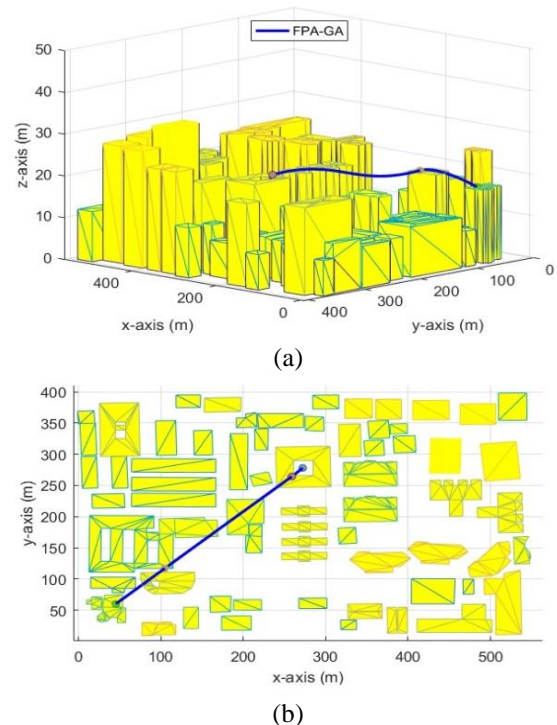


Figure. 14 The path planning of the quadcopter for the fourth scenario: (a) 3D view, and (b) Top view

Table 9. The improved FPA-GA percentage of mean path length in variable situations

Scenario No.	1 <sup>st</sup> (%)	2 <sup>nd</sup> (%)	3 <sup>rd</sup> (%)	4 <sup>th</sup> (%)	5 <sup>th</sup> (%)
Algorithm					
GA	6.5	2.4	8.9	10.5	33.6
FPA	8.7	4.3	8.5	11.9	23.1
BA	18.3	29.5	20.1	27.2	55.5
PSO	5.1	4.4	8.5	9.9	29.8
WOA	2.6	3.5	16.4	18.9	50.5
IWOA	1.03	4.4	21.5	20.4	53.9
IWOA-PSO	0.85	3.4	6.4	2.2	26.4

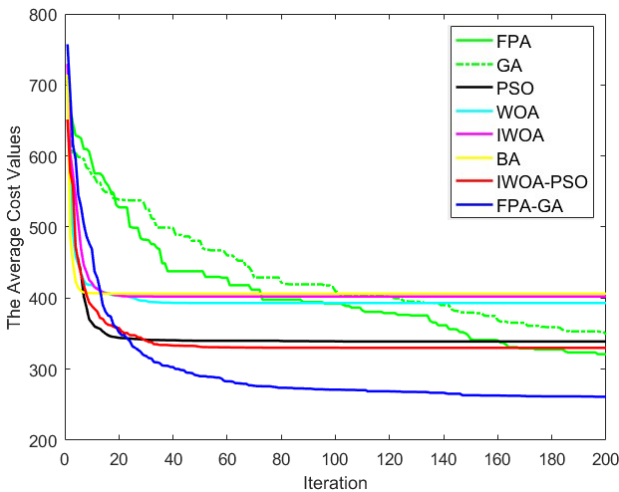


Figure. 15 The Average cost value performance for algorithms at fifth scenario

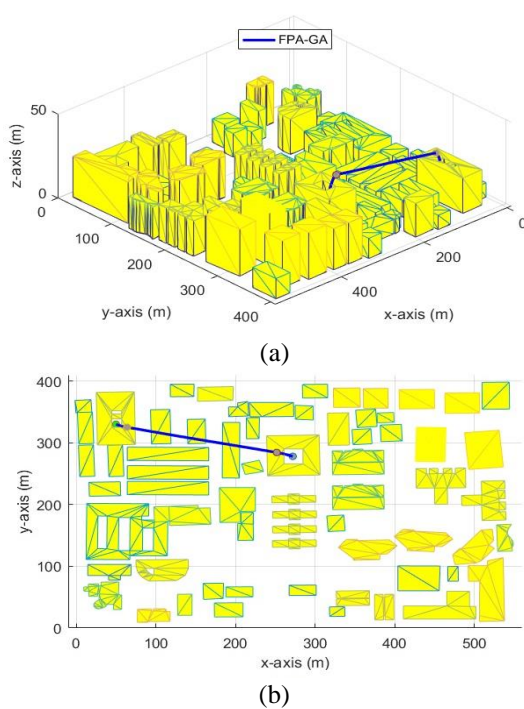


Figure. 16 The path planning of the quadcopter for the fifth scenario: (a) 3D view, and (b) Top view

#### 4. Conclusion

This research offers a novel hybrid FPA-GA algorithm that is inspired by artificial pollination in order to identify an off-line optimum 3D route plan with collision avoidance in a realistic, known 3D environment (University of Technology, Baghdad, Iraq). The cubic polynomial with two via points is used to represent the path to give the quadcopter more freedom in collision avoidance over the shortest distance. We chose five trip scenarios for the quadcopter in order to evaluate the performance of a hybrid FPA-GA and compare its performance with

seven algorithms named (GA, FPA, BA, PSO, WOA, IWOA, and IWOA-PSO). The comparison is based on four parameters: path length, mean path length, standard deviation, and worst path. According to the findings, the shortest quadcopter path length in all scenarios is found by a hybrid FPA-GA with collision avoidance in all trails. At the same time, the other algorithms do not reach the best solution and fall into local optimal for all scenarios at the same iteration.

In terms of the mean path length, the proposed FPA-GA algorithm enhanced the mean path length compared with other algorithms. The proposed hybrid algorithm with GA improves by 2.4% in the second scenario and up to 33.6% in the fifth scenario, while improving the FPA based on percentage mean path length from 4.3% to 23.1% in variable scenarios. The largest enhancement is with BA, where the enhancement percentage range is from 18.3% to 55.5%. while the PSO, WOA, IWOA, and IWOA-PSO enhanced ranges are (4.4–29.8%), (2.6–50.5%), (1.03–53.9%), and (0.85–26.4%), respectively.

When we compared the proposed algorithm's standard deviation to that of other algorithms, we discovered that it had the lowest value, ranging from 0.87 to 5.66 for all five scenarios.

On the other hand, the worst cost values for the algorithms were compared, and the proposed algorithm's lowest worst value was found to be closest to the best length in all scenarios, whereas other algorithms' worst values are so far from the best values that the algorithms fall into local optimality in some cases.

We can conclude that the hybrid FPA-GA has the strong capacity to determine an ideal route in a realistic, known 3D environment from the take-off point to the landing point without colliding in both simple and difficult situations. where the proposed algorithm is successful in striking a balance between exploitation and exploration operations and preventing the algorithm's performance from falling below the local optimal. Additionally, the small values of standard deviation in all tested scenarios guaranteed that the optimal safe path would be found in each trial.

#### Nomenclature

$t$	Time (s)
$x, y, z$	Axis coordinates (m)
$v_x$	The velocity component on x-axis (m/s)
$v_y$	The velocity component on y-axis (m/s)
$v_z$	The velocity component on z-axis (m/s)
$a_0, a_3$	Trajectory equation coefficients for x-axis
$b_0, b_3$	Trajectory equation coefficients for y-axis

$c_0: c_3$	Trajectory equation coefficients for z-axis
$L_p$	Path length (m)
$P_0$	Punished value
$A$	The variables solution
$g^*$	The best solution
$\rho$	Switch probability
L	Lévy flight
R	Random number $\in [0,1]$
S	Step length
$\Gamma(\lambda)$	Standard gamma function
$\lambda$	Scaling parameter
$\epsilon$	Random number in $[0,1]$

### Conflicts of interest

The authors declare no conflict of interest.

### Author contributions

The conceptualization and validation were done by Abbas A. Kareem, Bashra K. Oleiwi, and Mohamed J. Mohamed. The methodology, software, formal analysis, and writing were contributed by Abbas A. Kareem, where the investigation was done by both Abbas A. Kareem and Mohamed J. Mohamed, and the supervision was done by both Bashra K. Oleiwi and Mohamed J. Mohamed.

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