








# UAV Smart Navigation: Combining Delaunay Triangulation and the Bat Algorithm for Enhanced Efficiency

Akshya Jothi<sup>1</sup> , M. Sundarrajan<sup>1</sup> , R. Gayana<sup>2</sup> ,  
and Seifedine Kadry<sup>3,4,5</sup>  

<sup>1</sup> SRM Institute of Science and Technology, Chennai, India  
akshyaj@srmist.edu.in

<sup>2</sup> K. Ramakrishnan College of Engineering, Tiruchirappalli, India

<sup>3</sup> Department of Applied Data Science, Noroff University College,  
Kristiansand, Norway  
skadry@gmail.com

<sup>4</sup> Artificial Intelligence Research Center (AIRC), Ajman University,  
Ajman 346, United Arab Emirates

<sup>5</sup> Department of Electrical and Computer Engineering,  
Lebanese American University, Byblos, Lebanon

**Abstract.** In the realm of unmanned aerial vehicles (UAVs), path planning is crucial. The objective is to create a safe, practical, and optimum flight route for UAVs to fly across unfamiliar terrain while avoiding obstacles. Because of their high computational complexity and inability to handle changing surroundings, traditional route planning algorithms confront hurdles in real-world applications. As a result, academics have created many sophisticated ways to handle UAV route planning challenges. This research provides a unique technique for intelligent UAV route planning. The program first divides the research region using the Delaunay Triangulation method. After obtaining the partitions, the coverage points are located, and the issue is framed as the Traveling Salesperson Problem (TSP). The Bat Optimization Algorithm (BOA) is used to find an optimum route for the TSP. The suggested technique seeks to find the best route for UAVs in dynamic situations. The suggested approach was verified by comparing it to other existing algorithms. The findings demonstrate that the suggested method can construct an optimum route that meets all requirements while avoiding obstacles. Moreover, the method may swiftly identify a new route as the environment changes. The study findings show that the suggested approach beats the other techniques in total computing time, saving roughly 0.03 s. Moreover, the suggested technique reduces the UAV's route by around 0.02 cm, substantially improving existing algorithms.

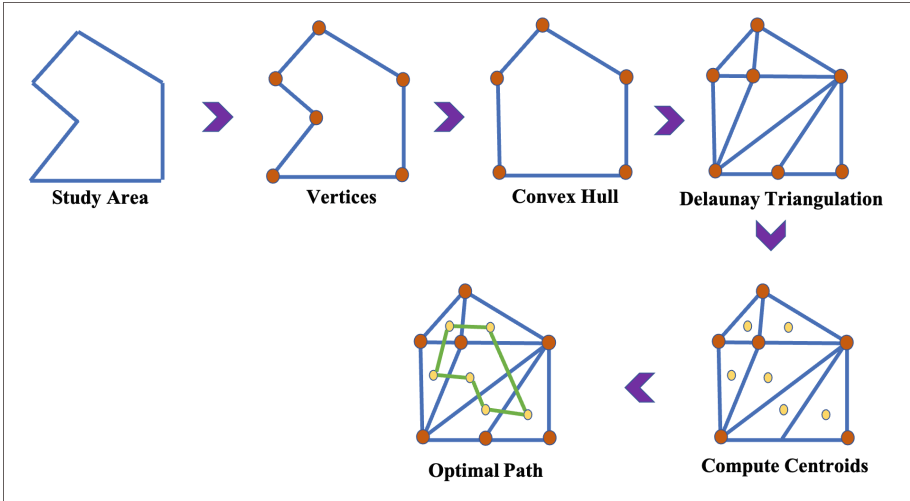
**Keywords:** Path Planning · Intelligent UAVs · Bat Optimization · Delaunay Triangulation · Area Partitioning · Convex Hull

## 1 Introduction

Unmanned Aerial Vehicles (UAVs), commonly known as drones, are aircraft that fly remotely without the presence of a human pilot. UAVs may be outfitted with a broad range of sensors and cameras, making them ideal for anything from military reconnaissance and surveillance to search and rescue missions, disaster relief, and agricultural monitoring. Aerial photography and videography are examples of how they may be utilized for entertainment. UAVs are getting more sophisticated as technology progresses, capable of autonomous flying and difficult tasks such as obstacle avoidance and course planning.

UAVs, or unmanned aerial vehicles, may be used with CPP to optimize flight patterns and boost efficiency. CPP entails determining the quickest and most direct path to a location while considering topography, weather, and barriers into consideration. By employing CPP, UAVs can traverse difficult surroundings and achieve their goals swiftly and securely. UAVs may use CPP in various ways, including real-time mapping and route planning. Swarm intelligence, which includes coordinating the motions of several UAVs to accomplish a shared objective, is another method that UAVs might employ CPP. Swarm intelligence may enhance efficiency and lessen the danger of collision or other incidents by applying algorithms to optimize the flight paths of each UAV.

In this study, we used Bat optimization (BO) to solve the CPP issue for intelligent UAVs. BO is a metaheuristic algorithm inspired on bat echolocation behavior that may be used to address the critical path planning (CPP) issue for unmanned aerial vehicles (UAVs). CPP seeks the shortest and most efficient route between two places while accounting for numerous limitations such as obstructions, topography, and weather conditions. The BO method employs a population of bats that alter their location and velocity by criteria to find the best answer. The bats communicate with one another and modify their behavior depending on the results of prior searches. This enables them to effectively traverse the search space and arrive at a near-optimal answer. To apply BO to the CPP issue for UAVs, the method is updated to consider the problem's special restrictions, such as the requirement to avoid obstacles or travel over difficult terrain. The bats are depicted as unmanned aerial vehicles (UAVs), and their locations and speeds are modified depending on environmental data acquired by sensors and cameras on board. The BO method is used to develop a series of optimum UAV pathways, which are then assessed and compared to determine the most efficient and effective route. UAVs can navigate through difficult surroundings and reach their goals swiftly and securely by employing BO to solve the CPP issue, making them a useful tool for a broad variety of applications. BO is a successful method for addressing the CPP issue for unmanned aerial vehicles, providing a viable solution for real-world applications. Figure 1 depicts the general architecture of the suggested technique.



**Fig. 1.** Architecture Diagram.

## 2 Literature Review

Many exciting strategies are being developed by writers worldwide to discover the ideal route for an Intelligent UAV. As the utilization of unmanned aerial vehicles (UAVs) grows, so do the applications for which they are used. [1] discusses recent advancements and future potential for using UAVs in the cryosphere. The article shows how, because to their high geographical and temporal resolutions, unmanned aerial vehicles (UAVs) are becoming a useful tool for exploring the cryosphere. Fan, B. et al. in [2] provide an in-depth examination of the development and present applications of unmanned aerial vehicle (UAV) technology. It encompasses everything from the airframe and motor system to the sensors on the UAV. This article also discusses the current and potential applications of unmanned aerial vehicles (UAVs) in agriculture, construction, and surveying. The author of [3] outlines how UAVs may be utilized effectively in various industries such as agriculture, mining, SAR, and environmental monitoring. The author of [4] investigates the viability of utilizing unmanned aerial vehicles (UAVs) and artificial intelligence (AI) in the mining industry. The article discusses the advantages of employing unmanned aerial vehicles (UAVs) with sensors and cameras for geological mapping, mineral exploration, and mine monitoring.

As a first step in finding an ideal route, the flight region must be divided into several divisions so that the CPP algorithms may be easily deployed. McLaughlin et al. proposed in [5] utilizing an immunity-based approach to evaluate whether or not a UAV's sensors and actuators are malfunctioning. Acevedo et al. [6] provide a successful distributed area division technique in their study to support cooperative monitoring applications using many UAVs. Luna et al. propose a

rapid multi-UAV path planning technique to get the highest possible coverage in aerial sensing applications [7]. Priyadarsini et al. [8] provide a computational geometric technique for route planning for intelligent UAVs in their research. This approach provides a route planning algorithm employing a Voronoi diagram and Delaunay triangulation that can work in difficult environments while ensuring complete coverage.

Different efforts are also being made to determine the best route for UAVs. The authors offer an overview of how AI has been used to determine paths for groups of unmanned aerial vehicles in [9]. (UAVs). The writers stress the practicality of these tactics and explore their advantages and disadvantages. Akshya et al [10] describe a graph-based route planning algorithm for UAVs utilized for area coverage. This approach enhances route planning by segmenting the area into grids and using graph theory ideas.

Certain route-planning algorithms employ evolutionary algorithms in very particular ways. Priyadarsini et al. demonstrate how to apply evolutionary algorithms for efficient and effective UAV route planning [11]. The approach enhances overall route planning using evolutionary algorithms to discover the shortest path across each part. Gul et al. [12] propose a meta-heuristic optimization approach to solve the issues of multi-objective route planning for autonomous guided robots. The technique combines particle swarm optimization, grey wolf optimization, and evolutionary programming to optimize route planning while reducing parameters like energy consumption, path length, and collisions. Song et al. [13] provide an improved particle swarm optimization approach for smooth route planning of mobile robots using a continuous high-degree Bezier curve. Yahia et al. [14] use meta-heuristic tools to explore path-planning optimization for UAVs in detail. Malyshev et al. propose using evolutionary optimization approaches to synthesize trajectory planning algorithms [15]. The method uses evolutionary algorithms to fine-tune the parameters of the planning algorithm, resulting in more effective trajectory planning. Overall, the articles in this collection provide a broad range of techniques to enhance UAV route planning via AI, optimization algorithms, and segmentation methods. These strategies are intended to improve the utility, performance, and security of UAVs in various situations.

### 3 Solving Coverage Path Planning Problem

When it comes to deploying UAVs in real-time applications, one of the most crucial restrictions is the solution of CPP. It is critical for unmanned aerial vehicles (UAVs) to find the shortest route for numerous reasons. For starters, it enables the UAV to finish its task more quickly, saving time and energy. This is particularly crucial in applications like search and rescue, surveillance, and inspection when the UAV must cover a big area quickly. Second, determining the shortest route reduces the likelihood of an accident or collision with a barrier, such as a building or a tree. The UAV may avoid needless diversions or obstructions by choosing the most direct path, lowering the risk of damage or harm. Finally, selecting the shortest route may increase the UAV's battery life, a significant factor for battery-powered UAVs. The UAV can preserve energy and remain in the

air for extended periods by selecting the most efficient path, expanding its range, and minimizing the need for regular recharging. The following sub-sections will go through the numerous procedures we took in this research to solve the CPP issue successfully.

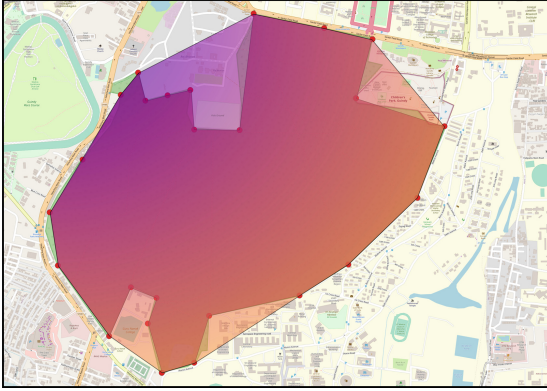
### 3.1 Area Partitioning - Delaunay Triangulation

We explored building a polygon with random coordinates as vertices as a starting step to discover an optimum route by solving the CPP problem. This polygon will be used as the region of investigation for the suggested algorithms. The procedure is picking random coordinates inside the flight space and linking them to form a polygon with the randomly chosen locations as vertices. Figure 2 depicts the randomly chosen vertices. This polygon acts as the UAV's flight path's border, and the UAV will fly inside it while avoiding any obstacles or no-fly zones. This strategy may be effective when the flying environment is complicated and creating a precise flight plan is challenging.

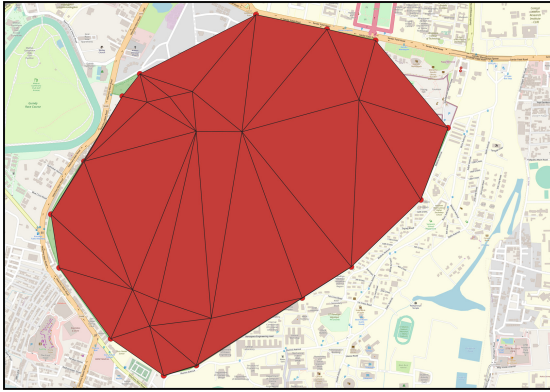


**Fig. 2.** Selection of Vertices.

After selecting random coordinates as vertices, we constructed a convex hull using the Graham Scan technique to improve route planning for UAVs further. The Graham Scan technique is a well-known approach for calculating the convex hull of a collection of points in a plane [26]. By using the Graham Scan technique to build a convex hull, the final form is a polygon with a minimum perimeter that encompasses all of the randomly picked vertices, as illustrated in Fig. 3. This is particularly advantageous when the vertices are not uniformly distributed, since it creates a smoother and more efficient route for the UAV to follow. After constructing a convex hull, the next step we have adopted for area partitioning is the application of Delaunay triangulation [27], as seen in Fig. 4.



**Fig. 3.** Convex Hull - Study Area.



**Fig. 4.** Delaunay Triangulation - Study Area.

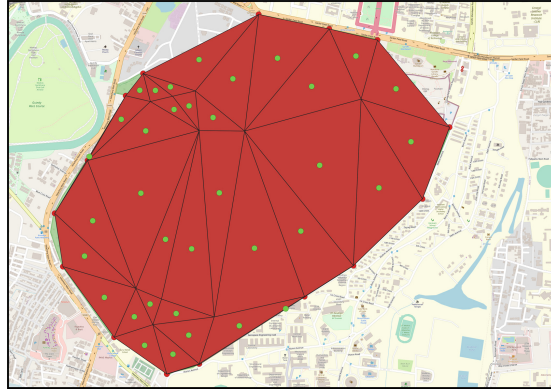
The circumcircle of each triangle in the Delaunay triangulation has no additional points in its interior, which is one of its important features. This attribute may be stated numerically using the triangle circumcircle equation:

$$(x - m)^2 + (y - n)^2 = rad^2 \quad (1)$$

where  $(x, y)$  are the coordinates of a point,  $(m, n)$  are the coordinates of the triangle's circumcenter, and  $rad$  is the circumcircle's radius. Delaunay triangulation, in the context of UAV route planning, may assist in discovering possible areas of interest or risks inside the flight space by creating a precise network of triangles linking the randomly generated vertices. This is particularly important when the flying environment is complicated or has many obstacles, as it may assist in identifying regions where the UAV should avoid or pay special attention.

### 3.2 Computation of Coverage Points

The next stage is to find the coverage spots after partitioning the region. As the covering point in the suggested method, we calculated the centroids for each triangle. Figure 5 shows the computed centroids for the partitioned region.



**Fig. 5.** Centroids - Delaunay Triangulation.

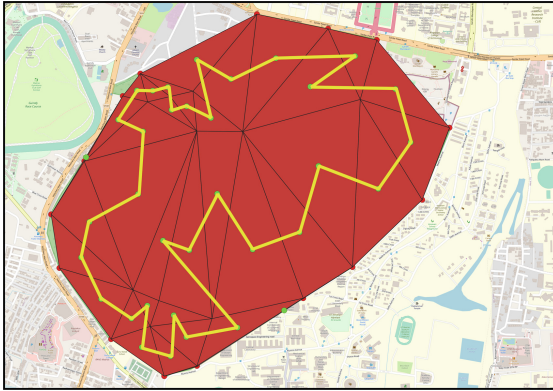
The centroid of a triangle is the point at where the triangle's three medians connect, and it may be computed using the formula below:

$$Cent = (M + N + P)/3 \quad (2)$$

where Cent is the centroid and M, N, and P are the coordinates of the triangle's vertices. The centroids may be utilized as possible UAV waypoints. After we have the centroids, we can rename the issue the Traveling Salesperson Problem (TSP), which can be solved using any evolutionary technique. We used the Bat optimization technique in our suggested study.

### 3.3 Solving TSP - Bat Optimization

The Traveling Salesman Problem (TSP) entails determining the shortest route that visits a set of cities and returns to the originating location. In our proposed work, we assume the coverage point to be a city, and the UAV must visit every calculated centroid. Bat optimization is a metaheuristic optimization technique based on bat echolocation activity. The calculated route using BOA is shown in Fig. 6.



**Fig. 6.** Convex Hull - Study Area.

To solve TSP using Bat optimization through the centroids of Delaunay triangulation, we can follow these steps:

1. Generate a set of points representing the cities that must be visited.
2. Define the objective function to be the total distance traveled during the tour, which is the sum of the distances between consecutive centroids in the tour.
3. Initialize a population of bat solutions, each representing a potential city tour.
4. For each bat solution, calculate its fitness value (i.e., the total distance traveled during the tour) using the objective function.
5. While the stopping criteria are not met, perform the following steps:
  - (a) Generate a new solution by adjusting the bat's position based on its current position and velocity.
  - (b) Evaluate the fitness of the new solution.
  - (c) Update the position and velocity of the bat based on the current and new solutions.
  - (d) If the new solution has a better fitness value than the current solution, replace the current solution with the new solution.
6. Return the best solution found as the solution to the TSP.

We may limit the number of cities to examine and simplify the issue by utilizing the centroids of the Delaunay triangulation as prospective cities to visit. Moreover, bat optimization is well-suited to handling combinatorial optimization problems like TSP, and it can often discover high-quality solutions in a reasonable period.

## 4 Experimental Results

The experimental results were obtained from QGIS. In the first stage, polygon geometries were taken and their values, such as area and perimeter, were calculated. Table 1 summarizes some of them.



**Table 1.** Polygon Geometries.

ID	Area	Perimeter
1	0.000231	0.078581
2	0.000354	0.084567
3	0.000476	0.092546
4	0.000598	0.097834
5	0.000673	0.099361

After obtaining the convex hull for the vertices chosen, the area and perimeter of the polygon were computed again, and various ID examples are presented in Table 2. According to both tables, even if the overall area to be covered increases when using the convex hull approach, the perimeter that the UAV must travel is lowered while simultaneously lowering the number of vertices. This might allow the UAVs to travel as little as possible inside the research region.

**Table 2.** Convex Hull Geometries.

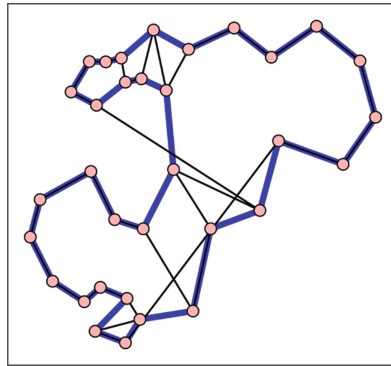
ID	Area	Perimeter
1	0.000246	0.078531
2	0.000367	0.084524
3	0.000489	0.092529
4	0.000612	0.097820
5	0.000682	0.099317

After the geometries are determined, we must apply the Delaunay Triangulation to the acquired area and compute the centroids for each division. The centroids serve as coverage points, which are then utilized to pose the issue as a TSP. We calculated the distance matrix for the centroids before solving the TSP, and a few of them are shown in Table 3. After getting the centroids, we used the Bat optimization technique to solve TSP and find the best route. Figure 7 depicts the optimum route achieved by using the suggested approach.

**Table 3.** Centroids - Distance Matrix.

InputID	TargetID	Distance
22	9	2165.882
22	2	1566.086
22	7	1862.168
22	5	1694.044
22	19	180.407
22	19	275.138
22	20	271.170
19	16	438.149
19	8	1894.559
19	22	325.767

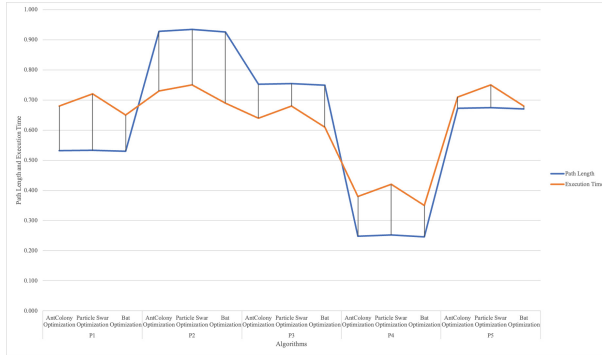
The ideal route is also compared to other known techniques such as Ant Colony and Particle Swarm optimization. Table 4 summarizes the findings for one particular polygon. We can derive the tour length and duration of travel by UAV from the table for the region partitioned and the method employed. The same procedure is followed with four more polygons, and the entire comparison analysis graph is displayed in Fig. 8.



**Fig. 7.** Optimal Path - Bat Optimization Algorithm.

**Table 4.** Comparison of paths obtained using various algorithms.

Algorithm	Path Length	Execution time
Ant Colony Optimization	0.532	0.68
Particle Swarm Optimization	0.533	0.72
Bat Optimization	0.530	0.65



**Fig. 8.** Optimal paths obtained for various polygons.

## 5 Conclusion

Unmanned aerial vehicle (UAV) path planning is a significant job in the area of robotics and autonomous systems. It entails creating a safe, practical, and optimum flight route for unmanned aerial vehicles (UAVs) to fly through new terrain while avoiding obstacles. The research provides a unique route-planning technique for intelligent unmanned aerial vehicles (UAVs). The method uses Delaunay Triangulation, the Traveling Salesperson Problem (TSP), and the Bat Optimization Algorithm (BOA) to determine an ideal flight route for unmanned aerial vehicles (UAVs) in dynamic situations while avoiding obstacles. The performance of the proposed method was verified by comparing it to other existing algorithms, and the findings demonstrate that it beats other algorithms in terms of total computing time and route length traveled by the UAV. Moreover, the suggested method can swiftly discover a new route as the environment changes. Because of the large savings in computing time and route length followed by the UAV, the technique provides a possible solution to path planning challenges for intelligent UAVs. According to the analysis findings, the suggested approach outperforms other current algorithms in terms of calculation time by roughly 0.03 s. Moreover, as compared to existing methods, the suggested technique considerably improves the route traveled by the UAV by reducing it by around 0.02 cm. Further study may be conducted to investigate its applicability in other connected sectors and improve its performance.

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