

UAV Path Planning Based on Butterfly Optimization Algorithm in Three-Dimensional Space

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ABSTRACT

The BOA is a novel optimization algorithm, which is inspired by the butterfly and enables the searching for the best solutions in a respective search area. The algorithm can be set to targeted goals like the amount of distance needed to cover, or/and the presence of an obstacle, or the completion of the particular mission objectives. I applied the BOA to generate paths of UAVs on a three-dimensional space and considered the objectives of collision urgency, energy consumption, and near-optimal path planning. Specifically for the assessment of the algorithm, I simulated the application of MATLAB and applied multiple scenarios both on two-dimensional and three-dimensional environments. I also benchmarked the BOA with two other algorithms including the Ant Colony Optimization and Particle Swarm Optimization (PSO). The results proved that the BOA performed better than the GA in terms of cost function and the time required to arrive at the optimal solution, especially in 3D solid terrain. By analyzing the simulation results, the flexibility of the BOA in a 3D environment is evident when new changes take place in the environment. Moreover, the algorithm showed rather swift reaction in terms of path acting in response to various unexpected obstacles. The proposed BOA is viable for the path planning of UAVs in three-dimensional space and effective compared to the other optimization algorithms.

Submitted: November 14, 2024

Published: January 21, 2025

 10.24018/ejcompute.2025.5.1.147

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Keywords: 3D space (3DS), Ant Colony Optimisation, Butterfly Optimization Algorithm BOA, UAV route planning.

1. INTRODUCTION

Since UAV field is quite significant in today's world and since the need to have an accurate and precise prediction of the UAV's path cannot be overemphasized, having considered earlier findings made by other researchers, we then presented the use of the Butterflies Optimization Algorithm. This is done by specifying the pre- and post-conditions, modeling the goals and risks, and embedding a set of control points for the UAV in a vector space that defines its three-dimensional path [1]. The factors considered include the total distance to be covered; some kind of genetic fitness function is also defined to check the believability of the path solution. This function takes into account factors such as obstacles on the road, the distance traveled, and the smoothness of the path traveled.

The problem of UAV path planning in three-dimensional space is challenging, given that the best path needs to be identified to prevent collision while

considering the best possible path. Classical algorithms, most of the time, cannot perform various feature analyses considering the haphazard environment [1]. The intention of this study is to design a UAV path planning technique relying upon the Butterfly Optimization Algorithm (BOA) for objectives such as shortest distance, minimum interference, and achievement of mission goals [2]. It also stresses enhancing collaboration between UAVs in highly integrated environments [3], [4].

The Butterfly Optimization Algorithm (BOA) is a nature-inspired metaheuristic algorithm that mimics the behavior of butterflies, drawing on two key aspects of their movement: in terms of the movement of one participant ('the butterfly itself') and the movement of two participants together ('two butterflies'). This algorithm is used to solve optimization problems that are experienced, especially in the real world. In BOA, the "flowers" with petals could be considered as solutions in some search space,

and they try to find the best solution by mimicking the behavior of butterflies. The algorithm is self-organizing, and the solutions approach further optimization through, for instance, butterflies changing their positions to achieve the best results. There are numerous applications of BOA for solving optimization problems, and this paper shows that it is a promising technique because of its ability to expand solution spaces and obtain accurate or near-accurate solutions [5]. Currently, it is embraced in many fields and is said to give the best solutions.

UAV path planning is best described as the creation of the correct course for an Unmanned Aerial Vehicle (UAV) or drone to fly with preference to other available paths in the space to be navigated. This process involves aspects of mission constraint, challenges, safety, and regulatory aspects that would enable UAV to accomplish its mission [6]. Path planning may be either by automation or by human commands and can be used to steer UAVs in services like surveillance, mapping, search and rescue, and precision agriculture [7].

Issues that are relevant to the systematic planning of UAVs in 3D cities [8]. Their approach identified the key of avoiding obstacles and reducing the UAV's flight time, with swarm behaviour and individual path search of BOA. To assess the versatility of the algorithm, generally experienced in unmanned aerial vehicle systems, this study was able to establish that the algorithm could quickly adapt to dynamic changes encountered. Likewise, Li and Sun (2021) proposed the BOA for the path planning of multiple UAVs in the 3D operating environment [9]. From their study, the authors were able to identify that BOA was proficient in solving issues in multi-agent systems, where UAVs collaborate towards a common goal to accomplish tasks that need coordination and at the same time, avoid an accident. The authors stated that, in manners of convergence rate and path quality, BOA was superior to other generalization of optimization techniques particularly in conditions that held dense traffic. Wang *et al.* (2022) described another application of BOA in UAV path planning in three-dimensional environments, for use with fully autonomous UAVs and partially manned UAVs [10]. Their work demonstrated that BOA was effective in a range of conditions, from mostly stable environments in which there are minor disruptions to heavily dynamic regimes in which the UAV needs to make significant corrections to its flight path due to unexpected impediments or changes in goals.

The aim of the study is to apply the BOA to generate paths of UAVs in a three-dimensional space and consider the objectives of collision urgency, energy consumption, and near-optimal path planning. Specifically for the assessment of the algorithm, I simulated the application of MATLAB and applied multiple scenarios both in two-dimensional and three-dimensional environments. I also benchmarked the BOA with two other algorithms, namely, the Ant Colony Optimization and Particle Swarm Optimization (PSO).

2. METHODOLOGY

2.1. Proposed Method

The goal of my research is to design an enhanced meta-heuristic algorithm for optimization of the UAVs' path in a third environment. It also notes that it wants to minimize the traveled distance and, most importantly, avoid, to the best of its effort, hitting objects in its course and also utilize less power.

This is done based on the use of an intelligent agent to establish the finer points in between the checkpoints along the UAV path to minimize movements and, therefore, energy consumption. The fitness function considered the distance moved, energy consumed, and collision and did not consider time.

Yet, the latter will be compared to the results obtained by applying other algorithms like Ant Colony Optimisation and Particle Swarm Optimisation in 2D and 3D simulations. The goal is to increase the UAV performance in real-world applications by finding an approximate solution which improves path efficiency and energy consumption.

2.2. Search Phase: Calculation of the Fitting Function

The algorithm has three phases: the initialization, in which I declare the objective function that I seek to maximize or minimize; the solution space; and the parameters by which the algorithm will be regulated. I also decide how many first butterflies are necessary to start the search process; I place them in the solution place and calculate their fitness by means of the objective function. When in the iteration phase, I make up fancy butterflies and start off the iterative search. The butterflies dance the solution space, assigning themselves positions closer to the best solution. The last stage of the algorithm is the cessation of finding the assessment's optimum in accordance with set conditions. During this process, the position of the butterflies is improved gradually step by step, and the constructive is built up to the better solution as per the requirement of the problem.

$$d(x, y) = (x - y)^2 \quad (1)$$

$$pl = \begin{cases} \sum_{i=1}^L i - 1 & \text{if } i = 1 \\ d(pi, pi + 1), 0, \text{ if } \dots \text{ otherwise} \end{cases} \quad (2)$$

2.3. Drone Movement

In (3), the term 'fragrance' used is the measurement of the small and density of the emitted odor while the 'sensory modal' unit is the inputs of the formative sense, that is, smell. The fitness measure deals with H describing the intensity of the stimulus, which is related to some function that inherently possesses this intensity. Last but not least, "power" describes the mode of control in the algorithms that identify differential degrees of sensitivity through the sensory form.

$$\text{fragrance} = \text{sensorymodality} \times (\text{fitness}(H))^{\text{power}} \quad (3)$$

In this framework, the "mode" means the sensor input pattern and the signal processing mechanisms to implement the form of that energy as compact as possible. The

TABLE I: SIMULATION PARAMETERS AND TECHNIQUES

Parameters	Value
Simulation environment	Matlab
Population size	100
Start point	(0, 0, 0)
End point	(40, 40, 30)
Number of test repetitions	100
The number of butterflies	50
Simulation dimensions	3D
Input type	Fixed

user can select any one of the parameters which are in the range $[0, 1]$ to control power and the selected sensory modality. These two features have a control and are significant in the stochastic evolution of the prediction rates, which, in turn, measure the control of the speed of convergence of the learning algorithm.

3. RESULTS

Ladies and gentlemen, simulation specs and approaches are critical when it comes to helping one to understand how the various components and techniques work. Depending on the context or discipline of the subject of simulation, more details may be presented, but in a general sense, the topic can be outlined as follows based on the area of simulation exercised.

In the (Table I) context of route planning in the 3D space, the proposed algorithm allows the vehicle to move through spherical obstacles and random parameters. The UAV is launched from the reference point (0, 0, 0) and establishes the connection with the REF point (20, 20, 20), with the cyclicity of 300 times. The coordinates at each iteration also give different paths, but updating the ally tends to give the best solution. The algorithm depends on randomness to select paths in preference to minimize or optimize the path taken. Finally, they have identified that an iterative process in the selection of the best path. It also shows the capability of an algorithm in changes in 3D parameters and, therefore, can effectively work in dynamic settings.

In Fig. 1, the competition results, and computer simulations were made in both 2D and 3D environments randomly as well as using the optimal parameter setting. In this assessment, path length and cost were used in defining the efficiency of the selected routes for reaching the target market. The graphs shown in Figs. 2 and 3 are three algorithms moving within a randomized 2D environment.

This enabled the comparison to reveal the procedures underpinning each algorithm's ability to generate optimal paths with minimum length and cost as the focus. Random and optimal criteria were applied to assess how the algorithms handled the obstacles and the dynamics depicting the relative merits and demerits of the two methodologies.

Fig. 2 reveals that the same notion of intermediate points applies to the basic algorithm. Fig. 3 also depicts the same point by applying the advanced algorithm. For instance, the first conventional algorithm uses one intermediate point, and the first and the second proposed

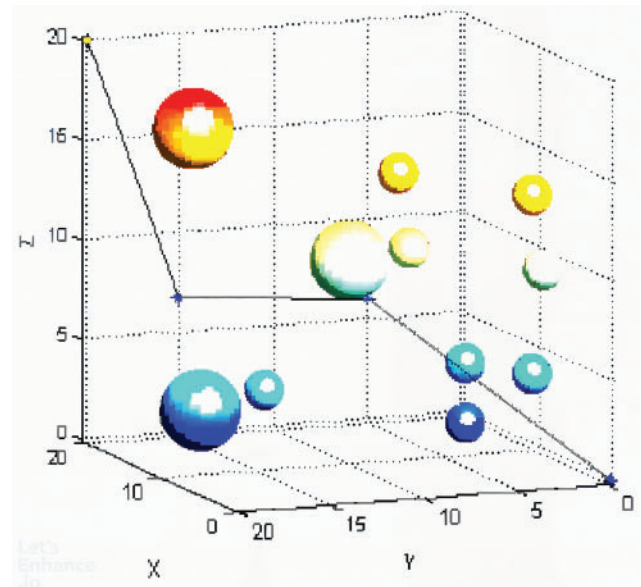


Fig. 1. Path selection.

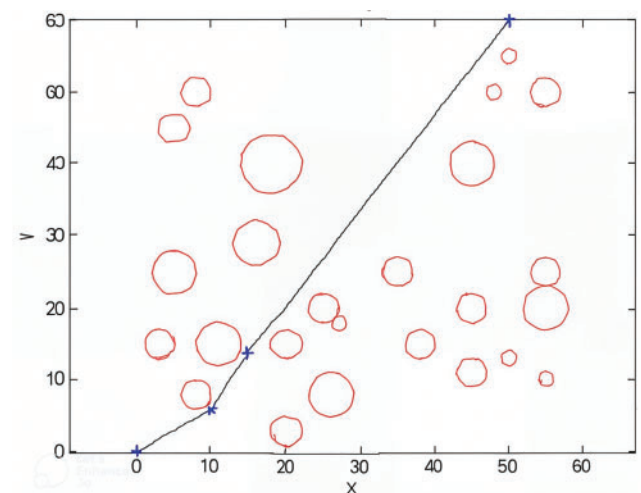


Fig. 2. The path designed by the BOA algorithm.

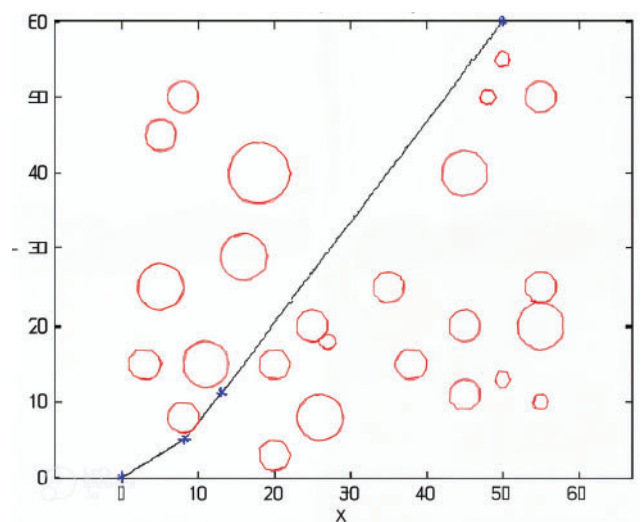


Fig. 3. The path designed by the PSO algorithm.

algorithm uses two of them, but they are located in different places. These differences are on account of the flexible

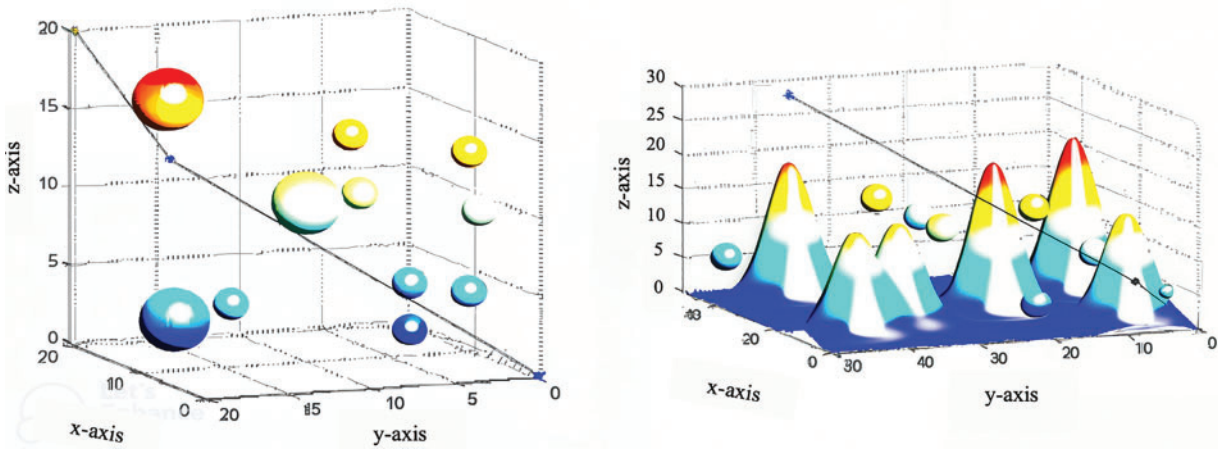


Fig. 4. The path designed by the BOA algorithm.

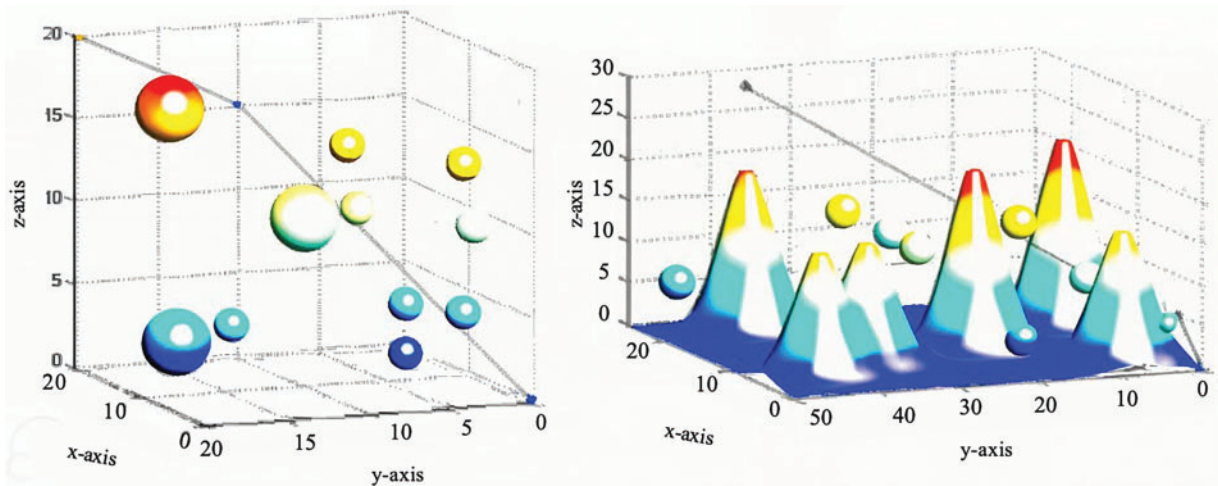


Fig. 5. The path designed by the PSO algorithm.

choices made by the algorithms on where to place intermediate points and how to manipulate the coefficients, which in turn produce different trajectories.

Figs. 4 and 5 intend to show paths in the 3D environment, which makes the paths' computational modeling more challenging since the algorithms have to work in one more dimension. These analyses help the understanding of the algorithms' working and learning characteristics in both aspects, which is manifested by the ability of path jumps to show the algorithms' ability to pick wanted parameters. It proves the algorithms to be better in flexibility as well as working performance as compared to other methods.

The generation curves presented in (Fig. 6) indicate the behaviour of the cost path function and the optimal places determined with the use of the PSO and BOA algorithms in 2D and 3D models. This performance characterization stresses the synchronous dissimilarities of these algorithms. For instance, in the 2D environment, the efficiency of the algorithm rises up to 250 percent after 15 trials after which the cost slightly oscillates. However, from (Fig. 7) we can see that the PSO algorithm converges much more slowly than the two other algorithms, and it may take more steps in order to achieve a similar level of efficiency.

The analysis suggests that the BOA algorithm achieves lower costs with fewer iterations compared to the PSO

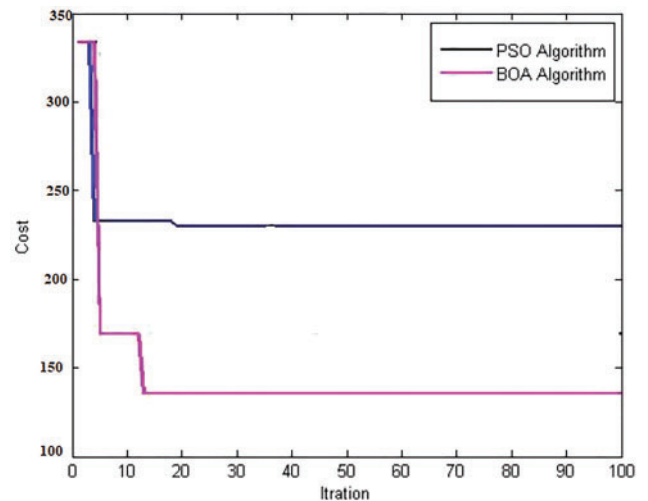


Fig. 6. Cost convergence curve in 2D space with random parameters.

algorithm. In 3D space, BOA stabilizes at an average cost of 230 units after 32 iterations, while PSO reduces the cost from 300 to 290 in the first 10 iterations and then remains relatively stable. Additionally, parameter optimization, such as through greedy algorithms, significantly reduces costs. As shown in Fig. 7, tuning parameters clearly enhance algorithm performance, underscoring the

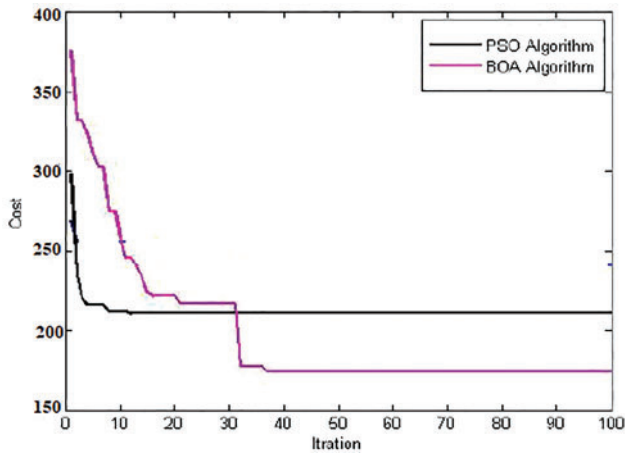


Fig. 7. Cost convergence curve in 3D space with random parameters.

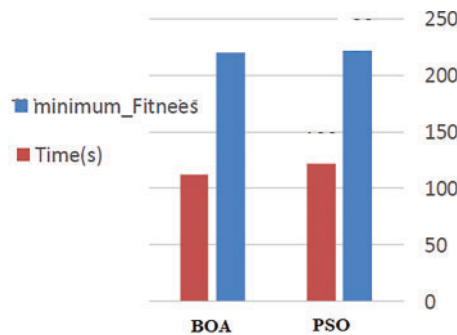


Fig. 8. Comparison graph of execution time and the lowest value of the fitting function in two meta-heuristic algorithms.

importance of parameter adjustment for achieving optimal results.

The main goal of this analysis is to compare the results of meta-heuristic algorithms in terms of execution time and fitness value. The data is plotted in a chart such that the horizontal axis depicts the run/iteration number of the algorithm, the left axis depicts the execution time, and the right axis depicts the least fitness value obtained at the end of each run. Looking at trends of execution time and fitness value across iterations, different algorithms are highlighted using different colors or markers. It also provides a legend to differentiate the algorithms; the title of the chart reads, Comparison of Execution Time, and Solution Quality for Meta-Heuristic Algorithms. The analysis here considers changes in execution time and fitness values in order to evaluate which algorithm is better placed to provide a good quality solution while using the least time as in Fig. 8.

4. CONCLUSION

Therefore, the Butterfly Optimization Algorithm (BOA) also seems to be a promising solution for the three-dimensional Unmanned Aerial Vehicle (UAV) path planning problem. In addition, the results of the algorithm prove a convergence with respect to the optimal path, low energy consumption, as well as successful passing of dynamic obstacles. Nevertheless, when compared to the mature meta-heuristic optimization algorithm like the Particle Swarm Optimization (PSO) algorithm, BOA performed well in areas like route minimization and

collision-sensitive pathways. This thesis is indicative of the ability of BOA in real-world UAV mission parameter optimization in real-world scenarios or clinical environments. So, more sophisticated research could be conducted with its extension on large-scale UAV fleets, using obstacle-moving behaviors and applying machine learning methods to improve the algorithm's flexibility and robustness.

CONFLICT OF INTEREST

The authors declare that they do not have any conflict of interest.

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