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Drone Design Optimization with Swarm Networking using Particle Swarm Algorithm

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Abstract: In this paper we have proposed a swarm network of Blended Body drones. Relevant comparison was made with respect to conventional drones, in terms of aerodynamic stall angle, gliding ratio. We have also implemented a software architecture to aid in guiding the swarm to the desired target location. Artificial Potential Function and Particle Swarm Algorithms were used for the purpose of collision avoidance and path optimization. Further, a concept model for a carrying-cum-launching pod for carrying and ejecting a drone swarm, was proposed. All analysis for the same was made in static medium in an analytic software.
Keywords: Swarm network, Blended body, Artificial Potential Function, Particle Swarm Algorithm, Launching pod.

I. INTRODUCTION

In this article, the objective is to demonstrate the effectiveness of a blended body swarm network from an aerodynamic perspective and to further implement a swarm control algorithm for a group of UAVs capable of self-organising and path autonomous path planning, following a mission led by a leader drone, while ensuring collision avoidance.

We have identified a blended body design for our drone. A blended body may be defined as fixed-wing aircraft which has no clear dividing line between the wings and the main body of the craft [1]. The bended body design provides aerodynamics and environmental benefits. Reduced wetted area, structurally efficient use of wing span, optimum span loading, relaxed static stability provides aerodynamic advantage in blended body [2]. It may also be given a wide aerofoil-shaped body, allowing the entire craft to generate lift and thus reducing the size and drag of the wings. Compared to conventional, blended body creates a thickening of the wing root area, allowing a more efficient structure and reduced weight [3]. Further, we realised the objectives of self-organisation and path planning. Previous works included simpler methods minimizing objective function, to arrive at an optimized path for the swarm. The Gradient Descent algorithm was one such method, where the gradient is to move down the steepest direction, for optimizing a roughly continuous and differential unconstrained cost function [4]. However, such methods require the optimization problem to be differential. We have used an improved approach, derived from meta-heuristics and real time biological systems, like bird flocks, bee swarms, wolf-pack, etc. For our purpose, we use a particle swarm optimization (PSO). It is a swarm intelligence-based technique that is used to an approximate solution by iteratively trying to search solutions or particles, with regards to a given measure of quality around a global optimum. Particle movement is dictated by their own best position in the search-space, as well as the entire swarm's best-known position. PSO does not make any assumptions, can skim through large search spaces for suitable particles or solutions, and does not require the problem to be differentiable. The PSO algorithm has shown very good performance with minimal search term with minimal computation time and relatively simple implementation. These performances have oriented us to choose PSO.

II. METHODOLOGY

Our research methodology is divided into three fields: (i) analysis of blended body drone design, (ii) concept design of swarm launching pod and (iii) implementation of swarm control architecture.

A. Mechanical Analysis Of Blended Body Drone

Appropriate aerofoil was selected for the analysis and same aerofoil was used in both drone design. Lift depends on various factors, basically velocity, density of air, coefficient of lift, area of the wing and also shape of the wing. For analysis of aerodynamic characteristics of both the drone design, the parameters like velocity, density of air, area of wing has been kept constant. Analyses were performed in an analytical software and various aerodynamic parameters were compared. All the analyses were performed in the same range of parameters.

Lift(L)=1/2*ρ*v2*Cl*S;

Velocity is kept constant for all the analyses at 10 m/s and analyses were performed to observe the influence of drone design, shape and configuration in lift generation.

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While performing the experiments we kept all the parameters like wing span, aerofoil type, etc. same for both cases, blended body and conventional body. All the analyses were performed in static medium.

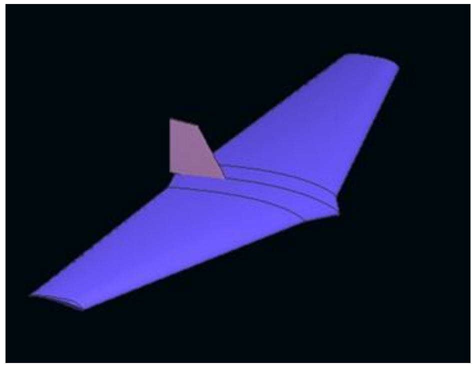

Figure 1 Blended body drone design

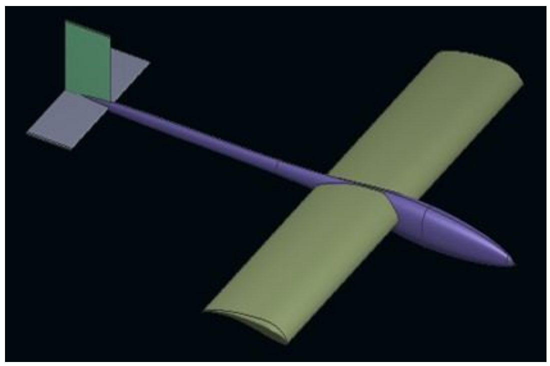

Figure 2 Conventional drone design

1) *Cl vs α plot:* The graph is plotted with α on x-axis while Cl on y-axis i.e., it is graphical representation of coefficient of lift changing with respect to angle of attack. Cl moves linearly with respect to α due to direct proportionality. The angle at which Cl becomes maximum is known as stall angle. Further this angle, if angle of attack is increased, then there will not be any lift generated making the pane unstable.

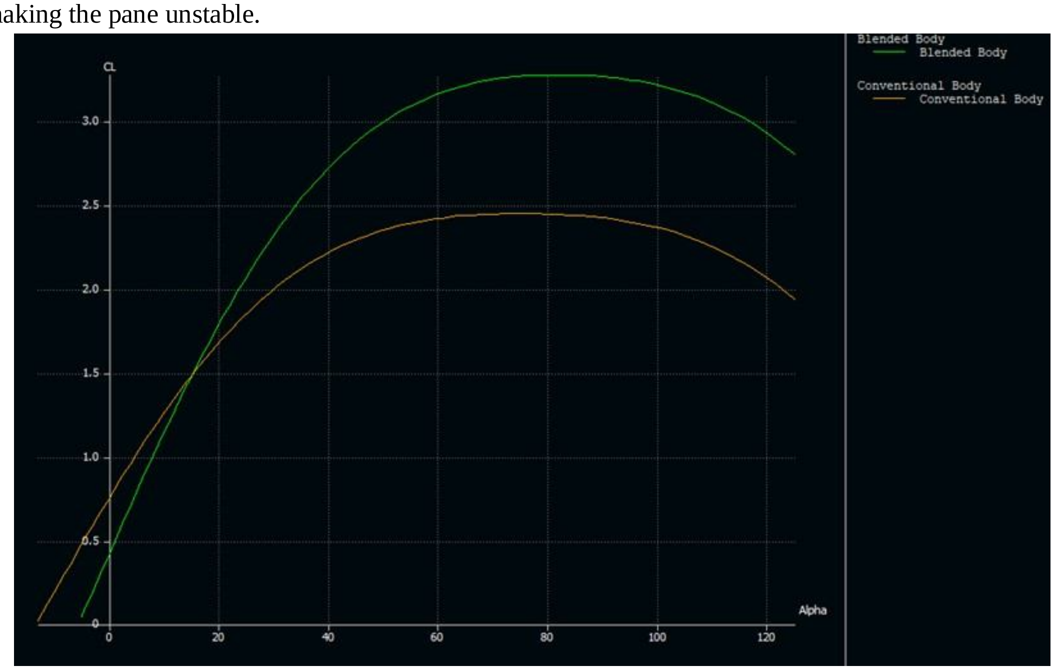

Figure 3 Cl vs Cd

B. Proposed Swarm Launching Pod Concept

While talking about swarm drones, too many drones need to be handled and launch at a time. So, we have suggested a concept design of a carrier cum launching pad which can hold multiple drones and also act as a launching pad. The carrier missile can also to use to carry the drones to a particular destiny from where the drones can be launch for operations.

Figure 4 Carrier cum Launching Pod

C. Swarm Networking Algorithm

To meet the objectives, we implemented a solution where Artificial Potential Functions were developed for the purpose of obstacle avoidance and collision aversion. Further, a probabilistic Particle Swarm Optimization Algorithm was used to find the optimal paths for the swarm.

1) *Artificial Potential Algorithm:* The potential function for the drones is focused on avoiding obstacles, avoiding other drones, and moving towards the final location. The mathematical expression for this potential function of the kth follower drone is:

$$J_k = \sum_{i=1}^{N_0} \Phi_1(P_k, P_0^i, r_0^i) + \sum_{\substack{i=1 \\ i\neq 1}}^{N_d} \Phi_2(P_k, P_i, r_i) + \gamma \|P_k - P_f\|^2$$

In this case, φ1 generates potential based on a drone being close to an obstacle, φ2 generates potential based on the proximity of the kth and i-th drones, and the last term helps move the kth drone to the final location, Pf. γ helps weight the importance of making it to the final location compared to the other parts of the cost function.

The form of φ1(Pk, Pj, rj) is the following:

$$\delta = ||\mathbf{P}_k - \mathbf{P}_j||$$
$$\phi_1 = \begin{cases} \alpha e^{-\left(\frac{3\delta}{r_j}\right)^2} & \delta \leq r_j \\ 0 & \delta > r_j \end{cases}$$

The form of φ2(Pk, Pj, rj) is the following:

$$\delta = ||\mathbf{P}_k - \mathbf{P}_j||$$
$$\phi_2 = \begin{cases} \alpha e^{-\left(\frac{3\delta}{r_j}\right)^2} & \delta \leq r_j \\ 0 & \delta > r_j \end{cases}$$

A note to make is that α may be a different value for each of the functions above, so there is no assumption that they share the same value. The goal is to find values for γ, α for each function, β, and τ such that the desired performance is met. For example, a large γ will speed up the movement of the swarm towards the desired end location. Smaller values for α will also make it so collisions are more likely, while a large value will help ensure collisions are avoided. Too large a value for α, however, risks getting drones halted around a neighbouring drone or obstacle more easily.

2) *Particle Swarm Algorithm:* The PSO algorithm, introduced by Kennedy and Eberhart [5], [6], is a population-based stochastic approach for solving continuous and discrete optimization problems. The position of a particle in PSO represents a candidate solution for the optimization problem. Individual particles search for a better position in the search space by changing their migration velocity according to behavioural models of bird flocking. The key to the implementation of the PSO algorithm is to set up a reasonable optimality function. If the potential solution of the optimization problem is regarded as a particle, the particle continuously flies in space, and the position is adjusted according to its own experience and the experience of the best individual in the process of searching for the best position. The particle swarm algorithm first initializes to obtain a set of random solutions, and then iterates and finds the optimal solution by tracking the best particles in the current space. In the multi-dimensional search space, m particles form a group. In the t-th iteration, the position and velocity of the i-th particle are Xi,t and Vi,t respectively. The particle updates its position and velocity by supervising two optimal solutions. The first is the optimal solution sought by the particle itself, i.e. personal best pbesti, and the other is the optimal solution currently sought by the whole group, i.e. global best gbestt. When searching for these two optimal solutions, particles update their speed and new position according to the following formula:

$$V_{i,t+1} = w^{*}V_{i,t} + c_1^{*}rand^{*}(pbest_i - X_{i,t}) + c_2^{*}rand^{*}(gbest_t - X_{i,t})$$

$$X_{i,t+1} = X_{i,t} + \lambda^{*}V_{i,t+1}$$

w is the velocity inertia factor; c1 and c2 are the learning factors; Rand is the random number between [0,1]; λ is the velocity coefficient.

3) *PSO Implementation:* This optimization approach utilizes stochastic sampling within the search space with movement similar to various naturally observed phenomena, such as food search processes in bees. The approach utilized in this document seeks to minimize an unconstrained objective cost function, J, by an M iteration swarm procedure using N swarm particles.

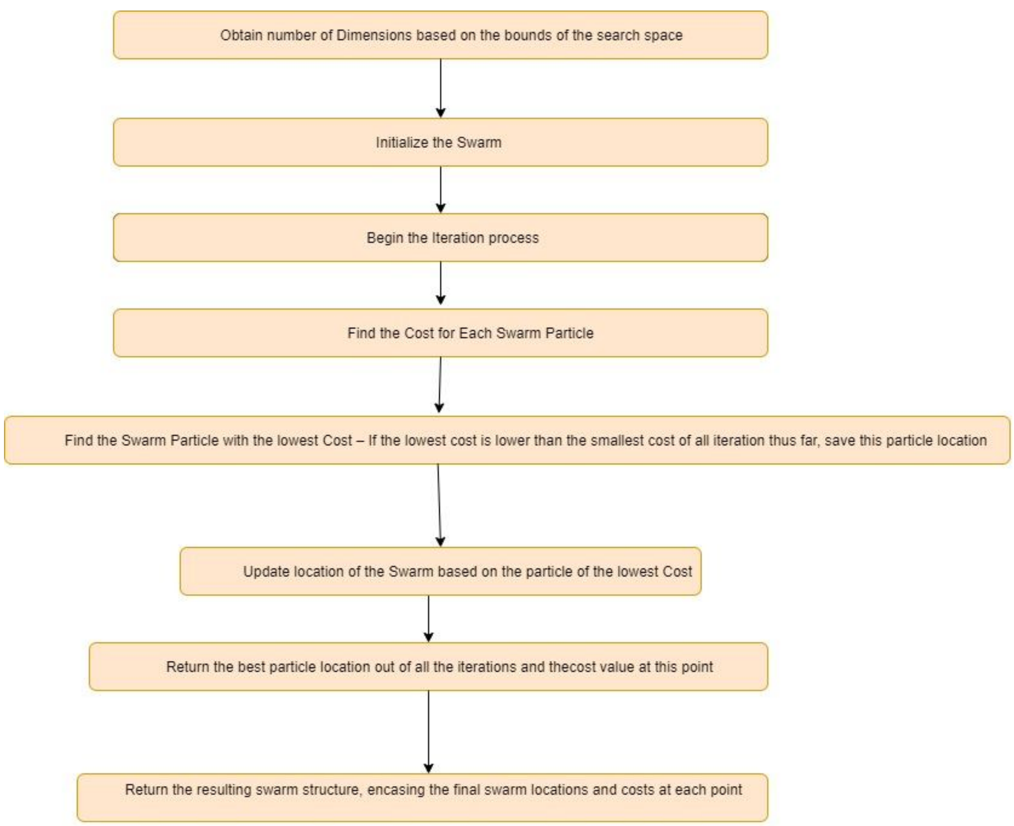

Figure 5. Algorithm Pseudocode

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III.SIMULATION

We created a simulation environment where the swarm moves towards the specified target coordinates, with the entire swarm moving in pursuit of a lead drone. The drones are represented with green dots and obstacles with red dots.

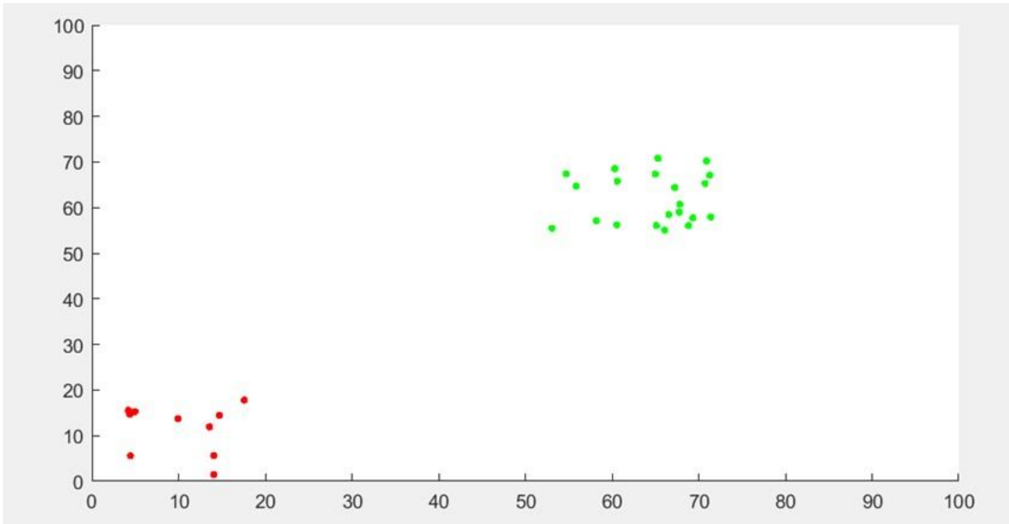

Figure 6 Drone swarm starting its movement towards target

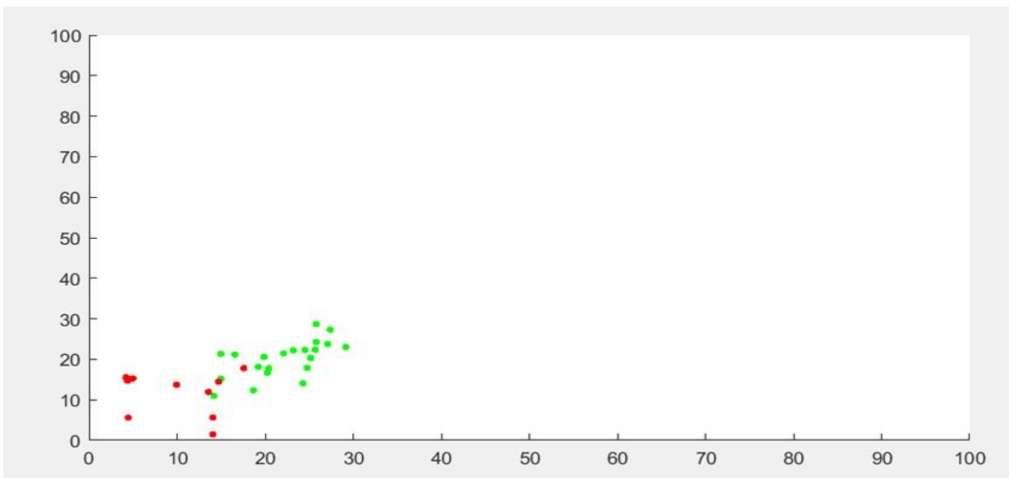

Figure 7 Swarm encountering obstacles

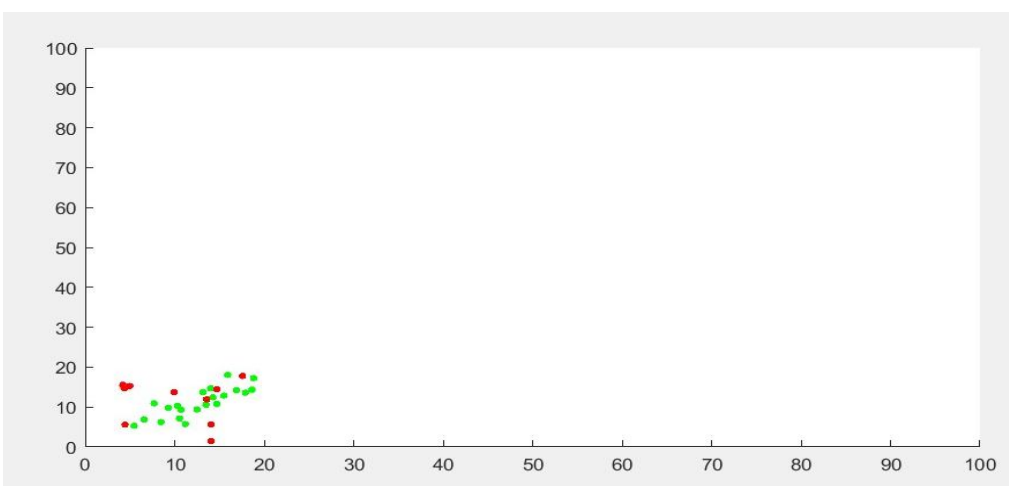

Figure 8. Swarm avoiding collision with obstacles and with other swarm members

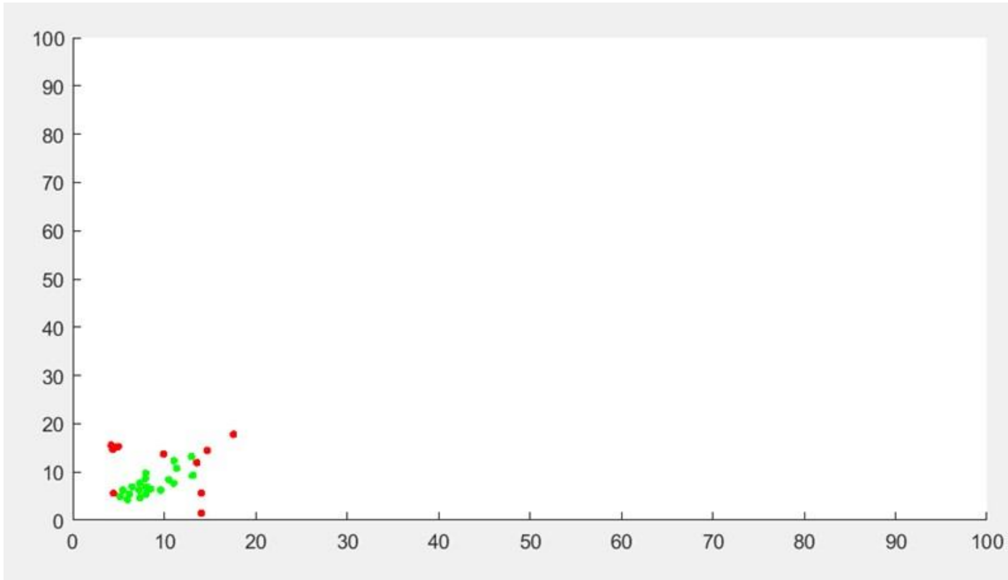

Figure 9. Swarm approaching target coordinates

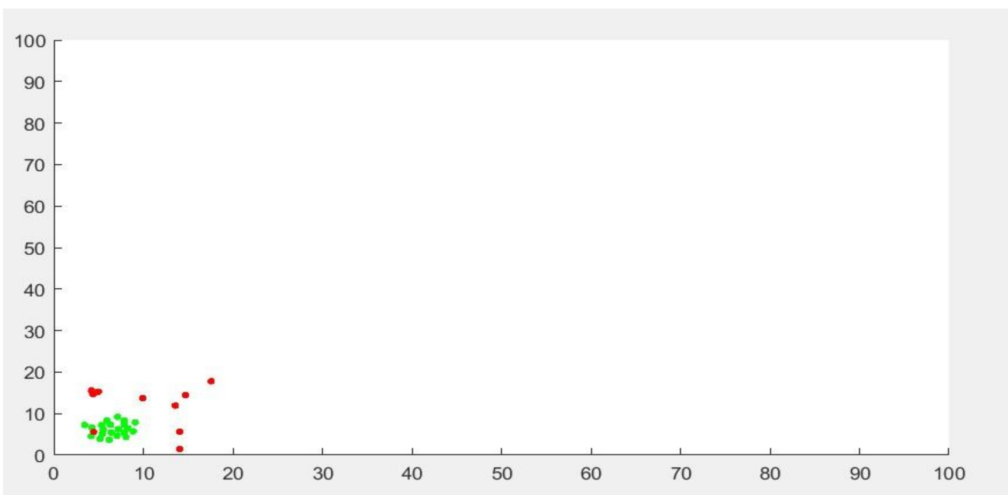

Figure 10. Swarm members gathering around target coordinates for mission fulfilment

IV. RESULTS AND DISCUSSION

In this paper we have discussed about Blended Body Swarm Drones and suggested a concept design of a carrying cum launching pad which can be used to carry the drones and also from which the drones can be released. We have also done comparative analyses of aerodynamic characteristics of Blended body with conventional body drones which usually have fuse and wings. In blended body drones the entire body is the lifting surface so it generates more lift compare to conventional drones which has only wings as the lifting surface and fuse non lifting surface. The fuse in blended body has aerofoil profile body which generates lift. The stall angle is also high for blended body as we got from the analyses as 82º blended body and 75º for the conventional body. The gliding ratio is also more for blended body compared to conventional body. From the Cl vs Cd graph, we can see that the blended body is giving more lift than conventional body for same amount of drag. Being have good gliding ratio blended body is more energy efficient than conventional body thus requires less energy source to move. Hence Blended body drones can be preferred over conventional drones. The launching pod is capable of carrying and launching multiple blended body drones.

Further, we implemented a swarm control algorithm using Artificial Potential and PSO algorithms. We simulated a swarm network in MATLAB software and observed the algorithms effectiveness in ensuring collision avoidance while manoeuvring towards the target point, taking an optimized path.

Repeated simulation revealed that the swarm avoided all collisions effectively, during the entire optimized path and was able to navigate to the target location with a greater convergence rate than other methods like Gradient Descent algorithm.

V. CONCLUSION

This paper describes research on an optimal drone design, for incorporation into a swarm model, and a concept launching pod for the swarm. A blended body design was identified and upon appropriate analysis it was concluded that the proposed design provides improved aerodynamic performance, and energy efficiency. A concept model for a swarm launching vehicle was presented. The design was formulated with the intent of fitting an optimum number of drones in limited space and providing air-deployment capability. Further, a swarm control architecture, combining Artificial Potential Function and PSO algorithms, was implemented to ensure optimized path planning and collision free mission completion. PSO is a robust population-based optimization technique that applies the concept of social interaction to problem-solving. This algorithm was observed to be effective in generating a satisfactory path trajectory for the swarm mission and avoid collisions.

Future scope in this research would be to introduce a decentralized swarm network, capable of compensating for the loss of the lead drone in real time. Moreover, the method implemented this paper, ensures local minima, however, a migration towards a global optimum might not always be the case. Hence, an updated algorithm can be implemented to avoid the swarm getting trapped in a local optimum, in the event of the elimination of a swarm member.

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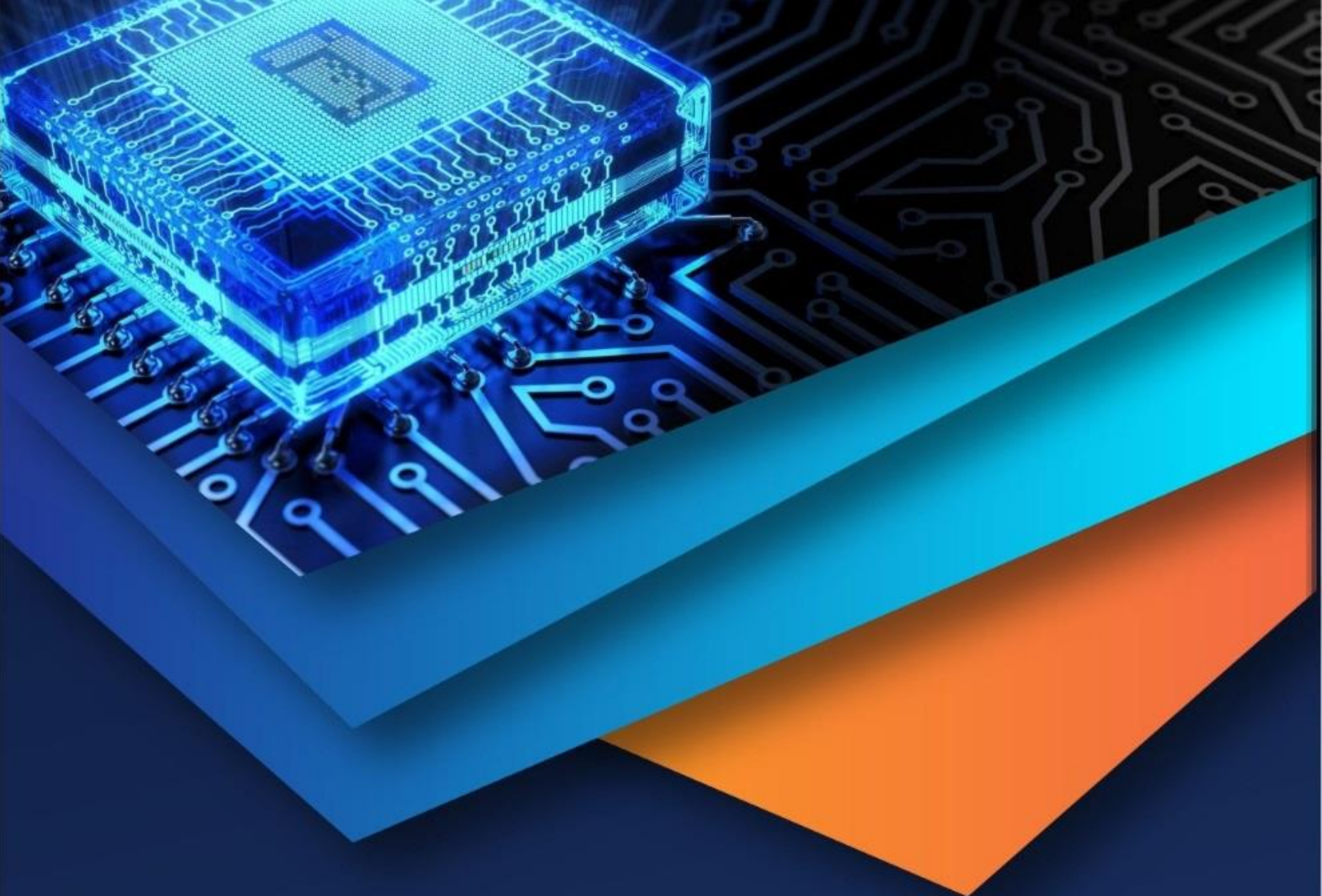

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