

PAPER • OPEN ACCESS

## Obstacle avoidance for multi-UAV path planning based on particle swarm optimization

To cite this article: E N Mobarez *et al* 2021 *IOP Conf. Ser.: Mater. Sci. Eng.* **1172** 012039

View the [article online](#) for updates and enhancements.



**ECS** **240th ECS Meeting**  
Digital Meeting, Oct 10-14, 2021  
**We are going fully digital!**  
Attendees register for free!  
**REGISTER NOW**

# Obstacle avoidance for multi-UAV path planning based on particle swarm optimization

E N Mobarez <sup>1</sup>, A Sarhan <sup>2</sup>, and M M Ashry <sup>1</sup>

<sup>1</sup>Department of Optoelectronics and Control,

<sup>2</sup>Aircraft electrical equipment's, Military Technical College, Cairo, Egypt.

E-mail: mmaashry@mt.c.edu.eg

**Abstract.** Traffic Collision Avoidance System aims to help aircraft to avoid collision with any object or other aircraft. One of the functions of this system is that it avoids threatening UAV to collide, it also addresses each threat separately with the best collision avoidance and the best suitable horizontal separation with other aircraft in the optimal path. In this paper the flight path planning for UAVs was designed to avoid obstacles depending on how the particle swarm was improved. Optimization problems are improved by using swarm dynamics (evolutionary computational technology). This is by describing avoiding obstacles and adapt the path planning for UAVs. The concept of concurrent restructuring has been integrated into path planning to stay away from both static obstacles. This optimization technique designed to decrease processing time and the shortest route of the path planning.

## 1. Introduction

Multi-UAV is designed to perform various tasks in a specific environment [1], [2] and [3]. The working environment consists of different types of obstacles. UAVs can depart from their location to any destination points without pass through any obstacles. UAVs must efficiently return their tracks based on environmental change due to dynamic obstacles.

Particle Swarm Optimization is stochastic optimization based on the social behavior of some species to determine the required position in a swarm activity. It gathers local and global search techniques by balancing exploitation and exploration. In PSO, the workspace is initiate with stochastic particles in which each particle performs a possibility resolution to the problem. Each particle of the swarm randomly seeking in a multidimensional area. These particles update themselves with the optimum solutions of their experience as well as the social information collected from other particles. The optimum solutions of the particles are assess by the fitness function of their current position. The swarm modificate its location dynamically throughout the optimization operation to obtain the best solution. The velocity of each particle initiate randomly. The location of the Particles changed by updates their velocities. The velocity update is effected by three factors are particles current motion, particles previous experience and the influence of the whole swarm.

This paper is organized with an introduction in the first section. Second section represent the overview of Particle Swarm Optimization initialization parameters. Third section illustrate the effect of the PSO parameters, the Particles continuously update their positions and velocities, until they have accomplish the desired location. Each particle update its location with respect to its previous experience and experience of rest of the particles (Neighbors). Section four how to update the Fitness Value. Section



five represent obstacle Avoidance for Multi-UAV path planning based on PSO. The summary is comes in the last section.

## 2. Particle Swarm Optimization initialization parameters.

Particles continuously update their positions and velocities, until they have accomplish the desired location. Each particle update its location with respect to its previous experience and experience of rest of the particles (Neighbors) [5].

Each individual particle is consist of three vectors:

- The X- record the particle current location in the search area.
- The P- (P-best) records the position of the superior settling found far via the particle.
- The V- Particle gradient (direction) if it is not disturbed

Each particle are kept as part and member of the group (swarm) during the operation in PSO

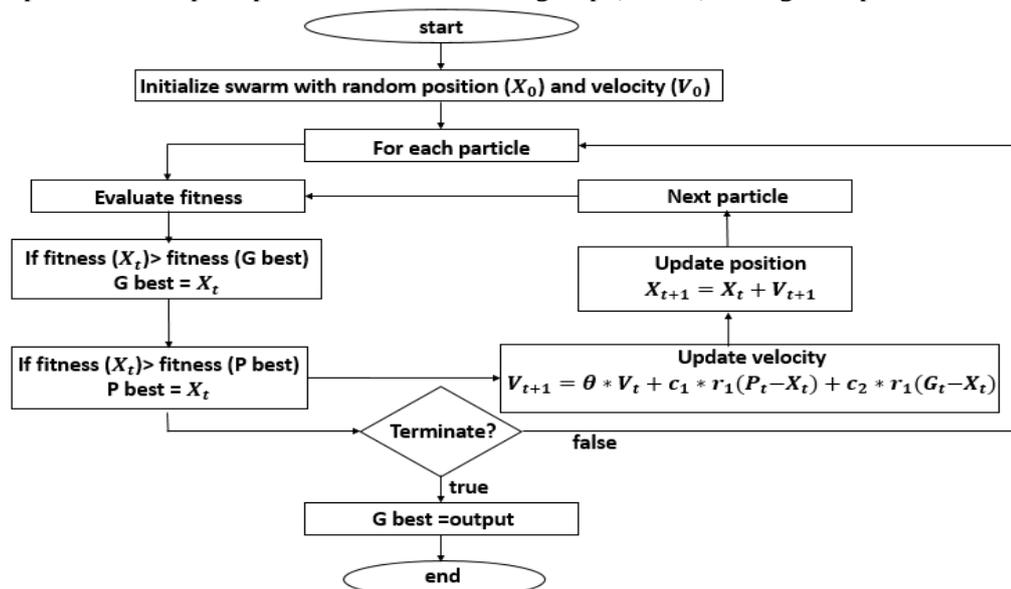


Figure 1. PSO Algorithm Schema [6].

Initialize location  $x_i$  and velocity  $v_i$  of  $n$  particles through the objective function  $f(x)$ ,  $x = (x_1, \dots, x_d)^T$  [8]. And find  $G^*$  from  $\min \{f(x_1), \dots, f(x_n)\}$  at  $t = 0$ , generate new velocity  $V_{t+1}$  using equation (2) and calculate new locations  $X_{t+1}$ , then evaluate the Objective function of a new locations  $X_{t+1}$  to find the present superior for each particle, and then find the current (global best)  $G^*$  as shown in figure (1) [5].

The main objective of PSO is to accelerate each particle to the superior position (P best) and the best global position (G best) obtained by any particle, with stochastic weighted (angles of particle direction), this is accomplished by addition of the V-vector to the X-vector to get another new  $X_{new}$  as in following equation (1). As shown in figure (2) [6].

$$X_{i \ t+1} = X_{i \ t} + V_{i \ t+1} * \Delta t \quad (1)$$

Then the new velocity is calculated by using the following equation (2):

Update velocity

$$V_{i \ t+1} = W * V_{i \ t} + \underbrace{c_1 * r_1 (P_{Best} - X_{i \ t})}_{\text{cognitive component}} + \underbrace{c_2 * r_2 (G_{Best} - X_{i \ t})}_{\text{social component}} \quad (2)$$

(current motion)	(cognitive/Particle memory	(Social/swarm	influence)
Inertia weight	influence) particle best	Global best solution	Distance
	solution (Distance to the	to the global best-all	particle
	particle best)	best location	

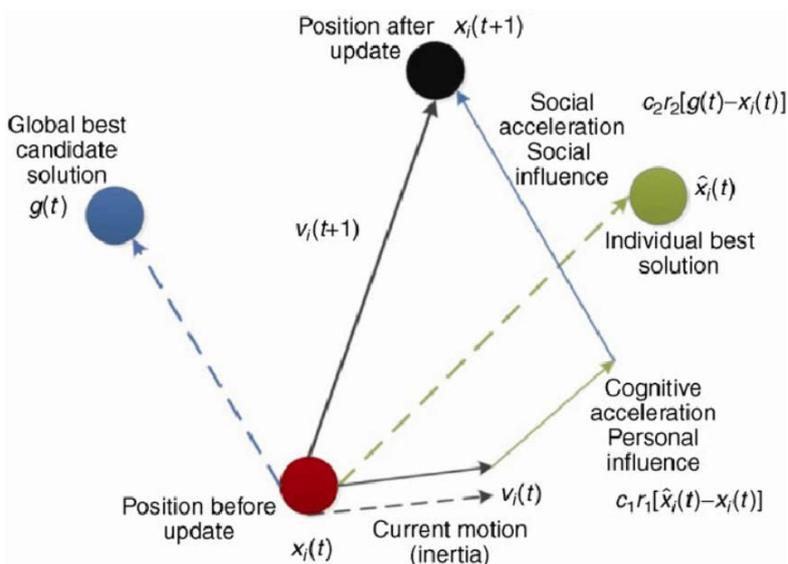


Figure 2. Particles motion.

### 3. The effect of the PSO parameters.

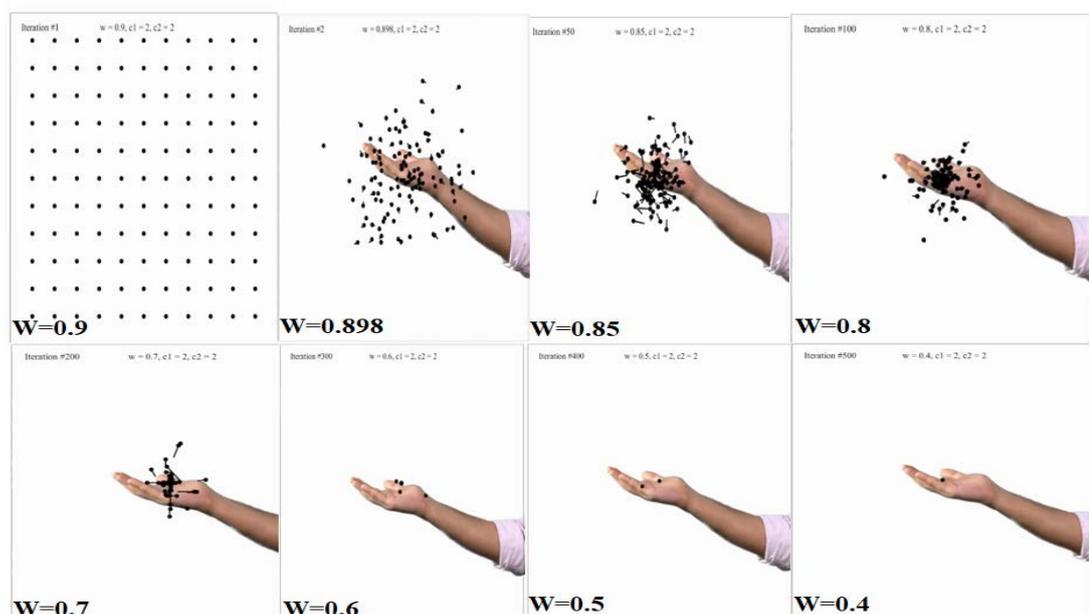
Where  $W$  an weight of inertia function (angle of particle travel) can be taken as a constant from 0.4 to 0.9 this to cause the particles converge more quickly i.e. Large inertia weight making easy for conduct global research, while small inertia facilities provide local search (controls exploits and explores of particles),  $r_1$  and  $r_2$  are two stochastic vectors, and the values takes from 0:1 each entry. The parameters  $c_1$  and  $c_2$  are the learning parameters or Acceleration coefficients effect on the personal and global leaders on the seeking operation [5], which can be taken from 0 to 2. Kennedy and Eberhart suggest to use values of  $c_1 = c_2 = 2$  also, Shi and Eberhart [5] proposed to use the value of ' $W$ ' from 0.8 to 1.4 as shown in table (1) [6].

The location of the Particles changed by updates their velocities. The velocity update is effected by three factors are particles current motion, particles previous experience and the influence of the whole swarm. Figures (3) and (4) represent the different factors that impact particles motion in PSO [6]. These figures shows the effectiveness of the updating parameters on the optimization mechanism of the particles. Figure (3) show the effect of parameter inertia weight  $W$  from [0.9: 0.4], when parameter  $W$  decreases. The exploration and exploitation process increases and converge looking for global best solution (hand) as shown in figure. Figure (4) show the effect of parameter Acceleration coefficients  $c_1$  and  $c_2$ , the small cognition parameter  $c_1$  and large social parameter  $c_2$  making quickly to conduct and converge to global position. The Large cognition parameter  $c_1$  and small social parameter  $c_2$  making slower and not converge to global position, because no information between particles.

Table. (1) PSO parameters. [6]

$W$	inertia weight factor range from (0.4 : 1.4)	
$c_1$	cognition parameter (self-confidence range 1.5 : 2)	(learning parameters or acceleration constant)
$c_2$	social parameter (swarm confidence range 2 :2.5)	
$r_1$	independent random variables uniformly distributed ( $r_1$ and $r_2$ are two stochastic vectors, and the values takes from 0:1 each entry)	
$r_2$		
$P Best$	is the personal best position achieved by the particle	
$G Best$	Is the globally best position achieved by the swarm	

### Simulation of PSO [C1=2, C2= 2]

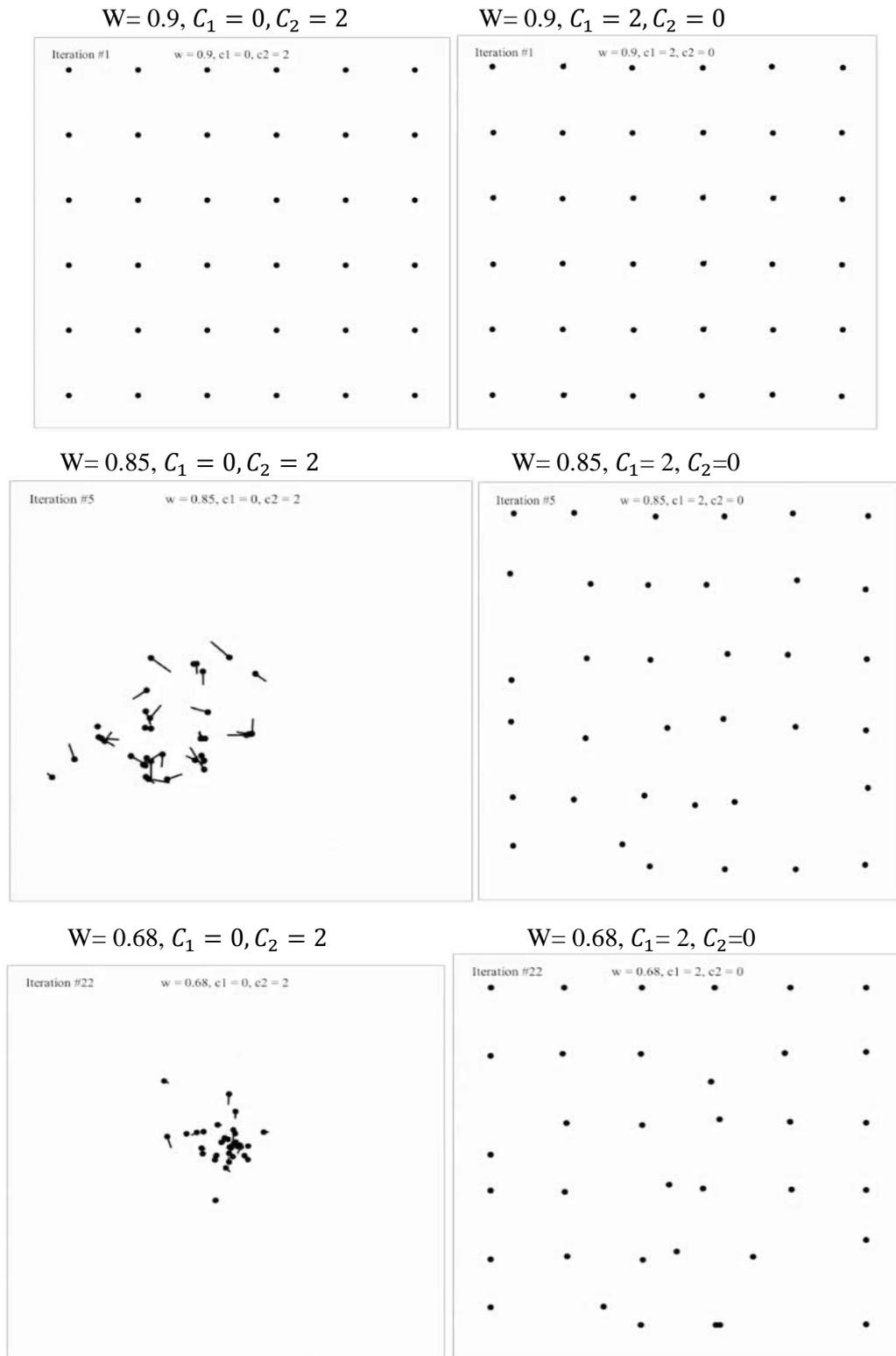


**Figure 3.** Effect of parameters inertia weight  $W$ .

Optimization is fulfilled utilize an objective function defined by the Euclidean distance between the beginning point  $(x_1, y_1)$  and the end point  $(x_2, y_2)$  as in equation (3).

$$\text{Distance} = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (3)$$

In PSO, the algorithm assess the fitness function for all the particles and the solution is optimized by iterative enhancement of the particles positions [6].



**Figure 4.** Effect of parameters cognition and social parameter  $C_1, C_2$ .

### 4. Update the Fitness Value.

In this section, the path planning tack place to avoid any kind of obstacles. At first, to keep a collision free course all the particles swarm must find out the obstacle’s positions, then they determine the displacement between the particles and the obstacles [6]. A collision tack place if the condition of the equation (4) occurred:

$$D_{obs}^a \leq 0 \tag{4}$$

Where  $D_{obs}^a$  describes the distance between obstacles and UAVs, then it considered as alert for collision. Here, the negative value of  $D_{obs}^a$  means that the location of the particles are inside the impact area. The particle swarm fitness values through the collision area is proposed by a larger positive functional value. As the optimization is considered as an issue reduction, the particles with larger fitness vales are not considered as the superior fitness function at all. So the trajectory within the impact area is averted.

So as to escape maneuver the particles from the impact area, the values of the parameters ( $\omega, c1, c2$ ) in equation (2) are increased. Thus, the particles velocities are also increased and they leave the collision area [6].

### 5. Path Planning by Obstacle Avoidance

A 2D surroundings is considered as a workspace. For obstacle avoidance, we considered various patterns of working surroundings. The map area of the surroundings is considered as a circle with different diameters of obstacles. The blue circles represent the static obstacles as shown in figure (5). Black line represents the trajectory (flight path) of UAVs. Yellow Square represent of initial position Green star represent of final position.

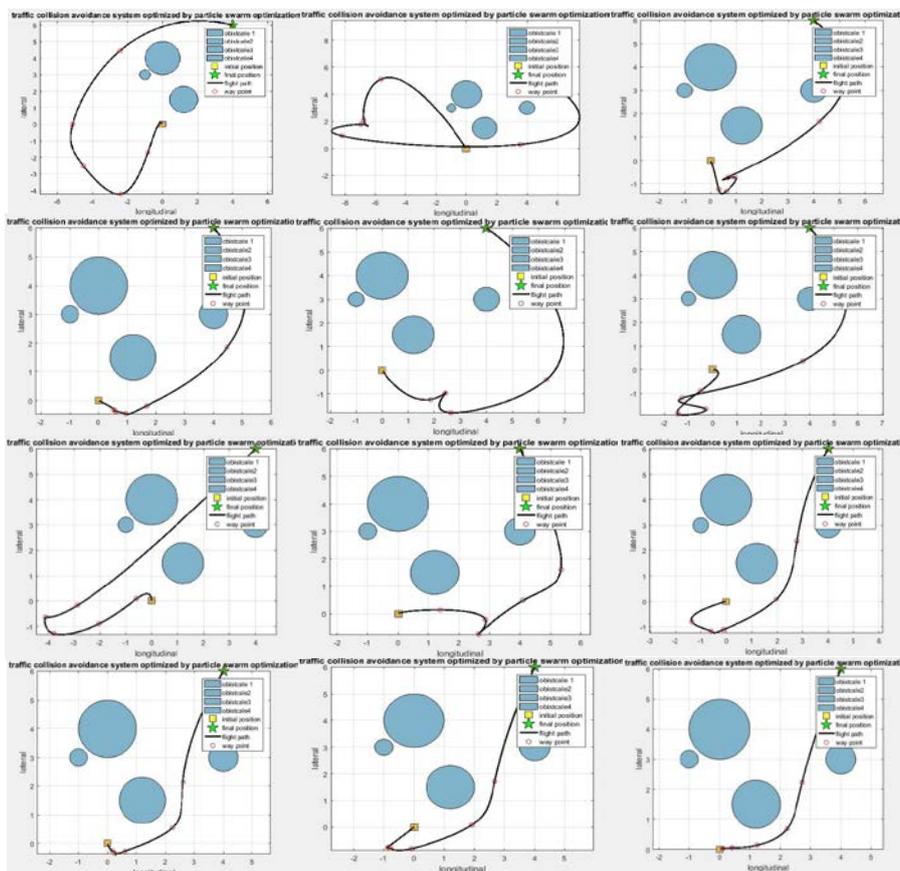


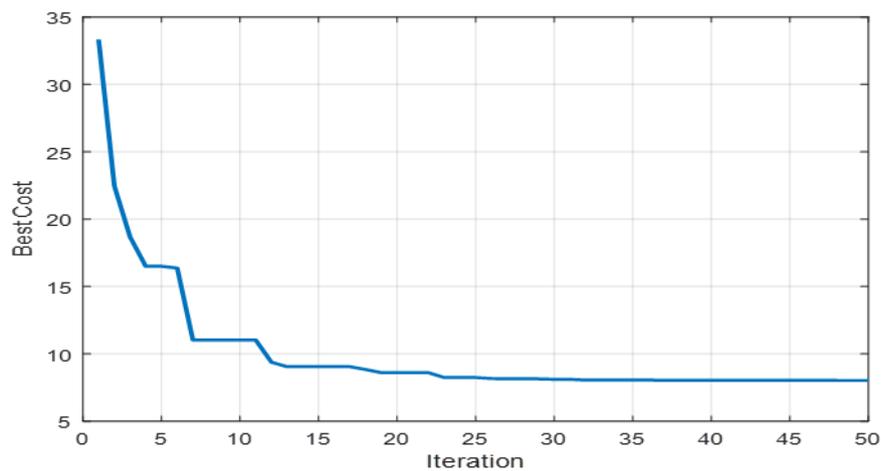
Figure 5. Sample of iteration steps to optimal solution.

Figure (5) shows that a brief or sample of the iteration where the particle swarm optimization looking for the optimal path from source (starting point) to the destination (end point) Including avoiding collisions with obstructions, the figure consist of a number of iteration starting from initial iteration upper-left one and it ends at lower-right one.

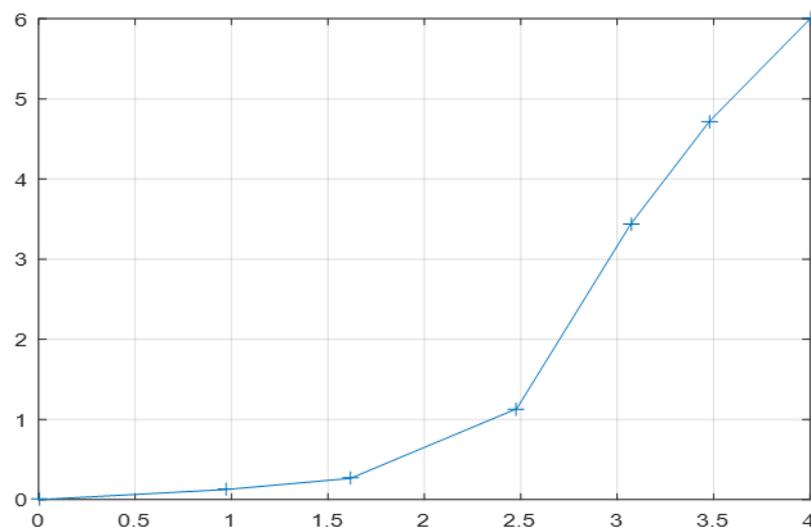
The figure (6) shows a relationship between the best cost and iteration steps where it was found that the cost was reduced with the aging of a number of iterations that got an optimal solution.

The cost of the final iterations for converging to the optimal path is shown in figure (6). This is a best cost function to achieve to the destination points without pass through any obstacles.

After getting optimal path from initial point to the destination, convert it to the heading angle from currently way point to next one as a reference command to the leader UAV as shown in figure (7).



**Figure 6.** Best cost according to iterations.



**Figure 7.** Way point on flight path.

In this section using the PSO to optimize the way points and best flight path to keep the UAVs in safe from obstacles through number of iteration for reach to best cost and optimum solution, and then convert the final flight path to heading angles, which using it as a reference command to leader UAV, so the followers UAV follow currently heading angle through leader UAV path as shown in figure (8).

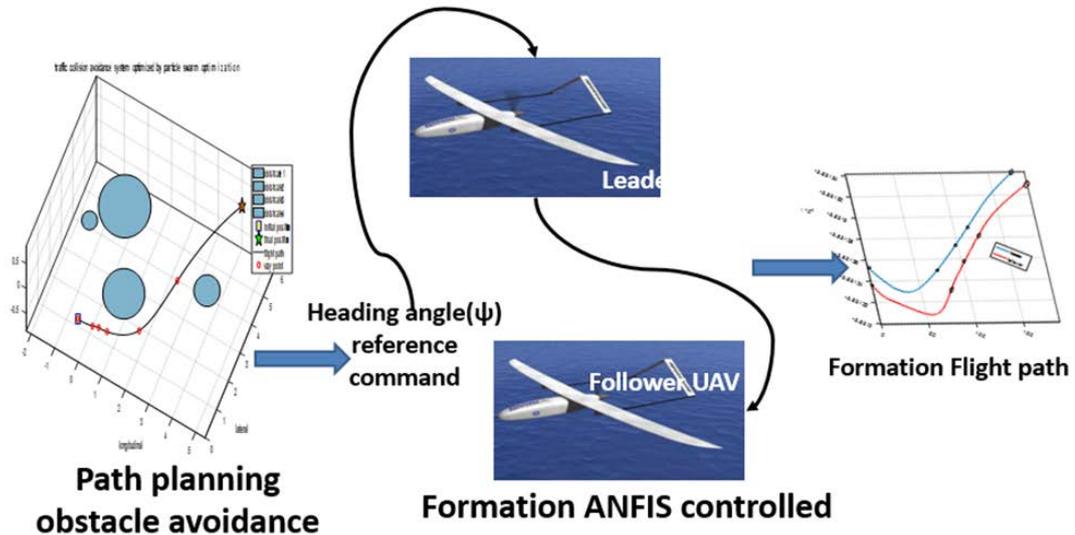


Figure 8. Traffic collision avoidance system.

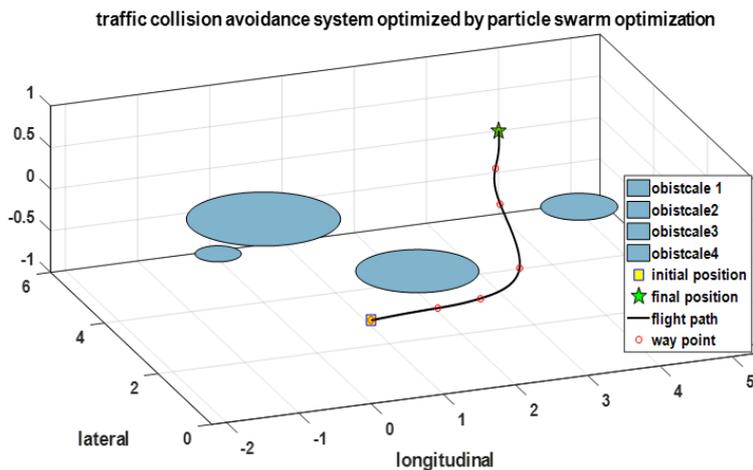
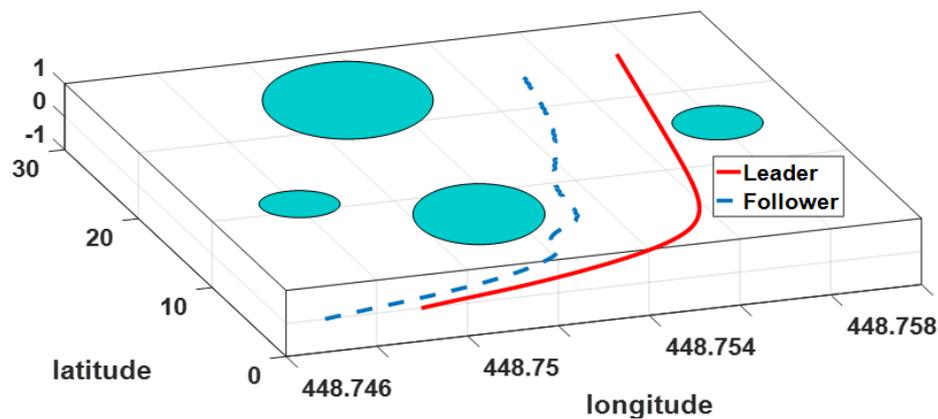


Figure 9. Optimal solution for UAV flight using PSO.

The figure (9) show the path planning of the final optimal solution to keep the UAV in safe from obstacles through number of iteration for reach to best cost and optimum solution.

The figure (10) illustrate that implementation of formation flight for two UAVs to the path planning, as shown in this figure the formation execute the heading according to the optimal path obtained from particle swarm optimization.



**Figure 10.** Path planning of multi-UAV.

## 6. Conclusion

In this paper the flight path planning for UAVs to avoid obstacles depending on how the particle swarm is designed. Optimization problems are improved by using swarm dynamics (evolutionary computational technology). This is by describing avoiding obstacles and adapt the path planning for UAVs. The concept of concurrent restructuring has been integrated into path planning to stay away from both static and dynamic obstacles. This optimization technique designed to decrease processing time and the shortest route of the path planning.

## References

- [1] Mobarez, E.N., Sarhan, A. and Mohamed, A.M., 2019, September. Modeling of fixed wing UAV and design of multivariable flight controller using PID tuned by local optimal control. In *IOP Conference Series: Materials Science and Engineering* (Vol. 610, No. 1, p. 012016). IOP Publishing.
- [2] Mobarez, E.N., Sarhan, A. and Ashry, M.M., 2019, December. Classical and Intelligent Multivariable Controllers for Aerosonde UAV. In *2019 Ninth International Conference on Intelligent Computing and Information Systems (ICICIS)* (pp. 350-355). IEEE.
- [3] Mobarez, E.N., Sarhan, A. and Ashry, M.M., 2019, December. Robust PID Flight Controller for Ultrastick-25e UAV. In *2019 15th International Computer Engineering Conference (ICENCO)* (pp. 150-156). IEEE.
- [4] Mobarez, E.N., Sarhan, A. and Ashry, M.M., 2019, December. Formation Flight of Fixed Wing UAV Based on Adaptive Neuro Fuzzy Inference System. In *2019 Ninth International Conference on Intelligent Computing and Information Systems (ICICIS)* (pp. 356-361). IEEE.
- [5] Wang, D., Wang, H. and Liu, L., 2016. Unknown environment exploration of multi-robot system with the FORDPSO. *Swarm and Evolutionary Computation*, **26**, pp.157-174.
- [6] Zhang, Y., Wang, S. and Ji, G., 2015. A comprehensive survey on particle swarm optimization algorithm and its applications. *Mathematical Problems in Engineering*, 2015.
- [7] Sarhan, A. and Ashry, M., 2013. Self-tuned PID controller for the Aerosonde UAV autopilot. *International Journal of Engineering Research & Technology (IJERT)*, **2(12)**, pp.2278-0181.