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Analysis of Path finding techniques for flying robots through intelligent decision making algorithms in Quantum inspired computing environment

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Abstract. Path planning is one of the most significant and challenging parts in the development of unmanned aerial vehicles. Over years many path-planning techniques are proposed and are being successfully used in various fields. Intelligent algorithms can be used for building autonomous drones. Though a number of algorithms haven been proposed in past few years but there is lack of research papers which compares different path planning algorithm and to find the optimal one by considering important parameters required for path planning of flying robot. Here we have used five varieties of algorithms ie ABC, ACO, PSO Quantum PSO, and hybrid algorithm which is a combination of ABC and PSO for path planning of our developed fixed-wing type flying robot for operating inside a closed room environment. We have used the quantum-inspired computing method as its search performance is better as compared to classical techniques. Then we tried to compare and find the best algorithm for our flying robot out of the above five algorithms using multi-criteria decision making (MCDM) and TOPSIS where the following parameters like minimum cost, the shortest path traveled, and the least time taken were considered to find the most relevant results for autonomous flying robot path planning.

Keywords: ABC, PSO, Quantum PSO flying robot, path planning, MCDM, TOPSIS

1 Introduction

Technological advancement has geared up the requirement for autonomous systems. The domain of autonomous flying robots is rapidly growing and in the last couple of years, the drone industry has seen a manifold increase. Autonomous flying robots have a wide range of applications in logistics, agriculture, industries, the medical sector, search and rescue missions, the military sector, etc [1]. They can perform the task of take-off and land autonomously. One of the essential parts of the development of a flying robot is path-finding techniques. To fly autonomously it is important to know the path through which it will traverse. Path planning takes into consideration the optimum travel distance to reach the target location, obstacle avoidance, minimizing energy consumption, and least computational time [2,3]. There are various types of path planning algorithms out of which it is challenging to choose the best one for our developed fixed-wing type flying robot for indoor application. Initially, we selected an artificial intelligence-based algorithm for our flying robot but this category also had multiple algorithms. So, we planned to use two types of decision-making processes ie MCDM and TOPSIS to verify which algorithm would be best for our flying robot based on cost and time factors.

2. Literature Review

Here we have reviewed several algorithms used for performing path planning for aerial vehicles, and their pros and cons. Yufeng proposed an optimization method followed by ants [4] for path finding of indoor unmanned aerial vehicles. Their modified weights used in the algorithm helped in achieving the optimal path efficiently. Zhe Zhang [5] has used algorithm path finding of aerial vehicles in three-dimensional conditions. Anand Nayyar, Nhu Gia Nguyen, et al. [6] proposed modified artificial bee colony optimization for route discovery of robots. The algorithm showed promising results for exploring the unknown path but early convergence was the major issue. Shikai Shao et al.[7] had used the swarm intelligence method for route discovery. The constant acceleration coefficient and maximum velocity were adjusted in such a manner that they can be adaptive to linearly varied patterns which enhanced the efficiency of aerial vehicles for path planning. Jong Jin Shin [8] and Y. Liu [9] utilized the PSO technique for the path-finding of autonomous systems in adverse conditions. N.Ozalp[10] used a parallel developmental algorithm. Yangguang Fu [11] proposed a quantum-based swarm intelligence-based technique for optimal path discovery. Quantum-based algorithms are revolutionizing the domain of optimization problems. M. Bagherian [12] proposed an evolutionary method as well as provided a comparative study on the obstacle avoidance strategy. V. Roberge [13] carried out a comparative analysis of popular algorithms ie PSO and GA. Many research papers were using genetic algorithms [14,15,16], aco [17,18,19], abc [20,21], pso [22,23,24], and hybrid algorithms [25,26,27] for performing path planning for intelligent flying robots. Most of the research papers used artificial intelligence-based path-planning algorithms instead of other analytical methods of path planning [28,29,30,31,32]. In this paper, we have used the four most widely used artificial intelligence-based path planning techniques ie aco, abc, pso, and hybrid algorithm for generating an optimal path for our developed aerial vehicle using MATLAB software, and then we have also tried to apply quantum inspired PSO model for obstacle avoidance of our flying robot and compare it with other artificial intelligence-based algorithms to find the most desirable algorithm for path planning of our flying robot. We have also gone through various research papers on MCDM techniques. Raja Jarray [33,34] used MCDM and TOPSIS model to evaluate the best path planning algorithm taking into account multiple objectives like path length and elapsed time to predict the best method.

3. Path planning Algorithms

Path planning algorithms are used to discover the most suitable path in which the aerial vehicle can traverse to reach the target point while optimizing the conservation of energy, cost, and time.

3.1 Artificial Bee Colony

It is an intelligent bio-inspired optimization method to find optimum results for problems with multiple objectives. It mimics the intelligent food-searching nature of honey bees. Karaboga[36] proposed the swarm intelligence-based technique in which primarily self-organization and division of work among the bee colony are its characteristics. The major components of the ABC algorithm are bees assigned with the task of collecting food and a group of those who are not assigned the task of food collection. Bees are assigned with task search for food sources and collecting nectar from flowers and sharing the information in their bee hive by performing the waggle dance. Onlooker bees keep an eye on the waggle dance by employed bees and then try to follow them to find the food source whereas scout bees randomly explore for food origin without following employed bees.

i)Initializing the algorithm

The vectors for food sources are initialized by scout bees which randomly search for food sources and are given as y_a = (y_1, y_2, y_3,…..

y_n). Each solution for food search can be represented as shown in equation 1 [36],

$$y_{a,b} = y_{min,b} + \text{rand}(0,1)*(y_{max,b} - y_{min,b}) \quad (1)$$

Where FS= Number of food origin

n= Number of parameters

b= 1, 2, ………. N

a= 1,2,………, FS

ii)Bees assigned with task stage

Employed bees search for food having more nectar and then evaluate the same using the fitness function, new solution for a food source is found by the following equation

$$u_{a,b} = u_{a,b} + \phi_{a,b}(y_{a,b} - y_{c,b}) \quad (2)$$

Where u_a refers to an innovative resolution for the food origin

$\phi_{a,b}$is random number between [-1,1]

$c \in [1,2, \ldots \ldots FS]$

Once the new set of solutions is generated and checked and the fitness value is calculated for a new solution The function with fitness value is given as

$$d = \begin{cases} \frac{1}{1+f(y_d)} & \text{if } f(y_d) \geq 0 \\ 1 + abs(f(y_d)) & \text{if } f(y_d) < 0 \end{cases} \quad (3)$$

Where $f(y_d)$ is an objective function

iii) In the further stage probability values are taken to enhance the solution

$$v_p = \frac{fitness\ d}{\sum_{a=1}^{FS} fitness\ d} \quad (4)$$

iv) Scout bee stage

The employed bees whose solution for food source does not improve after using fitness function then those solutions are abandoned and the bees are converted into scouts and they have to search for food sources randomly.

The following algorithm was implemented for the path planning of our developed flying robot using MATLAB software. We had taken random coordinate points of a 2d environment of a room where our flying robot need to find the optimum path. Figure 1 shows the optimal path generated by applying the ABC algorithm. Our simulation results obtained had cost function which deals with distance parameter as 5.43 units and time spent by flying robot for holding out to target location using optimal path is 6.95 sec after 150 iterations.

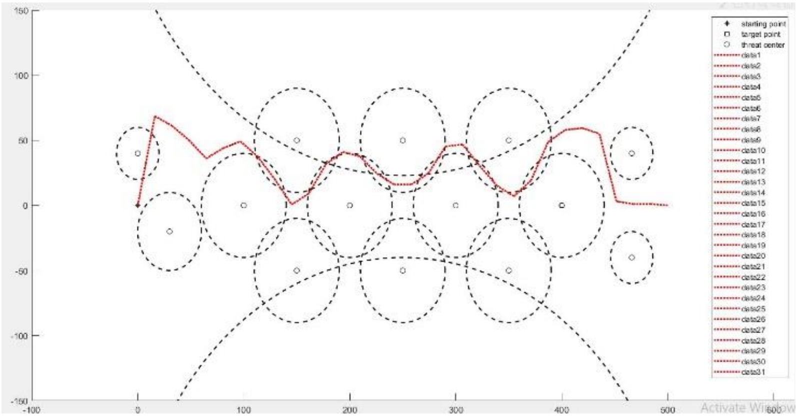

Fig1: Figure shows the optimal path generated by applying abc algorithm

3.2 Particle swarm optimization and Quantum Particle swarm optimization

It is a swarm intelligence based technique for generating the best solution by iterating continuously for nonlinear problems. It is an evolutionary Meta heuristics algorithm that mimics the bird's behavior for food source identification. Initially, the swarm population is taken by selecting m random solutions called particles. Fitness functions are revised to generate the desired position. The velocity and acceleration of the particles are revised by changing the fitness function to get the best global solution. The equation below helps to revise velocity and position [37],

$$u^{m+1} = \mathrm{w}u^{m} + t_1 * rand_1^{m} * (p_o^{m} - z^{m}) + t_2 * rand_2^{m} * (g_o^{m} - z^{m}) \quad (5)$$

$$z^{m+1} = z^{m} + u^{m+1} \quad (6)$$

m represents iterations, w represents weight function, t_1 represents position learning co-efficient and t_2 represents global learning co-efficient, $rand_1$ and $rand_2$ are random integer numbers that vary from [0,1]

u^{m+1}= velocity at m+1 iterations

z^{m}= position at m iterations

p_o^{m}= optimal position at mth iteration

g_o^{m} = global best solution at mth iteration

Initially, the starting point coordinates and threat points in a 2d closed room environment were assigned to the algorithm than using swarm intelligence it tries to discover the suitable path and keeps on updating outputs to get the best global optimal results. Figure 2 below shows the desired path obtained from the PSO in MATLAB. Our simulation results obtained had cost function which deals with distance parameter as 5.45 units and time traversed to arrive at the desired location using optimal path is 6.04 sec after 150 iterations.

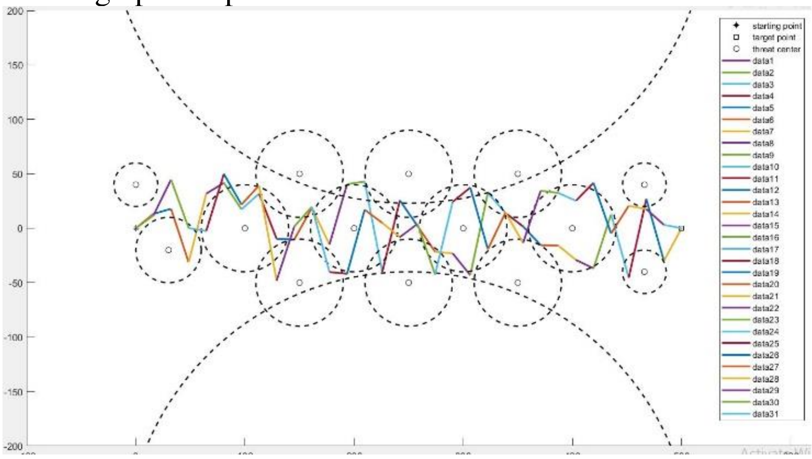

Fig2: Figure shows the optimal path generated by applying Particle swarm optimization

The concept of quantum-inspired PSO is based on the quantum mechanics domain. It is based on the wave function strategy of quantum theory. It tries to find the best position by exploring the best possibilities [38]. It can overcome the problem of assembling at a point as compared to the classical method. In quantum PSO movement of particles is given by wave function at any place in a defined functional region. The motion of particles is given by,

$x_i = p_o^m + \alpha(n_b - x) * \ln(1/ra)$

$x_i = p_o^m - \alpha(n_b - x) * \ln(1/ra)$

Where x_i is the location of ith particle

α is a contraction expansion factor that helps in the adaptive adjustment to reach the optimal solution

n_b is the best position, ra is the random number [0,1]

In our project, we have applied quantum PSO to our fixed-wing type flying robot model and the simulation results obtained showed cost function value as 3.4 units and time of execution as 4.75sec by carrying out 150 iterations.

3.3 Hybrid Algorithm

Hybrid algorithms are a combination of two different algorithms which combines the advantages of both algorithms to generate the best optimal path with better efficiency and eliminate the limitations of the existing algorithms. The search method of PSO is employed in three stages of the ABC algorithm by updating the velocity and position and when the particles are jabbed by regional minimum value and they can flee by utilizing random search[39] The search phenomena are good for ABC and convergence towards an optimal solution is good in PSO, so the combination of PSO and ABC algorithm can result in a good exploration of the optimal path.

Here we have used PSO and ABC algorithms for routing our developed aerial vehicle. Figure 3 below shows the optimal path obtained from PSO and ABC algorithm in a MATLAB environment. Our simulation results obtained had cost function which deals with distance parameter as 3.9 units and time traversed to arrive at the desired location using optimal path is 25 sec after 150 iterations.

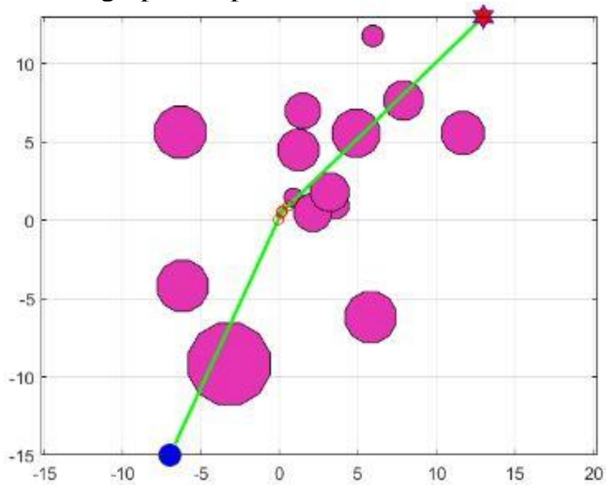

Fig3: Figure shows the optimal path generated by applying Particle swarm optimization

3.4 Ant Colony Method

It is an optimization technique that uses the probability method to predict the best path solution. It uses the natural communication phenomena used by ants for communication. Ants while searching for food leave pheromones on their path traversed, the path on which maximum pheromones are deposited is considered the path with the least distance to reach the target location. Here the ants move based on pheromones concentration, the likelihood of the ant's motion from one point to another is given by the below equation [40]

$$k_{ab}^{n} = \begin{cases} (p_{ab}^{\alpha}(t)d_{ab}^{\beta}(t) / \sum_{m \epsilon Q_n} \left(p_{ab}^{\alpha}(t)d_{ab}^{\beta}(t)\right), & m \epsilon Q_n \\ 0 & , m \notin Q_n \end{cases} \quad (7)$$

$$d_{ab} = \frac{1}{s_{ab}} \quad (8)$$

$$s_{ab} = \sqrt{(x_a - x_b)^2 + (y_a - y_b)^2} \quad (9)$$

Where k_{ab}^{n} = probability of n ants to move from a location to b location

p_{ab}= pheromone concentration on moving path

d_{ab}= distance function

s_{ab} = Euclidean distance from a to b location

α= pheromone factor

β= distance function factor

Here we have used the ACO algorithm for path optimization of our developed flying robot. Figure 4 below shows the optimal path obtained from the ACO algorithm in the MATLAB environment. Our simulation results obtained had cost function which deals with distance parameter as 3.8 units and time traversed to arrive at the desired location using optimal path is 15 sec after 150 iterations. Figure 5 shows the convergence of the cost function over 150 iterations carried out in the simulation.

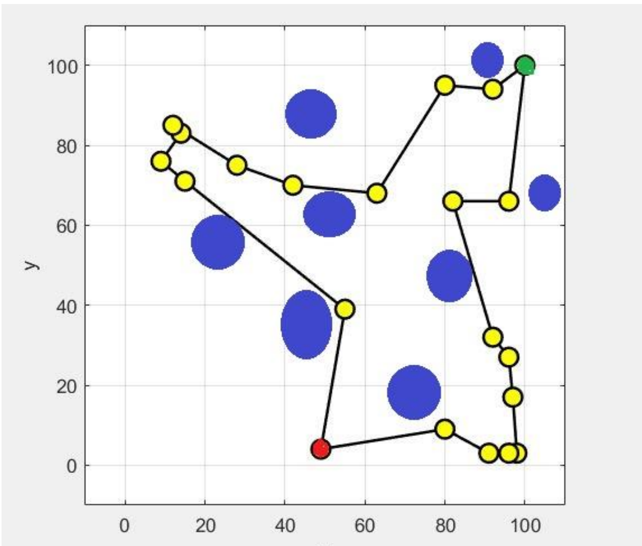

Fig4: Figure shows the optimal path generated by applying Ant colony optimization

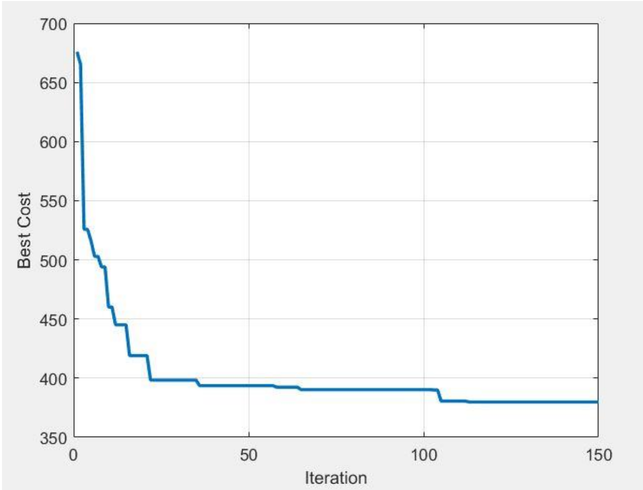

Fig5: Figure shows the convergence of cost function over 150 iterations

4. Comparison of the different algorithms using MCDM and TOPSIS

In this paper, five different algorithms were applied to fixed-wing type flying robots for path planning. To discover the relevant method for route discovery of our developed aerial vehicle for indoor application. we had taken a few random 2d points with random obstacle points to generate a simulation of the shortest path with obstacle avoidance in a MATLAB environment and applied a mcdm technique and TOPSIS to determine the suitable algorithm among the above five based on the distance traveled by the path and time taken for execution.

4.1 MCDM

The above-mentioned method uses multiple criteria for deciding the favorable condition for a particular application.[41] First, the criteria are classified into beneficiary and non-beneficiary categories. Those criteria lie in the non-beneficiary category we calculate the ratio of the minimum value of those criteria to the summation of all the values in the non-beneficiary category to form the normalized decision matrix. Then weightage for different criteria is set and multiplied with a normalized decision matrix to get the final performance score. We have applied the MCDM technique for our project, the steps of which are shown below. Here we have taken five algorithms ie ACO, ABC, PSO, hybrid PSO and ABC, and Quantum PSO, and compared them on basis of their cost function and execution time the values of which are shown in table 1.

Step 1: A decision matrix is formed by selecting two criteria for path finding

Table 1: The table shows the decision matrix for conducting MCDM on four path planning algorithms considering the criteria of cost and time.

Path Planning Algorithm	**CRITERIA**	
	Cost Function	**Execution Time(sec)**
Artificial Bee Colony(ABC)	5.43	6.95
Ant Colony Optimization(ACO)	3.8	15
Particle Swarm Optimization(PSO)	5.45	6.04
Hybrid Algorithm(PSO+ABC)	3.9	25
Quantum PSO	3.4	4.75

Step 2: Normalized Decision matrix to be formed. In this case, both cost function and time should be minimized for optimal results the following equation to be used[38]

$$D= \frac{\min(x_{ab})}{x_{ab}} \qquad (10)$$

Where D refers to normalized values

Table 2: The table shows the standardized decision matrix obtained

Path Planning Algorithm	CRITERIA	
	Cost Function	Execution Time(sec)
Artificial Bee Colony(ABC)	3.4/5.43 = 0.626	4.75/6.95 = 0.683
Ant Colony Optimization(ACO)	3.4/3.8 = 0.895	4.75/15 = 0.32
Particle Swarm Optimization(PSO)	3.4/5.45 =0.624	4.75/6.04 =0.786
Hybrid Algorithm(PSO+ABC)	3.4/3.9 = 0.87	4.75/25 = 0.19
Quantum PSO	3.4/3.4=1	4.75/4.75 =1

Step3: Finding the standardized decision matrix by multiplying desired weightage value

$$y = w \text{ X } D \qquad (11)$$

w = weight

y= weighted normalized values

Here we have taken the weightage value for the cost function (distance traversed) and time is taken to be 0.5 each.

Table 3: The table shows standardized values with weight function added into the decision matrix

Path Planning Algorithm	CRITERIA	
	Cost Function	Execution Time(sec)
Artificial Bee Colony(ABC)	(0.626X0.5)= 0.3495	(0.683 X 0.5)= 0.4345
Ant Colony Optimization(ACO)	(0.895X 0.5) =0.448	(0.32 X 0.5) = 0.16
Particle Swarm Optimization(PSO)	(0.624 X 0.5) = 0.312	(0.786X 0.5) =0.393
Hybrid Algorithm(PSO+ABC)	(0.87 X 0.5) =0.435	(0.19 X 0.5) =0.095
Quantum PSO	(1X0.5)=0.5	(1X0.5)=0.5

Step 4: Calculate the performance score

Table 4: The table shows the performance score and rank generated by the MCDM technique

Path Planning Algorithm	CRITERIA		Performance Score	Rank
	Cost Function	Execution Time(sec)		
Artificial Bee Colony(ABC)	0.313	0.342	(0.313+0.342) =0.655	3
Ant Colony Optimization(ACO)	0.448	0.16	(0.448+0.16) = 0.608	4
Particle Swarm Optimization(PSO)	0.312	0.393	(0.312+0.393) =0.705	2
Hybrid Algorithm(PSO+ABC)	0.435	0.095	(0.435+0.095) =0.53	5
Quantum PSO	0.5	0.5	(0.5+0.5)=1	1

Table 4 shows the performance score and rank generated by applying the MCDM technique. From the above calculation, it was found that the performance score for Quantum Particle swarm optimization was the highest, so we can say that Quantum particle swarm optimization is most effective as compared to the other four algorithms for path planning of flying robots using distance and time, and criteria for evaluation.

4.2 TOPSIS

It is the method in which multiple criteria are taken into consideration and also similarity preferences are considered for the selection of the best solution out of a given set of solutions. TOPSIS works on the method in which we find the minimum distance from the absolute positive solution [42]. We have used the TOPSIS method to check the best alternative for our pathfinding for flying robots out of the four swarms intelligent methods studied and then used a quantum-inspired model to find the best alternative for our path planning algorithm. Here we have applied ACO, ABC, PSO, hybrid PSO, and

ABC and Quantum PSO for path planning of flying robots based on their cost function and execution time the table has been built as shown in table 5. The steps of TOPSIS applied in our project are shown below

Step 1: A decision matrix is formed by selecting two criteria for path finding

Table 5: The table shows the decision matrix by selecting two criteria for path finding

Path Planning Algorithm	**CRITERIA**	
	Cost Function	**Execution Time(sec)**
Artificial Bee Colony(ABC)	5.43	6.95
Ant Colony Optimization(ACO)	3.8	15
Particle Swarm Optimization(PSO)	5.45	6.04
Hybrid Algorithm(PSO+ABC)	3.9	25
Quantum PSO	3.4	4.75

Step 2: Normalized Decision matrix to be formed. The equation for normalization is given below [40]

$$S_{ab}=\frac{x_{ab}}{\sqrt{\sum_{b=1}^{n} x_{ab}^{2}}} \ldots\ldots\ldots\ldots (12)$$

Where S_{ab} is the normalized values

X = each algorithm parameters

a= 1,2 … m

b= 1,2……n

m=no of substitute

n=no of criteria

Table 6: The table represents the standardized decision matrix for TOPSIS

Path Planning Algorithm	**CRITERIA**	
	Cost Function	**Execution Time(sec)**
Artificial Bee Colony(ABC)	5.43/10.019 = 0.542	6.95/30.94 = 0.225
Ant Colony Optimization(ACO)	3.8/10.019 = 0.379	15/30.94 = 0.485
Particle Swarm Optimization(PSO)	5.45/10.019= 0.544	6.04/30.94 = 0.195
Hybrid Algorithm(PSO+ABC)	3.9/10.019 = 0.389	25/30.94 = 0.808
Quantum PSO	3.4/10.019 = 0.339	4.75/30.94 = 0.154
$\sqrt{\sum_{b=1}^{q} x_{ab}^2}$	$\sqrt{5.43^2 + 3.4^2 + 3.8^2 + 5.45^2 + 3.9^2}$ = 10.019	$\sqrt{6.95^2 + 4.75^2 + 15^2 + 6.04^2 + 25^2}$ = 30.94

Step 3: Evaluate the standardized decision matrix with weights

y = w X S_{ab} ………. (13)

Here we have taken the weightage value for the cost function (distance traversed) and time is taken to be 0.5 each.

Table 7: The table shows weighted normalized values in the decision matrix for TOPSIS

Path Planning Algorithm	**CRITERIA**	
	Cost Function	**Execution Time(sec)**
Artificial Bee Colony(ABC)	(0.542X0.5)= 0.271	(0.225 X 0.5)= 0.1125
Ant Colony Optimization(ACO)	(0.379X 0.5) =0.19	(0.485 X 0.5) = 0.243
Particle Swarm Optimization(PSO)	(0.544 X 0.5) = 0.272	(0.195X 0.5) =0.098
Hybrid Algorithm(PSO+ABC)	(0.389X 0.5) =0.195	(0.808 X 0.5) =0.404
Quantum PSO	(0.339X0.5)= 0.17	(0.154X0.5) = 0.077

Step 4: Find the perfect solutions using the weighted function method. For cost function and time the minimum value is the positive perfect result and the maximum output is the negative result.

Table 8: The table shows positive and negative ideal solutions generated from the decision matrix

Path Planning Algorithm	**CRITERIA**	
	Cost Function	**Execution Time(sec)**
Artificial Bee Colony(ABC)	0.271	0.1125
Ant Colony Optimization(ACO)	0.19	0.243
Particle Swarm Optimization(PSO)	0.272	0.098
Hybrid Algorithm(PSO+ABC)	0.195	0.404
	0.17	0.077
Positive Ideal solution k^+	0.17	0.077
Negative Ideal solution k^-	0.272	0.404

Step 5: Evaluation of euclidean distance of individual parameters

$$e_b^+ = \sqrt{\sum_{a=1}^{p}(v_{ab} - k^+)^2} \quad \ldots\ldots\ldots\ldots (14)$$

$$e_b^- = \sqrt{\sum_{a=1}^{p}(v_{ab} - k^-)^2} \quad \ldots\ldots\ldots\ldots (15)$$

Where e_b^+= euclidean distance from a positive perfect results
e_b^-= euclidean distance from a negative perfect results

Table 9: Table shows the Euclidean distance of individual parameters from the weighted normalized decision matrix

Path Planning Algorithm	**CRITERIA**		e_b^+	e_b^-
	Cost Function	**Execution Time(sec)**		
Artificial Bee Colony(ABC)	0.271	0.1125	0.107	0.292
Ant Colony Optimization(ACO)	0.19	0.243	0.167	0.181
Particle Swarm Optimization(PSO)	0.272	0.098	0.104	0.306
Hybrid Algorithm(PSO+ABC)	0.195	0.404	0.328	0.077
Quantum PSO	0.17	0.077	0	0.343
Positive Ideal solution k^+	0.17	0.077		
Negative Ideal solution k^-	0.272	0.404		

Step 6: Calculate the relative proximity to an ideal solution

$$c_a = \frac{e_b^-}{e_b^+ + e_b^-}$$

Table 10: The table shows performance scores and rank using TOPSIS

Path Planning Algorithm	**CRITERIA**		e_b^+	e_b^-	**Performance score** c_a	**Rank**
	Cost Function	**Execution Time(sec)**				
ABC	0.271	0.1125	0.107	0.292	$\frac{0.292}{(0.292+0.107)} = 0.732$	**3**
ACO	0.19	0.243	0.167	0.181	$\frac{0.181}{(0.167+0.181)} = 0.52$	**4**
PSO	0.272	0.098	0.104	0.306	$\frac{0.306}{(0.306+0.104)} = 0.75$	**2**
Hybrid Algorithm(PSO+ABC)	0.195	0.404	0.328	0.077	$\frac{0.077}{(0.328+0.077)} = 0.19$	**5**
Quantum PSO	0.17	0.077	0	0.343	$\frac{0.343}{(0+0.343)} = 1$	**1**
Positive Ideal solution k^+	0.17	0.077				
Negative Ideal solution k^-	0.272	0.404				

Table 10 shows the performance score and rank generated by applying the TOPSIS method. After calculating the relative proximity which gives the performance score, the algorithm with the maximum performance score will be ranked 1. As shown in the table Quantum

PSO algorithm is ranked 1, so we can say that Quantum particle swarm optimization is most effective as compared to the other four algorithms for path planning of flying robots using distance and time, and criteria for evaluation.

5. Conclusion

In this paper, we have applied different artificial intelligence-based optimization techniques to find an initial path to be traversed by our developed fixed-wing aerial vehicle having a payload proportion of 2kg in a closed room environment. We have carried out 2d simulations of different path planning algorithms like aco, abc, pso, and hybrid PSO and ABC algorithms in MATLAB using random 2d coordinates and random obstacles in a 2d environment. After performing the analysis we applied multi-criteria decision-making and the TOPSIS approach to detect the best algorithm out of the four techniques used for path finding of the aerial vehicle taking into consideration the distance traversed and time for execution. It was found from both methods that Particle swarm optimization will be the best path planning algorithm based on the cost function and time minimization criteria and then we again applied the quantum PSO technique as quantum-inspired models have better performance. And the results from quantum PSO were also compared with ACO, ABC, PSO, and hybrid PSO and ABC algorithms, and it was found applying the MCDM technique that quantum PSO is the best path planning technique for flying robots with optimized cost function and execution time.

6. FUTURE SCOPE

As we have initially found the best path to be traveled by our flying robot further we will be working on a backpropagation algorithm so that our flying robot can return from the target location to the source location without human intervention.

DECLARATION

The research has not been funded. It contains no conflict of interest. The data used for research and the result generated are included in the article to be published. Code for the results can be provided on reasonable request to corresponding author.

DATA AVAILABILITY

The data used for research and the result generated are included in the article to be published.

7. REFERENCES

[1] Eric Feron, “Aerial Robotics”, Springer, 2008, pp 1010 -1013

[2] K. Nonami , F Kendoul , "Autonomous flying robots, unmanned aerial vehicles, and micro aerial vehicles", Springer, 2010, pp 14

[3] Yang Liang, J Qi , “ A literature review of UAV 3d path planning”, 2016, pp 1-3

[4] Yufeng He, Qinghua Zeng, “Path planning for indoor UAV based on ant colony optimization”, IEEE, 2013, pp 2919-2923

[5] Zhang Zhe, Jian Wu, Cheng He, “Optimal path planning with modified A-Star algorithm for stealth unmanned aerial vehicles in 3D network radar environment”, Journal of Aerospace Engineering, April 2021, pp. 1-6

[6] Anand Nayyar, Sandeep Kumar, “Robot path planning using modified artificial bee colony algorithm”, Advances in intelligent system and computing book series, October 2019, pp.367

[7] Shikai Shao, Peng Yu, “Efficient path planning for UAV formation via comprehensively improved pso”, Elsevier, vol 97, Feb 2020, pp. 415-430

[8] Shin Jong-Jin, Bang Hyochoong, “UAV path planning under dynamic threats using an improved PSO algorithm”, International Journal of Aerospace Engineering, Vol 2020, pp.17

[9] Y Liu, X Zhang, X Guan, "Adaptive sensitivity decision-based path planning algorithm for an unmanned aerial vehicle with improved particle swarm optimization," Aerospace Science and Technology, 2016, pp. 92-102

[10] N Ozalp and O.K Sahingoz, "Optimal UAV path planning in a 3D threat environment by using parallel evolutionary algorithms," International conference on unmanned aircraft systems, May 2013, pp. 308 –317

[11] Wang Lei, Lui Lili, 'Proved quantum particle swarm optimization for offline path planning in AUV's", IEEE, vol 8, 2020

[12] M Bagherian, A Alos, “3D UAV trajectory planning using evolutionary algorithms: a comparison study” Aeronautical Journal, 2015, vol. 119, pp. 1271–1285

[13] V Roberge,M Tarbouchi, and G Labonte, “Comparison of parallel genetic algorithm and particle swarm optimization for real-time UAV path planning, ” IEEE, 2013, vol. 9, pp. 132 –14

[14]Sonmez Abdurrahim, ‘optimal path planning for UAV using genetic algorithm”, IEEE, July 2015

[15] Aditya S Gautam , Nilamani Verma, "Path planning for the unmanned aerial vehicle on genetic algorithm and artificial neural network in 3D", International conference on data mining and intelligent computing, Sept 2014

[16] Y VolkanPehlivanoglu, "An enhanced genetic algorithm for path planning of autonomous UAV in target coverage problems", Applied Soft Computing, Vol 112, November 2021

[17] De Santis Roberta, Montanari Roberto, 'An adapted ant colony optimization algorithm for the minimization of the travel distance of pickers in manual warehouses', European Journal of Operational Research, May 2018, Vol. 267, pp 120-137

[18]Yue Longwang, "unmanned vehicle path planning using a novel ant colony algorithm", IEEE, 2017

[19] J Cheng , Z Miao , "An improved aco algorithm for mobile robot path planning", Eurasipjournal on wireless communication and network, 2019, pp.1-6

[20] Yan Zhonghua, "Artificial bee colony constrained optimization algorithm with hybrid discrete variables and its application", Acta Electronica Malaysia (AEM), 2018, pp.18-20

[21]Muntasha Gholiyana, Shin Young, "Performance analysis on artificial bee colony algorithm for path planning and collision avoidance in swarm unmanned aerial vehicle", IEEE, April 2021

[22] X Li ,A.P. Engelbrecht , 'Particle swarm optimization—an introduction and its recent developments,' In Proceedings of genetic and evolutionary computation conference, 2007, pp. 3391–3414

[23] Bergh Van den, A.P.Engelbrecht, 'A study of particle swarm optimization particle trajectories,' Information Sciences,2006, pp.937– 971

[24] Bergh Van den, "Analysis of particle swarm optimization", Ph.D. thesis, University of Pretoria, South Africa, 2002.

[25] M.Geethanjali, R Bhavani , 'PSO trained ANN-based differential protection scheme for power transformers,' Neurocomputing Volume 71, 2008, pp. 904–918

[26] B. Booba , T.V. Gopal , 'Comparison of Ant Colony Optimization & Particle Swarm Optimization in Grid Environment' International Journal of Advanced Research in Computer Science and Applications, Vol.1, November 2013

[27] Zhang Tianze, "Hybrid path planning of a quadrotor UAV based on Q-Learning algorithm, 37th Chinese Control Conference (CCC), IEEE Xplore,October 2018

[28] Ritu Maity, Ruby Mishra, P.K. Pattnaik , "Flying robot path planning techniques and its trends", Elsevier, June 2021, pp.1-6

[29] Candeloro Mauro, Lekkas Anastasios M., Jeevith Hegde, "A 3D Dynamic Voronoi Diagram-Based Path-Planning System for UUVs", IEEE, September 2016

[30] Islam Fahad, Malik Usman, Hasan Osman, "RRT*-SMART: A Rapid Convergence Implementation of RRT*", International Conference on Mechatronics and Automation (ICMA), 2012

[31] Pettersson Per Olof "Probabilistic Roadmap Based Path Planning for an Autonomous Unmanned Aerial Vehicle", 2004, pp. 5

[32] Hrvoje Kaluder, Misel Brezak, Ivan Petrovic, "A visibility graph-based method for path planning in dynamic environments", MIPRO, May 2011,pp-23-27

[33] Raja Jarray , “Intelligent Decision Making Approach for Multi-Criteria Path Planning of Unmanned Aerial Vehicles”, 7th International Conference on Automation, Control Engineering & Computer Science (ACECS), vol.64, 2020, pp.2-9

[34] Hamurcu Mustafa,Eren Tamer, “Selection of Unmanned Aerial Vehicles by Using Multicriteria Decision-Making for Defence”, Journal of Mathematics Volume 2020, 2020, pp.11

[35] Yang Liang, Qi Juntong, “A Literature Review of UAV 3D Path Planning”, 2016, pp. 1-3

[36] Rkaa T Kamil , Mohamed," Path Planning of Mobile Robot Using Improved Artificial Bee Colony Algorithm", Engineering and Technology Journal, Vol. 38, 2020, pp.1384-1395

[37] Khuat Thanh Tung, " A novel hybrid PSO-ABC algorithm for effort estimation of software projects using agile methodologies", Journal of intelligent systems, March 2017

[38] Sun Jun, Fang Wei, "Quantum behaved particle swarm optimization; analysis of individual particle behavior and parameter selection", evolutionary computation, 2012

[39] Tarun Kumar Sharma, Millie Pant, “Blend of Local and Global Variant of PSO in ABC”, IEEE Xplore, August 2013

[40] Qi Duo, Zhang Hihao, “Path Planning of Multirotor UAV Based on the Improved Ant Colony Algorithm”, Journal of Robotics, Hindawi, 2022, pp.1-9

[41] C.L.Hwang, K Yoon , “Multiple Attribute Decision Making: Methods and Applications: a State-of-art Survey”, Springer,1981

[42] H Deng, C.H Yeh, “Inter-company comparison using modified TOPSIS with objective weights.” Computers & Operations Research, Pergamon, vol. 27, pp. 963–973

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