Path Planning of Mobile Robot Using Hybrid Algorithm Based on GA-IACO

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Abstract—**In recent years, path planning is considered the optimization problem which is important for mobile robot navigation. This study focuses on the algorithm based on GA and IACO to work in a static environment and solve the global path planning (GPP) issues. The considering approach is effective in solving the issues. The aim is to construct an efficient algorithm that finds the best possible path. This study combines GA-IACO to form a hybrid algorithm for the quick action of selecting the path and altering crossover operators, which decrease the falling risk. The simulations results verify that the robot travels from one to another point safely. It reaches the endpoint by eluding all the obstacles that are present in the way. It signifies that the proposed scheme is accurate and finds an optimal solution with higher efficiency and probability in a short time.**

Index Terms—**Robots, Path planning, IACO, and Genetic Algorithm**

I. Introduction

AERIAL vehicles attain a lot of devotion from different industrial and research societies [1]. Due to their high potential, they are widely used in many applications such as search and rescue operations, construction, exploration, manufacturing, etc. [2]. For any type of aerial vehicle or mobile robot, navigation is important for path planning. It helps the robot in mapping, localization, and path planning. It means that how it identifies its environment, locates itself, and finds its best possible path on the map respectively. Path planning is measured as an optimization problem [3-4]. A key technology used to search for optimal and hurdle-free paths. Thus, this study focuses on the path planning issue, task allocation problem, and design of a hybrid efficient algorithm based on GA and IACO [5]. The advantage of this scheme is that it reduces solve optimality, search space issues and results verify the capabilities and effectiveness of the proposed algorithms. Among all the optimizations methodologies such as Particle Swarm Optimization (PSO) and Tabu Search (TS) [6], this algorithm has a high approach to solve the above-mentioned issues. This represents the motivation of this study.

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The study aims towards the path planning of vehicles to get maximum benefits. This study [7] creates an algorithm based on GA and ACO to solve the planning problems. The main objective of the proposed algorithm is to substitute the bad characters with the new one in GA, which was created by the ACO. In [8] this study, the ACO method is used to solve the path-planning problem of mobile robots. Several maps evaluate the effectiveness of the algorithm. Every map attains the obstacles in dissimilar arrangements and has grid demonstration. Similarly, the results verify the approach of the algorithm. Furthermore, another study [9] uses the improved (IGA) algorithm for the path planning of robots for the welding operation. The workstation has a complexity from which path will create. The results show its reliability and effectiveness. In this study, the path planning algorithms were applied for a high number of grid maps to attain an optimal path. In addition, both methods namely exact and heuristic are considered.

Numerous algorithms are designed [10], evaluated, and implemented to solve the issues of grid maps. Lastly, another study a hybrid algorithm based on ACO and GA was created to solve the global path planning for the mobile robots. The first algorithm is used to detect the path, which is collision-free, and the second for the initial population.

The contributions of this manuscript are that a hybrid algorithm was designed based on GA and IACO to solve the robot global path planning (RGPP) issues [11]. The proposed algorithm attains the best features of both algorithms. By combing these algorithms, an effective search algorithm is created which trim the search space, advances the quality of the solution, and fastens the search time. This could be done by HDIP, transition rule probability, and MO. Secondly, a simulation study is presented to examine and evaluate the performance of the proposed algorithm. It clearly shows that the algorithm improves the quality of the solution. Lastly, this algorithm is also implemented on real-world robots. The simulation output shows the effectiveness and feasibility of the algorithm when activated in real-time.

The manuscript is organized as follows. The introduction is presented in section 1. The problem statement is defined in section 2. Section 3 defines the recent trends in the field of path planning. The description of GA and ACO is defined in section 4. Similarly, section 5 defines the environment model. In section 6, the phase of GA and section 7 phase of IACO are discussed. The simulations are done in section 8. Section 9 presents the conclusion of this manuscript.

II. Problems Related To Path Planning

This section defines the problems related to path planning. It aims to create a path for a robot that is collision-free from start to endpoint [12]. The robot dodges each obstacle present in the workstation by having some environmental information. The decided path must satisfy the time, energy, and distance. The objective of this study is to design a path planning effective strategy. The navigation function guarantees that how proficiently a robot travels in the environment. The moving vehicle knows about the environment. The robot uses localization, mapping, and addressing a function to identify and plan its path. Localization helps to know the location where it is and mapping helps to recognize where it is moving. The in the memory of the robot the map is set. Addressing helps the robot to target the point that demarcates to it. It also specifies where to go from the start position. The problems include both static and dynamic environments. In a static environment, the start and end position is fixed. Similarly, fixed hurdles and did not change over time. However, in dynamic the situation is inverse. The robot experience unwanted situations just because the position and hurdles changes over time. Path planning is divided into two types according to the knowledge of the robot. Firstly, the knowledge of the environment model as a map. This is called global path planning (GPP). Secondly, the robot has no information about the environment. In this case, it has to intellect the obstacle creates a predictable map that helps to avoid hurdles and provides a suitable path towards the end position. This is called local path planning (LPP). This study states the GPP problem in a static environment.

III. State of The Art

In this section of the manuscript, the recent trends in the field of path planning are discussed. In recent years, optimization algorithms developed which attains excellent performance and great potential to solve typical problems. ACO is one of the development. Recently, Q-learning gained a lot of attention in the path planning of autonomous vehicles. About [13], the IACO algorithm was proposed to solve the path planning problems in the environment, which attains obstacles. The simulation constant parameters are determined when the distance between the vehicle and obstacle is less than the threshold. The results verify the effectiveness of the proposed algorithm. Similarly, the accuracy and intensity of vehicles increased in path planning. In reference to [14], the IACO algorithm was proposed to solve the global path planning (GPP) problem. In this research study, the critical obstacle factor was used to determine the initial pheromone. This factor helps in improving the speed of the algorithm. Fuzzy control helps in developing a new pheromone rule. This method allows achieving a fast speed with high searching capability. Lastly, the simulation results verify that this method attains a high probability to attain the optimal solution. In [15] the study focuses on the problems of path planning as slow response speed, long path, unknown parameters, etc. An improved genetic algorithm (IGA) was developed to solve the path-planning problem. The algorithm uses the heuristic median intersection method to form the preliminary population. It improves the efficiency of the system and constructs multi-objective functions based on path length, security, and energy. Layered methods are used to design mutation operators (MO), crossover, and selection. The simulation result shows that the algorithm can improve the defects of GA. In reference to [16], a hybrid algorithm was created based on ACO and PGA called (ACOPGA). Initially, the pheromone diffusion model, initialization strategy, and update mechanism have introduced to improve the ACO algorithm. Thus, the efficiency and solution quality is increased. The optimization method based on PGA is designed to optimize the initial path to attain a better convergence rate. Lastly, the performance of an algorithm is verified by multiple tests. Simulation results verify the stability, adaptability, and effectiveness of the proposed algorithm.

IV. Description of Genetic Algorithm (GA) and Ant Colony Optimization (ACO)

GA was invented by John Holland in 1975 [17]. Utilize to solve search and optimization problems. The base of GA is formed by gene, population, and chromosome. It also maintains the solution called a chromosome. Its mechanism includes fitness evolution, selection, crossover, and mutation [18-19]. Generally, the algorithmic scheme followed by GA is presented in table 1. Firstly, a set of chromosomes is created at the start of the algorithm. Then, the evolution of every chromosome takes place individually to assess the fitness. Furthermore, for the fittest and optimal solution genetic transformation (GT) is applied. This whole process was repeated several times until the condition was verified. The most important advantage of this algorithm is that it congregates towards the optimal solution.

TABLE I
GA-Pseudo-Code

1-	Randomly Generate the Initial Population
2-	While Termination Condition No Met Do
3-	Using Fitness Function Evaluates Different Chromosomes of an Initial Population
4-	Apply GA Operators i.e., (Selection, Crossover, Mutation)
5-	End While

To solve the path planning problems, a GA algorithm is applied. Consider a scenario in which the environment is modeled as a graph. Firstly, initial population generation takes place. Each path is represented by the chromosome individually. Similarly, the vertex of the graph is represented by a genetic factor. In this algorithm, a vertex that creates a path designated randomly and to attain a viable path neighboring vertex must be linked. Individually, every path is examined and ranked after the generation by using the following fitness function.

$$f = \frac{1}{\sum_{a=1}^{n} D_{a,a+1}} \tag{1}$$

Whereas the number of the vertex that is creating a path is denoted by n. $D_{a,a+1}$ is the distance among the vertex a and $a+1$. The fittest path is selected by passing through the schemes of algorithms. Genetic Operators (GO) are used to attain a new solution from the existing solution. The steps were repeated several times until the targeted condition was reached.

In 1992, Marco Dorigo proposed this algorithm ACO [20] by inspiring the behavior of ants in real life. This algorithm is used to solve problematic issues related to optimization. Furthermore, this algorithm initially applied to the travelling salesperson problem (TSP) [21-22]. After then it was used to solve path planning and research problems. Generally, the algorithmic scheme followed by ACO is presented in table 2. Firstly, the initial value and different parameters are established during the initialization. Then, a loop is repeated several times to achieve the targeted condition. Ants generate a practical solution for an optimization problem. After that, the attained solution improved with the help of a procedure called local research. Lastly, the amount of pheromone was restructured.

TABLE II
ACO-PSEUDO-CODE

1-	Set Parameters
2-	Initialization
3-	While Termination Condition No Met Do
4-	Construct Ant Solutions
5-	Local Search Applied
6-	Pheromones Updated
7-	End While

To solve the path-planning problem, the ACO algorithm is applied. Consider a scenario in which flexible space is modelled as a graph. An ant starts creating a path from the start to the targeted position at every iteration by walking on the verge of the graph. The following vertex is selected according to the transition rule given below.

$$P^{u}_{a,b} = \frac{\rho^{\alpha}_{a,b} \times \omega^{\beta}_{a,b}}{\sum_{b \epsilon A(a)} (\rho^{\alpha}_{a,b} \times \omega^{\beta}_{a,b})} \quad (2)$$

Whereas the transition of probability for u^{th} ant from point a to b is given by $P^{u}_{a,b}$, $\rho^{\alpha}_{a,b}$ is the amount of pheromone joining a and $b, \omega_{a,b}$. $A(a)$ represents the set of the adjacent node which is still not stayed by the u^{th} ant. α and β define the weight of pheromone & distance respectively. The amount of pheromone joining two points a and b restructured as follows.

$$\rho_{a,b}(t+1) = (1-\sigma) \times \rho_{a,b}(t) + \sum_{u=1}^{M} \Delta \rho^{u}_{a,b} \quad (3)$$

$$\Delta \rho^{u}_{a,b} = \begin{cases} \frac{R}{l_u} \\ 0 \end{cases} \quad (4)$$

Whereas the evaporation rate is denoted by σ, the number of ants is M, and the amount of pheromone is represented by $\Delta\rho^{u}_{a,b}$ on the edge (a,b). R the constant and l_u is the length of the path created by the ant.

V. ENVIRONMENT MODEL (EM)

In this study, the grid-based model is used to signify the workstation of the vehicle. The workstation is divided into lattices. The hurdles/ obstacles inhabit more than one lattice depending on their size related to the size of the vehicle. Two types of EM is presented in this study which is path planning with obstacle and without obstacle. The workstation of the vehicle is defined by the two-dimensional map, which defines the start point, areas that attain obstacles/ no obstacle and, endpoint. In an area without obstacles, the connection points are organized in random positions. Furthermore, every point signifies the location/position in the environment. It is signified by the set of neighboring points and by two coordinates (X and Y). In an area with obstacles, the vehicle selects the best sequence of points to attain the best possible path. Consider a scenario with obstacles having a random point from 0 to 10. The best possible path is 0-3-8-10 in the figure below having a start position 0 and targeted position 10. The vehicle moves between points that are interconnected with each other. If an obstacle is presented in the followed path, the points remain unconnected. The points are randomly created and connected.

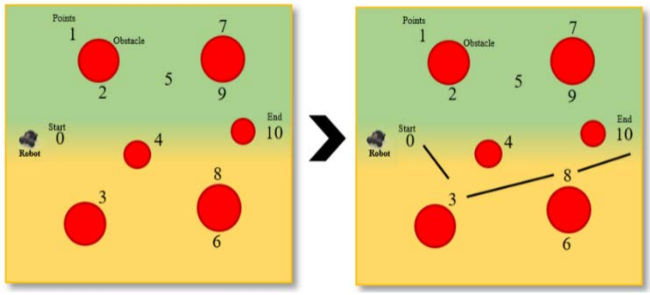


Fig. 1. Environment Model.

VI. A PHASE OF GA

This phase is used to advance the quality of a solution attained by improved optimization i.e. (IACO). The crossover operators (CO) were applied on the paths created by the ACO algorithm. It picks up two points 1 and 2, which are common from paths 1 and 2. Relating parts of both paths includes before point 1, selected points among point 1 and 2, and after point 2. To create a new path, the best points selected and the length of the path, which newly identified, are the same as those two paths. Consider the example below

Path 1	0	3	8	9	10
Path 2	0	2	5	8	10

8 and 10 are the two common points selected. Only the shortest path is created from paths 1 and 2. The target point is added in the length of the path attained (path 3) because it is smaller than both paths to get equality.

Path 3	0	3	8	10	10

VII. A PHASE OF IMPROVED ANT COLONY OPTIMIZATION (IACO)

IACO algorithm is used to create the set of best possible paths. The workstation modelled as a graph. Each ant can find the best path from the initial to a final point, move from one point to another, and made choice about the different position. The three steps are as follows in which execution takes place.

Step 1: Finding of Path

From the start to the endpoint, ants search for the best possible shortest path. During the journey towards the targeted point, the ant decides its next point smartly. Functions that are used in path planning to optimize the decision of an ant are as follows

Heuristic Distance Information Probability (HDIP)

The decision of the ant is based on the transition rule probability function [23]. HDIP is used in algorithms earliest iteration. The amount of pheromone is not important in the initial construction of paths. It also does not influence the building of the solution. This probability function is used to calculate the transition probability and to escape deficiencies. The function is given is as:

$$\rho_{a,b}^{u} = \frac{((C_{A(a),G} - c_{b,G}) \times \eta + \zeta)^{\lambda}}{\sum_{b \epsilon A(a)} ((C_{A(a),G} - c_{b,G}) \times \eta + \zeta)^{\lambda}} \tag{5}$$

Whereas the transition probability of u^{th} ant is denoted by $\rho_{a,b}^{u}$ from point a to b. $A(a)$ represents the set of points of a neighbor where ant not yet visited. The distance from the point b to the targeted destination is denoted by $c_{b,G}$. η , ζ , and λ are the constants. Lastly $C_{A(a),G}$ represents the maximum of all $c_{b,G}$.

Modified Transition Rule Probability (MTRP)

For the remaining iterations of the proposed algorithm, MTRP is used [24-25]. The function is defined as follows:

$$P_{a,b}^{u} = \frac{\rho_{a,b}^{\alpha} \times C^{\beta}}{\sum_{b \epsilon A(a)} (\rho_{a,b}^{\alpha} \times C^{\beta})} \tag{6}$$

Whereas, the transition probability from point a to b is represented by $P_{a,b}^{u}$. The amount of pheromone is denoted by $\rho_{a,b}$. $A(a)$ represents the set of points of a neighbor where ant not yet visited. α and β define the weight of pheromone & distance respectively.

Step 2: Optimization of path

The optimization of the path is divided into two parts, which are as follows:

Control of Ants:

The ants were observed when the creation of paths take place. If an ant moves from a definite onset distance, it will discard because the solution cost increases. The other reason is that it will not create the best possible path. It helps to disregard the bad solution and decrease the search space.

Mutation Operator (MO):

The best possible path was attained after the IACO algorithm iteration. Formerly, on the attained path MO was applied to get the superior solution. This is used to check all points and change the points to decrease the length of the final path.

Step 3: Upgradation of Pheromone

The amount of pheromone is progressed after every iteration with the help of all the all ants. The best solution was also built with the help of ants. The amount of pheromone is linked with every edge at which joints point *a* and *b*.

VIII. Simulation and Discussion

This section presents the simulations and proves the efficiency of the proposed algorithm in unlike environments. The simulations were done on the computer with the help of MATLAB software. The table below shows the comparison of the proposed algorithm in both environments in terms of length, execution time, and the number of nodes discovered during the total time of flight. Each environment attains different parameters as seen in the figure.

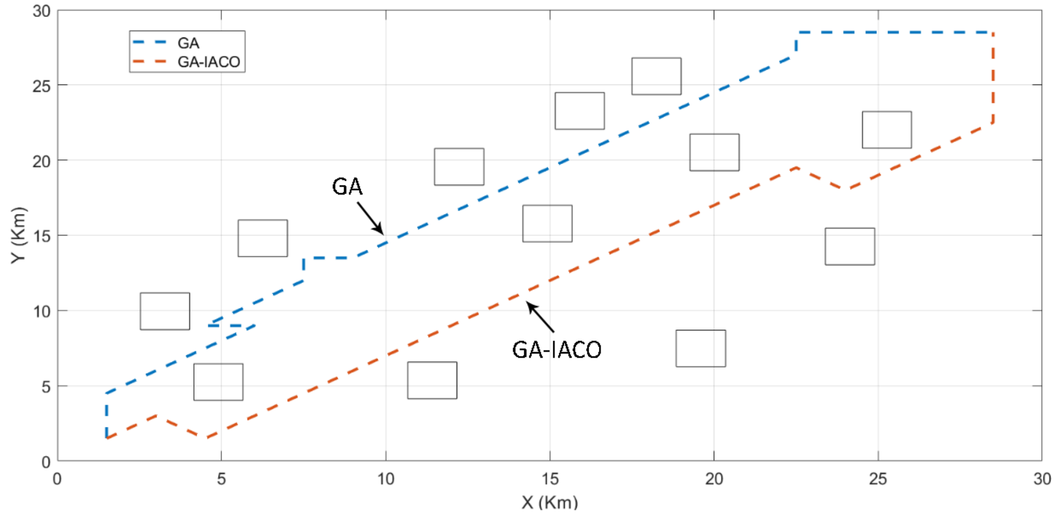
TABLE III
THE DIFFERENCE AMONG THE ENVIRONMENT (E1 & E2)

Environment	E-1	E-2
Length of the generated path (m)	18.25	16.97
Execution time (s)	0.2564	0.0998
Number of nodes discovered	3228	1135

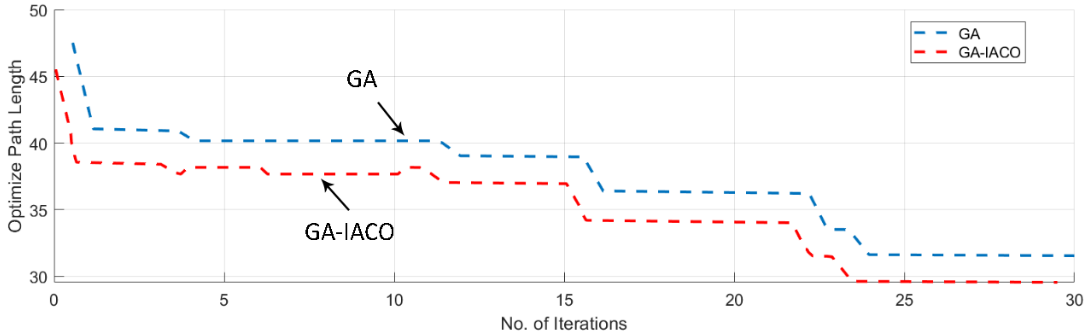
This study examines the scheme in three scenarios. These scenarios signify the common challenges faced in daily operations. The environment of the first scenario contains the different obstacles with different algorithms, the second scenario is free from the obstacles, and the other contains obstacles of different sizes using the GA-IACO algorithm.

Scenario 1

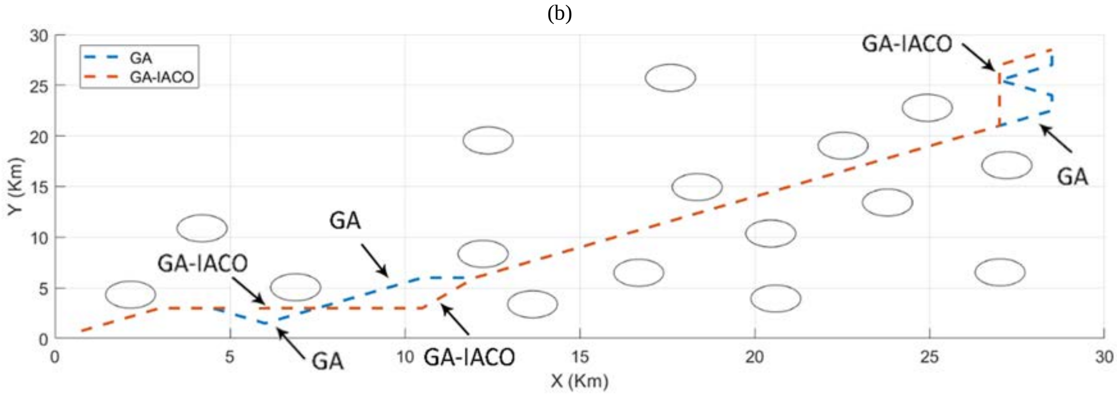
The simulation output shows the path planning of two robots with obstacles attaining different algorithms i.e. GA and GA-IACO. In (a) obstacles are present in the square and (c) obstacles are present in circles. The objective in this environment is to avoid each other and reach the targeted position with the shortest path. Figure 2(a-d) shows the optimal path for a solo objective in terms of length. As shown in the figure GA-IACO approach is more efficient and accurate in generating the optimal path as compared to GA individually. The proposed scheme generates the shortest path very quickly. The performance index PI (ratio among the length of a generated path to a straight line between start and end-point). The PI of the proposed scheme is approximately 1.2-1.5 which shows it attains the ability to generate the optimal path.



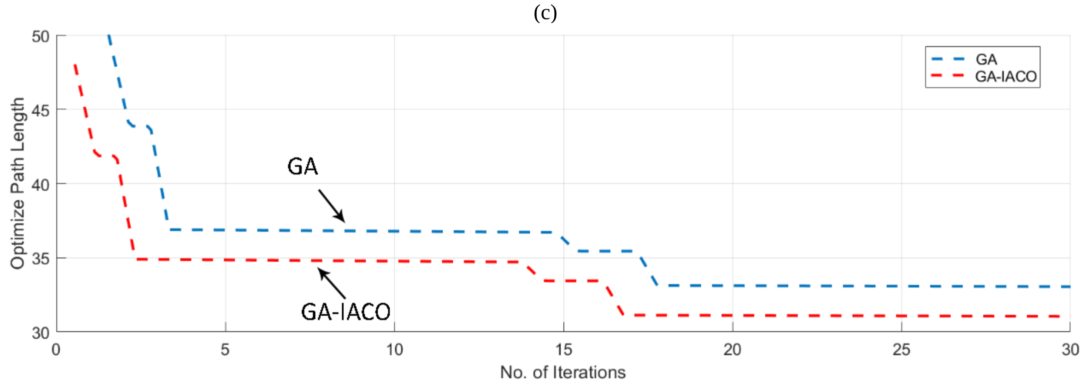
(a)



(b)



(c)



(d)

Fig. 2(a-d). Mobile Robot Optimal Path with Different Obstacles with GA & GA-IACO

Scenario 2

The simulation output shows the path planning of nine robots without obstacles from the start to the endpoint. No obstacles are present in the environment. The objective in this environment is to avoid the neighbor vehicle, preserve the created path, and reach the targeted position. Figure 3 shows the 2D environment in the XY plane showing the lengths in kilometers (km). The different color shows the individual mobile robot.The figure shows that all the robots reached the targeted positions with different path lengths. Figure 4 shows the iterative process of robots without obstacles.

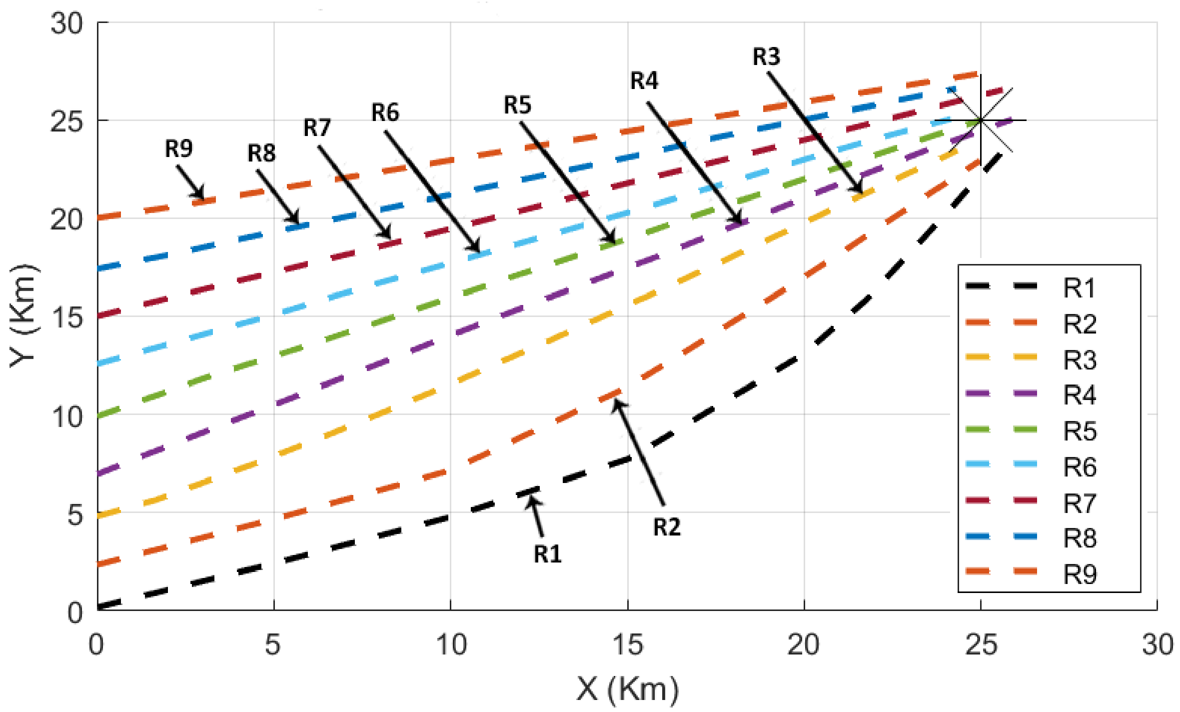


Fig. 3. Path Planning of Robots Without Obstacles

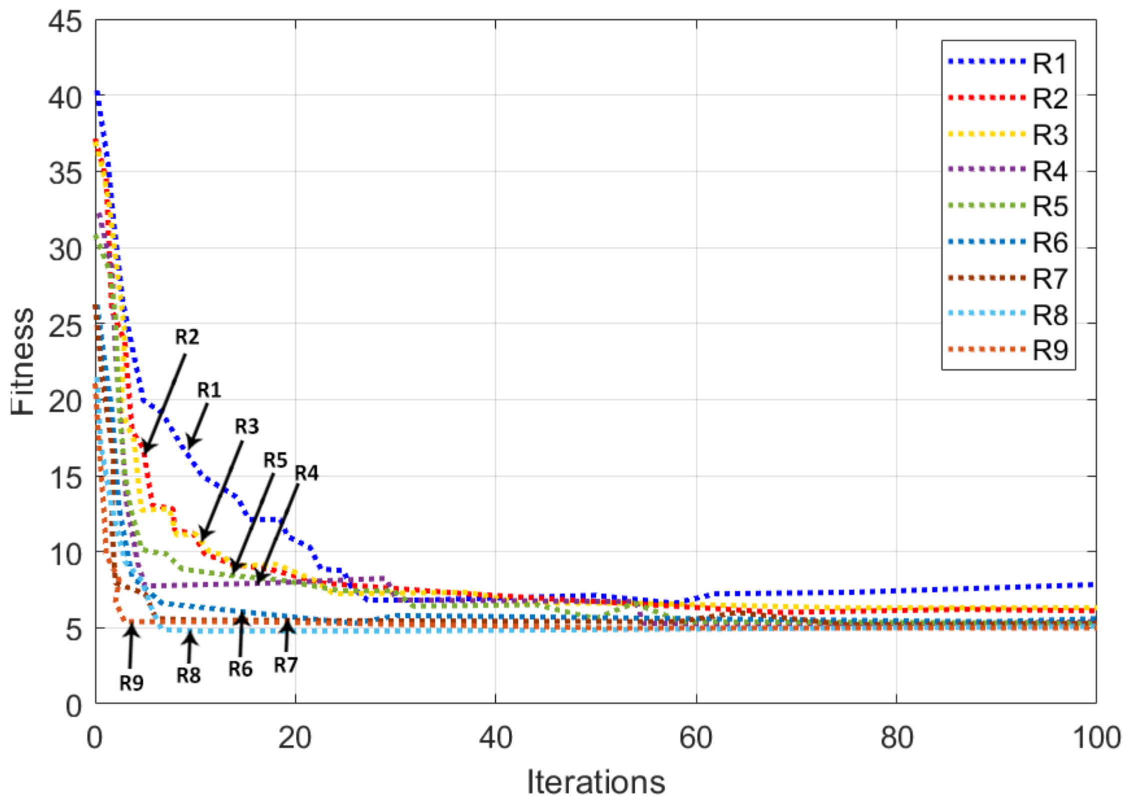


Fig. 4. The Iterative Process of Robots Without Obstacles

Scenario 3

The simulation output shows the path planning of nine robots with obstacles from the start to the endpoint. Eleven obstacles are present in the environment having different lengths and sizes. The objective is to dodge the obstacles, avoid the neighbor vehicle, preserve the created path and find the best possible path from start to targeted position. Figure 5 shows the 2D environment in the XY plane showing the different obstacles at different locations and lengths in meters (m). Each robot as seen in the figure represented by a different color. It is clearly shown from the figure those robots reached the targeted position by dodging obstacles present. Figure 6 shows the iterative process of robots with obstacles.

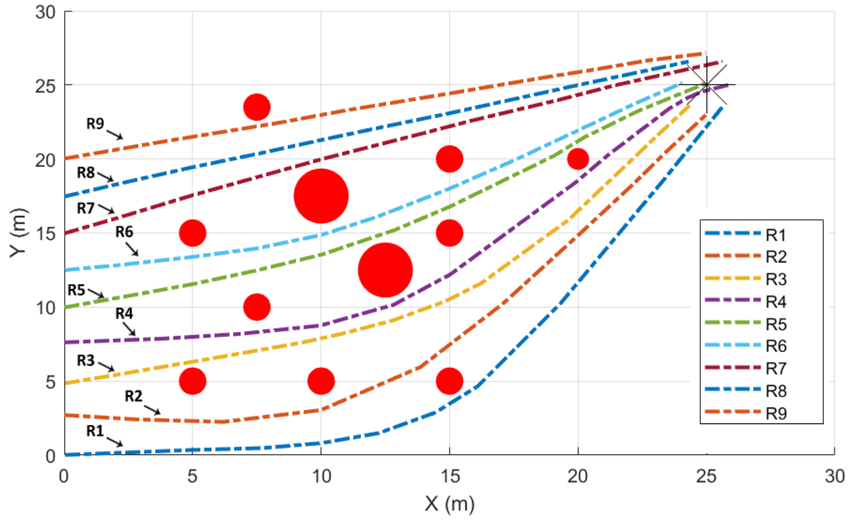


Fig. 5. Path Planning of Robots with Obstacles

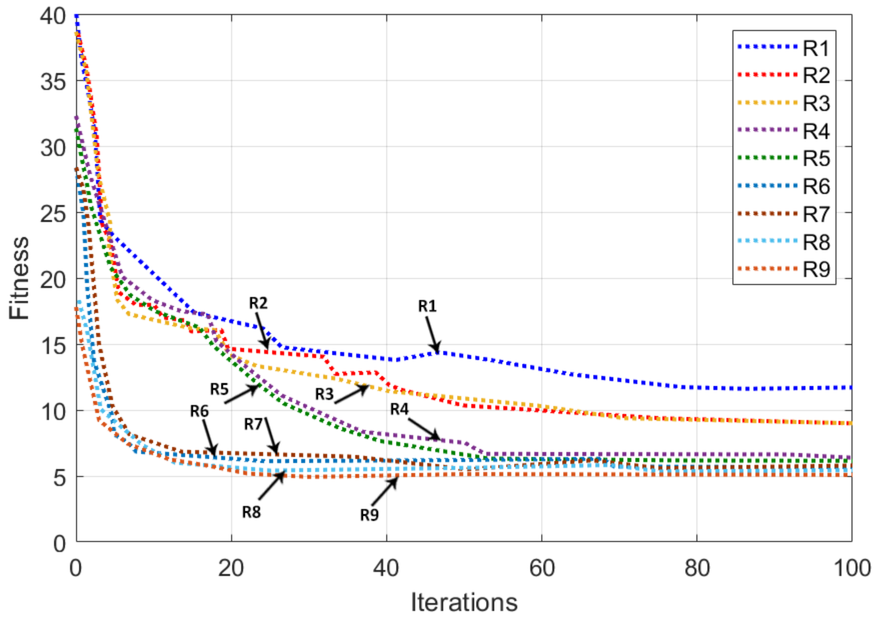


Fig. 6. The Iterative Process of Robots with Obstacles

The table below shows the starting, mid, and endpoint coordinates during the total time of flight. Each robot attains different origin points from the other to avoid collision among them.

TABLE IV
COORDINATES OF ROBOTS ALONG XY PLANE

Robots	*Starting Coordinates*	*Midpoint Coordinates*	*Endpoint Coordinates*
R1	(0,0)	(14,3)	(25,22)
R2	(0,3)	(14,6)	(25,21)
R3	(0,5)	(14,10)	(25,22)
R4	(0,7)	(14,12)	(25,23)
R5	(0,10)	(14,16)	(25,24)
R6	(0,13)	(14,18)	(25,25)
R7	(0,15)	(14,21)	(25,25)
R8	(0,17)	(14,23)	(25,26)
R9	(0,20)	(14,25)	(25,27)

IX. CONCLUSION

This study defines that the proposed algorithm GA-IACO shows an active performance to solve short path problems, which is considered an essential issue in the field of robotics. The approach based on GA and IACO is used to solve GPP in the static environment. The results show that the proposed scheme provides the best solution by using crossover and mutation operators in GA and improved form of ACO i.e. IACO. The advantage of the phase of GA is that it reduces the threat of subsiding into a local minimum by discovering various search spaces. The simulations result shows the performance of the algorithm when implemented in two different environments. IACO shows significant results in improving the quality of the solution. It also decreases the search space and time duration. The crossover operators offer a quick optimization, which helps to tune the solution. In conclusion, this scheme has a higher success rate in finding the best possible solution as compared to other techniques.

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