Optimization of an Autonomous Mobile Robot Path Planning Based on Improved Genetic Algorithms

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***Abstract*—Mobile robots are intended to operate in a variety of environments, and they need to be able to navigate and travel around obstacles, such as objects and barriers. In order to guarantee that the robot will not come into contact with any obstacles or other objects during its movement, algorithms for path planning have been demonstrated. The basic goal while constructing a route is to find the fastest and smoothest route between the starting point and the destination. This article describes route planning using the improvised genetic algorithm with the Bezier Curve (GA-BZ). This study carried out two main experiments, each using a 20x20 random grid map model with varying percentages of obstacles (5%, 15%, and 30% in the first experiment, and 25% and 50% in the second). In the initial experiments, the population (PN), generation (GN), and mutation rate (MR) of genetic algorithms (GA) will be altered to the following values: (PN = 100, 125, 150, or 200; GN = 100, 125, 150; and MR = 0.1, 0.3, 0.5, 0.7) respectively. The goal is to evaluate the effectiveness of AMR in terms of travel distance (m), total time (s), and total cost (RM) in comparison to traditional GA and GA-BZ. The second experiment examined robot performance utilising GA, GA-BZ, Simulated Annealing (SA), A-Star (A*), and Dijkstra's Algorithms (DA) for path distance (m), time travel (s), and fare trip (RM). The simulation results are analysed, compared, and explained. In conclusion, the project is summarised.**

***Keywords*—Genetic Algorithm; Bezier Curve; Obstacles Avoidance; Robot Optimization; Path Planning.**

I. INTRODUCTION

A wide range of autonomous tasks has been accomplished by mobile robots in a variety of industries and situations throughout the last several decades [1]–[3]. For robots to be able to travel and explore freely in complicated situations, collision-free route planning must be addressed [4]–[7]. The ability to navigate through a given environment is considered to be one of the most desirable characteristics of autonomous robots [5], [8]–[11]. Path planning is a method for an autonomous robot to get from the beginning point to the goal while traversing an environment that includes both static and dynamic obstacles [12], [13]. It is possible to divide path planning into global and local planning, depending on the scope of the map [8], [14]–[20]. Global path planning provides all the necessary data about the robot's known environment, while local path planning relies on partial or completely zero knowledge of the robot's environment to plan its course [14], [19], [21]–[24].

Nowadays, the genetic algorithm (GA) has been frequently used in mobile robot path planning problems due to its global optimisation and implicit parallel computing capabilities [25]. The GA simulates natural evolution using Darwin's genetic inheritance and variation models to find the best solution. To increase local optimisation and execution performance, the GA was given a generalised segmentation crossover operator [26]. An enhanced crossover operator prevented premature convergence from finding an optimal path in static situations.

Genetic algorithms can be used to optimize or approximate Bezier curves by adjusting the control points to find the best-fitting curve based on a given fitness function [27]. This approach is often referred to as Genetic Algorithms for Bezier Curve. In a genetic algorithm for Bezier curves, the control points of the curve are encoded as individuals in a population [4]. The algorithm then evolves the population over several generations using genetic operators such as selection, crossover, and mutation [18], [28]. A Bezier curve is a type of curve that is defined by a set of control points. It is named after the French mathematician Pierre Bézier, who developed the mathematical equations that describe these curves [4], [9], [29], [30]. The Bezier curve has recently been used in smooth path planning [27]. A genetic approach was suggested for mobile robot path planning to find the control points of segmented Bezier curves. A Bezier-curve-based enhanced genetic algorithm was presented for path planning in dynamic fields. A Bezier-curve-based path planner was also developed for autonomous cars [4], [27], [31]–[33].

This research uses state-of-the-art, global metaheuristic route planning techniques in which the location of all obstacles and other features of the environment are known in advance [29], [34]–[37]. It was decided to use an improvised genetic algorithm with a continuous Bezier curve (GA-BZ) to generate a path for a mobile robot that would allow it to reach its destination safely and smoothly [38]–[42] while avoiding any obstacles it might encounter [23], [43], [44]. The objective was to determine the optimal path length (m), travel time (s), and cost (RM). The environment was configured to have approximately 5%, 15%, 25%, 30%, and 50% obstructions occupying the workspace. In this investigation, two separate core tests will be performed. The parameters of genetic algorithms (GA) will be adjusted in the first set of tests as follows: population, PN = 100, 125, 150, 200; generations, GN = 100, 125, 150; and mutation rate, MR

= 0.1, 0.3, 0.5, 0.7. The effectiveness of AMR is compared to that of standard GA and GA-BZ with 5%, 15%, and 30% occupancy of the workspace, respectively. In the second experiment, the performance of the robot was evaluated using the GA, GA-BZ, Simulated Annealing (SA) [29], [45], A-Star (A*) [46]–[48], and Dijkstra's Algorithms (DA) techniques [49]–[53]. There will be comparisons between the outcomes, which will be examined and explained in depth. A summary of the findings will conclude the report.

II. Proposed Genetic Algorithms - Bezier Curve (GA-BZ)

The genetic algorithm function implements the genetic algorithm for determining the optimal route from the starting point to the destination. Using the *create_individual* function, the genetic algorithm initializes a population of individuals (paths) with random movements. The magnitude of the population determines the number of individuals in each generation. The algorithm then initiates a loop that continues for a predetermined number of generations. Using the fitness function, the fitness scores of the population's individuals are calculated for each iteration [21], [26], [54]. The fitness score indicates how efficiently an individual reaches the finish line while avoiding obstacles. A record is kept of the individual with the greatest fitness score. Additionally, the highest and average fitness scores of each iteration are recorded [21], [29], [54], [55].

Next, tournament selection selects individuals for reproduction [56]. Selecting a subset of the population and choosing the parent with the best fitness score is done arbitrarily. The specified parents undergo crossover to generate offspring. The crossover function swaps genetic material at a random crossing site. This yields two children. Mutations can occur in offspring after crossing over [18], [25], [57]. The mutate function randomly selects movements from individuals and then replaces them. Parents and offspring produce a new population. This generation becomes the next.

Selection, crossover, and mutation occur for the specified number of generations in each iteration. The algorithm converges towards better solutions as it progresses through the generations. At the conclusion of the algorithm, the optimal individual and its corresponding path are obtained [58], [59]. In addition, the algorithm can generate a Bezier curve (GA-BZ) path based on the optimal path of GA in order to improve the visualization of the path [4], [27], [31], [60].

Depending on the conditions of the experiment, the population (PN) is either PN=100, 125, 150, or 200, and the generation number (GN) is either 100, 125, or 150.

III. Workspace Modelling of GA-BZ

The path planning of the mobile robot is evaluated in a total of 5 different grid contexts, as illustrated in Fig. 1, Fig. 2, Fig. 3, Fig. 4, and Fig. 5. According to the illustration that can be found above, the workspace that is being displayed is split into two distinct sections. The first experiment that will be carried out will utilize barriers with percentages of 5%, 15%, and 30%, while the other studies will use barriers with percentages of 25% and 50%. This is carried out to prove that the proposed method can be implemented and is effective.

As can be seen in Fig. 1, Fig. 2, and Fig. 4, the components of the initial design that are shaded in grey denote the obstacles. The first significant experiment's objective was to evaluate how well an autonomous mobile robot would function in the environment described before using both the original version of GA and an enhanced version of GA. The outcomes of an AMR with varying parameters of genetic algorithms (population, generations and mutation rate) will be analyzed and evaluated in terms of journey distance, trip duration, and fare. The starting point and endpoints are fixed to (1,1) and (19,19), respectively. Each experiment includes different sets of parameters, either PN = 100, 125, 150, or 200; GN = 100, 125, 150; and MR = 0.1, 0.3, 0.5, and 0.7.

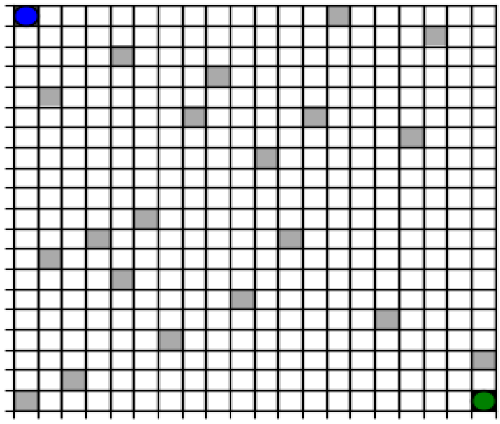

Fig. 1. Map of 5% Obstacles

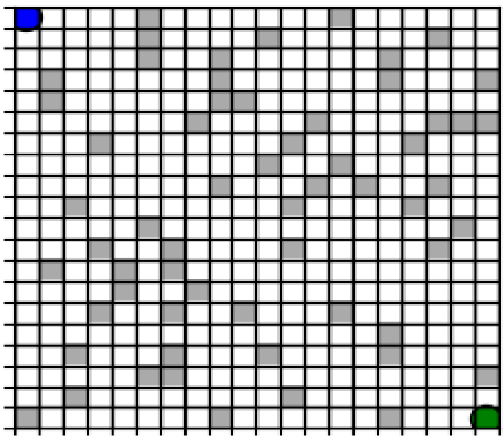

Fig. 2. Map of 15% Obstacles

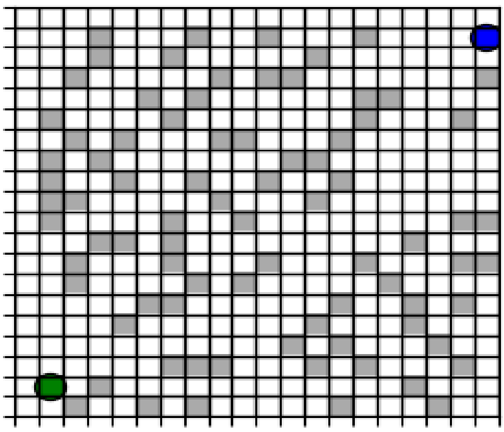

Fig. 3. Map of 25% Obstacles

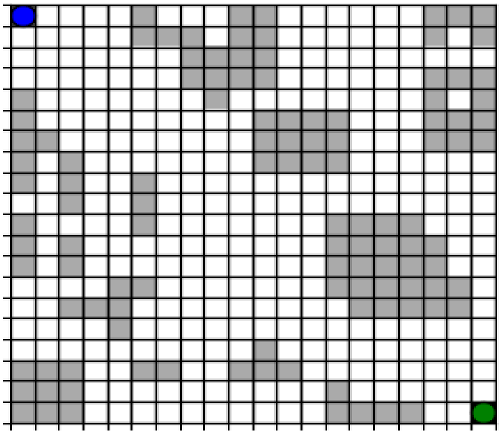

Fig. 4. Map of 30% Obstacles

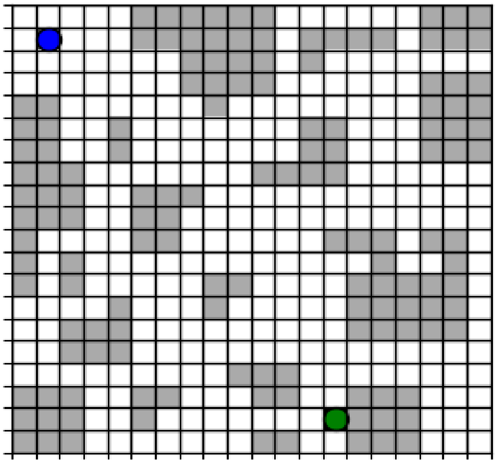

Fig. 5. Map of 50% Obstacles

Next, as can be seen in Fig. 3 and Fig. 5, the obstacles are the darkened parts of the original plan. The barriers are squares and rectangles, each with a different area. The objective of the final significant experiment was to determine how well an autonomous mobile robot would perform in an environment of 25% and 50% covered with barriers by multiple paths planning algorithms, including standard Genetic Algorithms (GA), improved Genetic Algorithms (GA-BZ), Simulated-Annealing (SA), A-Star Algorithms (A*), and classic Dijkstra's Algorithms (DA). In the map that is covered with 25% of the obstacles, the starting point is set to (1,19), and the final location is set to (18,1), whereas in the map that is covered with 50% of the obstacles, the starting point is set to (1,1) and the endpoint is set to (18,13). The GA-BZ development is analyzed in these tests with the following genetic parameters: PN = 150, GN = 150, MR = 0.5 (25%), and MR = 0.7 (50%). The findings of an AMR will be analyzed and evaluated in terms of the total amount spent on travel expenses, the total amount of time spent travelling, and the total distance travelled.

IV. Result and Discussion

This section will conduct two primary experiments to determine the shortest distance, time, and cost that the robot can travel. The first experiment will test how well robot path planning with genetic algorithms works in terms of the shortest distance, and time to journey. Additionally, in terms of the trip options with the lowest cost. In the first set of tests, the population, the number of generations, and the rate of mutation will be altered. In this experiment, the result of using only the classic GA will be compared to the result of using an improved version of GA that uses a Bezier Curve (GA-BZ) to find a smoother and more optimal path. There will be three different environments, each with its own set of barriers: 5% as the initial stage, 15% as the second step, and 30% as the third step.

The second set of studies will compare the efficacy of several algorithms in two simulated environments with varying levels of obstruction (50% free space, and a 25% obstacles cover). In this subsection, the following algorithms will be discussed: traditional genetic algorithms (GA), enhanced GA with Bezier Curve (GA-BZ), standard Simulated Annealing (SA), basic A-Star algorithms (A*), and a classical Dijkstra's Algorithm (DA). The environment employs a genetic algorithm with parameters PN = 150, GN = 150, and MR = 0.5 for 25% of the obstacles, and PN = 150, GN = 150, and MR = 0.7 for the remaining 50% of obstacles to generate the control points for the GA-BZ curve. Travel distance, time, and cost for the robot employing these various algorithms will be compared based on experimental findings and analysis.

A. *Performance of AMR in terms of Distances, Time Travel and Fare: 5% Obstacle*

The simulations were run, and the results for the journey distance, time required, and fare that was achieved are shown in Table I.

TABLE I. Performance of AMR: 5% Obstacles

			Classic Genetic Algorithms (GA)			Genetic Algorithms Combined with Bezier Curve (GA-BZ)		
PN	GN	MR	Distance Travel (m)	Time Taken (s)	Fare (RM)	Distance Travel (m)	Time Taken (s)	Fare (RM)
100	100	0.1	32.7279	65.4558	81.82	27.6141	55.2282	69.04
125	100	0.1	32.1421	64.2843	80.36	27.5492	55.0984	68.87
150	100	0.1	31.7279	64.2558	80.22	27.4821	54.9643	68.71
100	125	0.1	31.5563	63.1127	78.89	27.5769	55.1538	68.94
100	150	0.1	30.9706	61.9411	77.43	27.3164	54.6328	68.29
100	100	0.3	33.3137	66.6274	83.28	27.7699	55.5399	69.42
100	100	0.5	30.3848	60.7696	75.96	27.1666	54.3332	67.92
100	100	0.7	31.5563	63.1127	78.89	27.4138	54.8275	68.53

The standard GA's shortest path is 31.7279m (PN=150) with GN = 100 and MR = 0.1, followed by PN=125 (32.1421 m) and PN=100 (32.7279m). A population of PN=150 travels from starting point to goals in 64.2558 s, 1.2s faster than a population of PN=100, which takes 65.4558 s. The data tabulation demonstrates that from PN = 100 to PN 150 (GN = 100 and MR = 0.1), the fare decreases from RM 81.82 to RM 80.22. Based on the first GA sub analysis, PN =150 delivers the best distance, time, and fare from the initial point to the endpoint. By using the Bezier Curve, the optimal path was found, decreasing the total travel distance by 4.2458 meters (from 31.7279 meters to 27.4821 meters), the total travel time by 9.2915 seconds (from 64.2558 seconds to 54.9643 seconds), and the total cost by RM11.51 (from RM80.22 (GA) to RM68.71).

Next, with the population fixed at PN = 100 and the mutation rate at MR = 0.1, a second sub-experiment is conducted with three distinct generation values: GN = 100, 125, and 150. As the number of GN increases, the distance traveled by both GA and GA-BZ decreases from 32.7279 m

(GN=100) to 30.9706m (GN=150) and GA-BZ from 27.6141 m (GN=100) to 27.3164 m (GN=150), respectively. The GA-BZ exhibits a more optimal and cautious path not only in terms of path length but also in terms of real-time and cost. The GA-BZ completes the simulation and reaches the objective in 54.6328 s (GN=150), while the GA requires 61.9411 s (GN=150) to accomplish the same. Last but not least, the cost of the proposed algorithms is RM 68.29, which is RM 9.14 less than the cost of the baseline GA (RM 77.43).

In addition, the third subtest is conducted using mutation rates of 0.1, 0.3, 0.5, and 0.7 with the same number of generations and populations (100). Based on the obtained results, the GA-BZ demonstrates superior AMR performance in terms of distance, time, and cost compared to the conventional GA. Standard GA travels distances of 32.7279 m, 33.3137 m, 30.3848 m, and 31.5563 m, while enhanced GA (GA-BZ) travels distances of 27.6141 m, 27.7699 m, 27.1666 m, and 27.4138 m, respectively. The result obtained in terms of time taken and fare for the AMR to reach the destination point is random even when the mutation rate is increased. This is because the mutation operator introduces random changes in the genetic material of individuals in the population. While mutation can sometimes lead to improvements in the solutions, it is also a stochastic process that can introduce random perturbations. The MR=0.5 obtained the shortest distance of 30.3848 m (GA) and 27.1666 m (GA-BZ) in the third subsections of 5 per cent obstacles occupying workspace and throughout the experiment with the least time taken of 54.3332 s (GA-BZ) and RM 67.92 (GA-BZ) for the robot path planning.

4.1. Optimal Path Obtained by AMR (5%): Population (PN) is altered

The produced path achieved by both GA and GA-BZ is depicted in Fig. 6, Fig. 7, and Fig. 8 when the population is changed from PN=100 to 125 to 150, respectively. For the purpose of this experiment, the generation is equal to GN = 100, and the mutation rate is equal to MR = 0.1.

The experiment is carried out by shifting the population from PN = 100 to PN = 150 based on Fig. 6, Fig. 7, and Fig. 8. Standard genetic algorithms have a generation number (GN) of 100 and a mutation rate (MR) of 0.1. The path created in black is the path produced by conventional GA. The AMR travels from the (0,0) beginning position highlighted in blue to the (19,19) end target marked in green. The Bezier route is generated using the control points produced by the basic GA path. The path shown in red is the path produced by the proposed GA-BZ algorithm, which combines standard GA with a Bezier curve. As a result, a smoother and ideal path is produced.

As seen in Fig. 6, the path produced by GA, which is 32.7279m runs into the edge of the barrier. A more effective and efficient trajectory can be developed and optimised with greater obstacle avoidance using the GA-BZ path that is generated. The distance travelled by GA-BZ is 27.6141 m. Standard GA at PN = 125, GN = 100, and MR = 0.1 has a distance of 32.1421 m, as shown in Fig. 7, while the GA path distance is 31.7279 m, as shown in Fig. 8. The GA-BZ produces significantly shorter results than standard GA in both tests (27.5492m and 27.4821m, respectively).

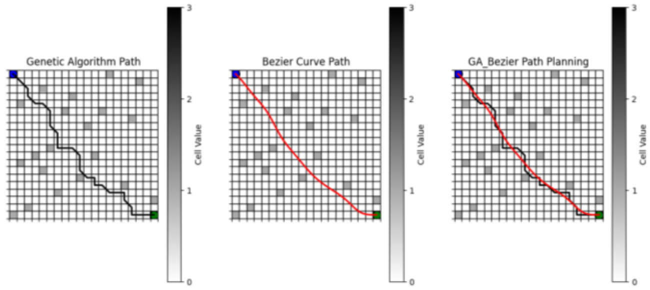

Fig. 6. Robot Performance in 5% Obstacles Occupying Workspace (PN = 100, GN = 100, and MR = 0.1)

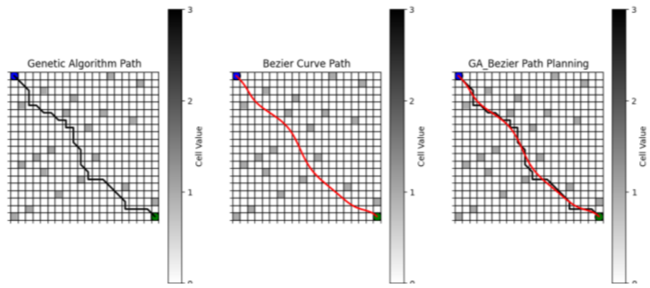

Fig. 7. Robot Performance in 5% Obstacles Occupying Workspace (PN = 125, GN = 100, and MR = 0.1)

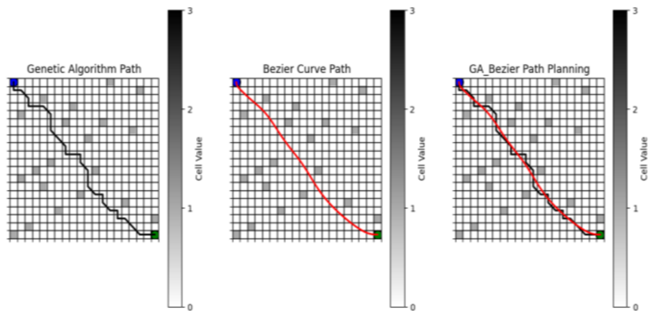

Fig. 8. Robot Performance in 5% Obstacles Occupying Workspace (PN = 150, GN = 100, and MR = 0.1)

4.2. Optimal Path Obtained by AMR (5%): Generation (GN) is altered

Fig. 9 and Fig. 10 demonstrate the GA and GA-BZ paths when the generation is altered from GN=125 to GN=150. For this experiment, the population is 100 and the mutation rate is 0.1.

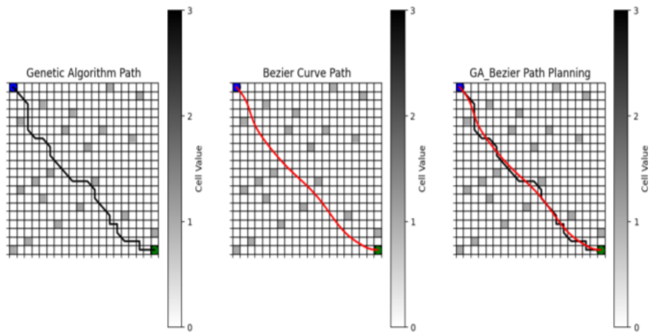

Fig. 9. Robot Performance in 5% Obstacles Occupying Workspace (PN = 100, GN = 125, and MR = 0.1)

In Fig. 9, the distance for standard GA is shown to be 31.5563 m when PN = 100, GN = 125, and MR = 0.1. In Fig. 10, the distance for the GA path is only 30.9706 m when PN = 100, GN = 150, and MR = 0.1. As shown in Fig. 9, there is a collision on the GA route. However, by utilizing the waypoints along this route, the combined algorithms (GA-BZ) are able to successfully sidestep the problems. In both tests, the distance travelled by the GA-BZ (GN=125 and GN=150) is much shorter than the distance travelled by the normal GA, which is 27.5769m (55.1538 s) and 27.3164m (54.6328 s), respectively. Also, the path of GA-BZ is smoother.

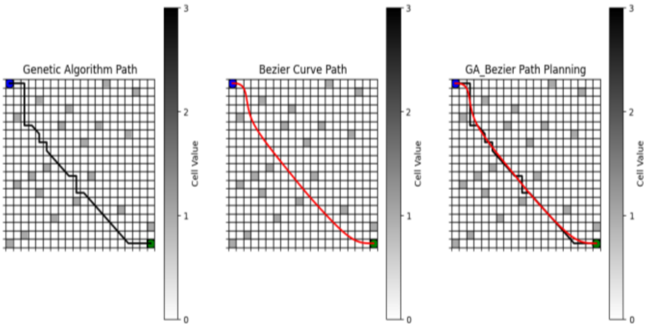

Fig. 10. Robot Performance in 5% Obstacles Occupying Workspace (PN = 100, GN = 150, and MR = 0.1)

4.3. Optimal Path Obtained by AMR (5%): Mutation Rate (MR) is altered

When the mutation rate is varied from MR=0.1, 0.3, 0.5, and 0.7 accordingly, Fig. 11, Fig. 12, and Fig. 13 demonstrate the generated path obtained by both GA and GA-BZ. The population is going to be equal to 100 throughout the duration of this experiment, and the generation rate is also going to be equal to 100.

To conduct the experiment depicted in Fig. 6, Fig. 11, Fig. 12, and Fig. 13, the mutation rate (MR) is varied from 0.1 to 0.3 to 0.5 to 0.7. Both the PN and GN are set to 100. The black line represents the conventional GA path. The AMR's route is shown in blue, beginning at coordinates (0, 0), with the destination shown in green at coordinates (19, 19). The Bezier path is made by extrapolating the control points from the original GA path. The proposed GA-BZ method combines regular GA with a Bezier curve, producing the red path shown. GA travels 32.7279m, 33.3137m, 30.3848m, and 31.5563m when MR = 0.1, 0.3, 0.5, and 0.7, respectively, while GA-BZ obtains a path length of 27.6141m, 27.7699m, 27.1666m, and 27.4138m. The GA-BZ results in a route that is both smoother and more efficient. The shortest distance travelled by GA-BZ in this experiment was 27.1666m (within 54.3332s) with the MR =0.5.

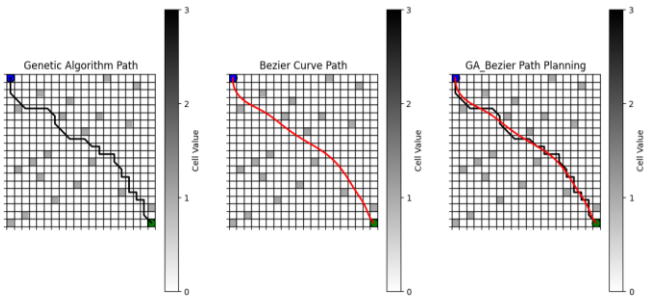

Fig. 11. Robot Performance in 5% Obstacles Occupying Workspace (PN = 100, GN = 100, and MR = 0.3)

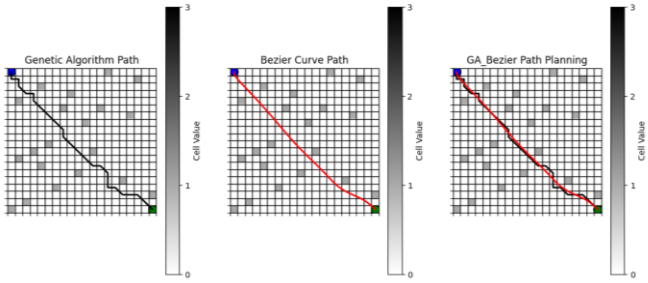

Fig. 12. Robot Performance in 5% Obstacles Occupying Workspace (PN = 100, GN = 100, and MR = 0.5)

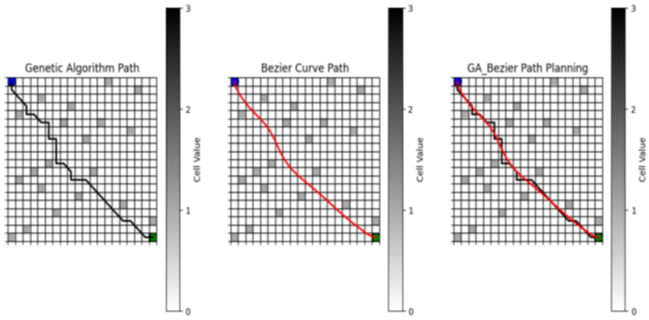

Fig. 13. Robot Performance in 5% Obstacles Occupying Workspace (PN = 100, GN = 100, and MR = 0.7)

4.4. Summarization of The First Sub-Experiment 1

A five per cent map shows that the best GA-BZ road distance is 27.4821m, which takes 54.9643s and costs RM68.71. The genetic factors for this robot's are PN=150, GN=100, and MR=0.1. The best distance for the normal GA is 31.7279m, which is 4.2458m longer than the best distance for the improved GA, GA-BZ. Using GA, it takes the AMR 64.2558s to get to its goals, and the total cost of the trip is RM80.22. Next, we changed the number of generations of the genetic algorithms. With PN=100, GN=150, and MR=0.1, the best paths for GA and GA-BZ were 30.9706m and 27.3164m, respectively. The GA-BZ takes a shorter amount of time (54.6328s) than the GA (61.9411s), and it costs less to travel (RM68.29) than the GA (RM77.43). Based on how well the robot did, we can say that path optimisation gets better in this setting as the number of genetic populations and generations grows. When adjusting the mutation rate with 5% obstacles occupying workspace, MR=0.5 performs best with the standard GA distance of 30.3848m, accomplishing the targets in 60.7696s and travel charge of RM 75.96. Compared to the GA-BZ, the proposed algorithms travel 27.1666m in 54.3332s with a cost of RM67.92 in a smoother and shorter way.

Based on the initial subenvironment with 5% barriers, GA and GA-BZ produce smoother and better routes as population and generation increase. Even with a higher mutation rate, AMR travel time and cost are unpredictable. The mutation operator makes random genetic changes to population members. Mutation is a chance process that can cause random changes and, sometimes, lead to better solutions. Using the GA-BZ path that is generated, a more effective and efficient trajectory can be designed and optimised with greater obstacle avoidance. The best results from sub-experiment 1 were obtained when the robot's MR was set to 0.5, the PN was set to 100, and the GN was set to 100, with the obstacles occupying 5% of the available workspace, as GA-BZ travels the shortest distance (27.1666m) and spends the least amount of time (54.3332s) and money travelling (RM67.92).

B. Performance of AMR in terms of Distances, Time Travel and Fare: 15% Obstacles

After running the simulations, the data obtained regarding the travelled distance, the required amount of time, and the fare obtained are presented in Table II. These findings were gathered in a setting containing approximately fifteen per cent of the whole environment.

TABLE II. PERFORMANCE OF AMR: 15% OBSTACLES

			Classic Genetic Algorithms (GA)			Genetic Algorithms Combined with Bezier Curve (GA-BZ)		
PN	GN	MR	Distance Travel (m)	Time Taken (s)	Fare (RM)	Distance Travel (m)	Time Taken (s)	Fare (RM)
100	100	0.1	30.9705	61.9411	77.42	27.5655	55.1312	68.91
125	100	0.1	34.4852	68.9705	86.21	28.0694	56.1388	70.17
150	100	0.1	33.8994	67.7989	84.74	27.7781	55.5563	69.44
100	125	0.1	32.1421	64.2842	80.35	27.6419	55.2839	69.10
100	150	0.1	33.3137	66.6274	83.28	28.0543	56.1086	70.13
150	100	0.3	32.7279	65.4558	81.81	27.7749	55.5498	69.43
150	100	0.5	31.5563	63.1126	78.89	27.5945	55.1890	68.98
150	100	0.7	32.1421	64.2842	80.35	27.6984	55.3969	69.24

According to the data in Table II, the shortest path for the standard GA when altering the population is 30.9705m (PN = 100) with GN = 100 and MR = 0.1, subsequently followed by PN = 150 (33.8994 m) and PN = 125 (34.4852 m). The travel time from the starting point to the final destination for a PN = 100 is 61.9411 s, less than the times needed for PN = 125 (68.9705 s) and PN = 150 (67.7989 s). The data shows the cheapest possible journey is RM 77.42, with a PN = 100.

The research indicates that PN = 100 provides the most optimal travel duration, cost, and path distance compared to PN 125 and PN = 150 with MR=0.1 and GN = 100. The Bezier Curve with obstacle avoidance was implemented to the best standard GA, and the optimal path length found in this subpart is 27.5655 m with the shortest travel time of 55.1312 s and a journey cost of RM 68.91 (PN = 100, GN = 100, MR = 0.1).

Next, a second sub-experiment is conducted with three distinct generation values: 100, 125, and 150, with the population fixed at PN=100 and the mutation rate at MR = 0.1. The longest distance travelled by standard GA is 33.3137 m (GN = 150), while the shortest distance travelled is 30.9705 m (GN = 100). The Genetic-Bezier path that uses the control points of standard GA shows that the distance travelled by GN = 100 has the shortest path length of 27.5655 m, and the GN = 150 have the longest path distance of 28.0543 m. Not only in terms of path length but also in terms of real-time and cost, the GA-BZ exhibits a more prudent and optimal path. The best GA-BZ completes the simulation and reaches the goal in 55.1312 s, with the cheapest fee of RM 68.91.

With the same PN =150 and GN =100, the next subsection of the test is run with 0.3, 0.5, and 0.7 mutation rates. According to the findings, the GA-BZ outperforms the traditional GA in terms of distance, time, and cost when it comes to AMR. The lengths covered by a standard GA are 32.7279 m, 31.5563 m, and 32.1421 m, while those covered by an enhanced GA (GA-BZ) are 27.7749 m, 27.5945 m, and 27.6984 m, respectively. The result obtained utilizing standard GA has the lowest fee travel of RM 78.89 (MR = 0.5), and the highest travel fee is RM 81.81 (MR = 0.3). The distance and time travel of MR = 0.7 lies in between them. Moreover, the performance of AMR using GA-BZ with MR = 0.3, 0.5 and 0.7 gained the duration and cost of 55.5498s (RM 69.43), 55.1890s (RM 68.98), and 55.3969s (RM69.24) respectively. Even with a large enough mutation rate, the AMR's arrival time and cost are still completely unpredictable. This is due to the fact that the mutation operator causes unpredictable shifts in the genetic makeup of the population as a whole. However, the proposed algorithms (GA-BZ) always provide a better outcome in terms of distance travel, time taken and cost travel compared to standard GA.

4.5. Optimal Path Obtained by AMR (15%): Population (PN) is altered

Fig. 14, Fig. 15, and Fig. 16 show the path produced by both GA and GA-BZ when the population is adjusted from PN=100 to 125 to 150, respectively. For the purposes of this experiment, the generation is set to GN = 100, and the mutation rate is set to MR = 0.1.

Based on Fig. 14, Fig. 15, and Fig. 16, the experiment is conducted by increasing the population size from 100 to 150. Standard genetic algorithms have 100 generations and a mutation rate of 0.1 per generation. The path generated in black is the result of conventional GA. The AMR travels from the blue-highlighted starting position (0,0) to the green-highlighted destination (19,19). The Bezier route is generated using the control points produced by the fundamental GA path. The red path is the result of the proposed GA-BZ algorithm, which combines standard GA with a Bezier curve. As a consequence, an optimal and smoother path is created.

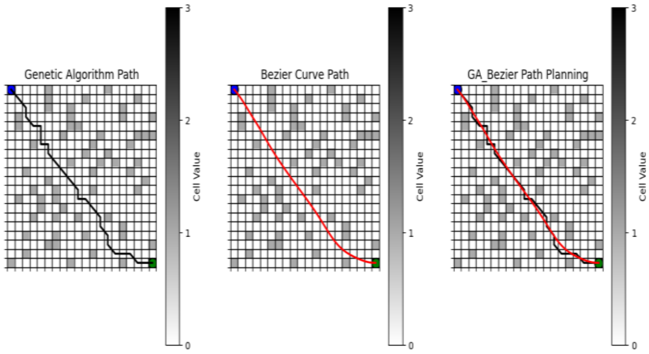

Fig. 14. Robot Performance in 15% Obstacles Occupying Workspace (PN = 100, GN = 100, and MR = 0.1)

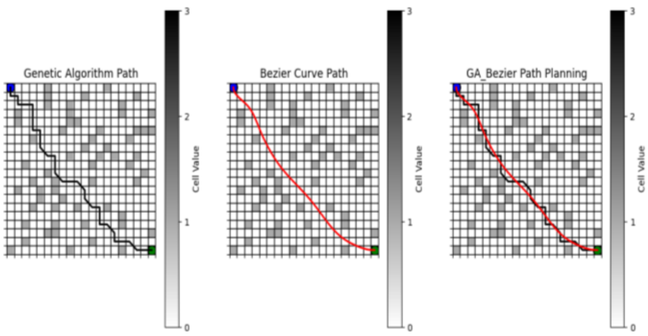

Fig. 15. Robot Performance in 15% Obstacles Occupying Workspace (PN = 125, GN = 100, and MR = 0.1)

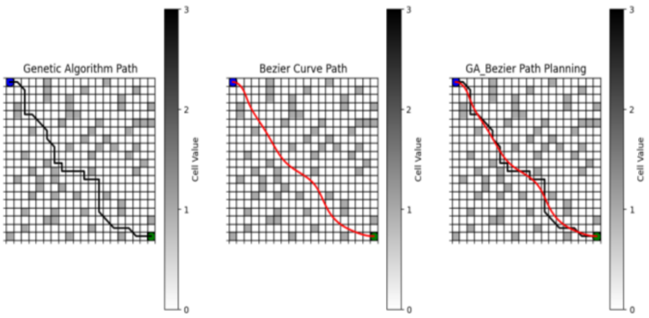

Fig. 16. Robot Performance in 15% Obstacles Occupying Workspace (PN = 150, GN = 100, and MR = 0.1)

As seen in Fig. 14, the path generated by GA has the shortest path distance of 30.9705m (61.9411 s) compared to the path generated in Fig. 15 and Fig. 16 which are 34.4852m and 33.8994m. However, the path generated with Fig. 15, PN = 125, GN = 100, and MR = 0.1, collides with barriers. A more effective and efficient trajectory can be designed and optimized with greater obstacle avoidance using the derived GA-BZ path. The best distance that GA-BZ has covered is 27.5655 m (PN = 100, GN = 100, and MR = 0.1). The GA-BZ takes 55.1312 s and costs RM 68.91 to reach its location.

4.6. Optimal Path Obtained by AMR (15%): Generation (GN) is altered

The GA and GA-BZ pathways are shown in Fig. 17 and Fig. 18 when the generation is changed from GN=125 to GN=150. The population size is set at 100, and the mutation rate is set at 0.1 in this study.

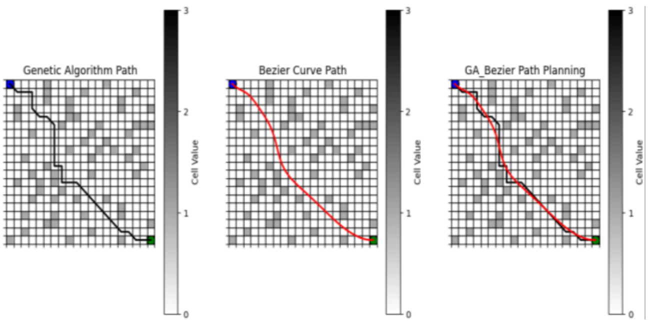

Fig. 17. Robot Performance in 15% Obstacles Occupying Workspace (PN = 100, GN = 125, and MR = 0.1)

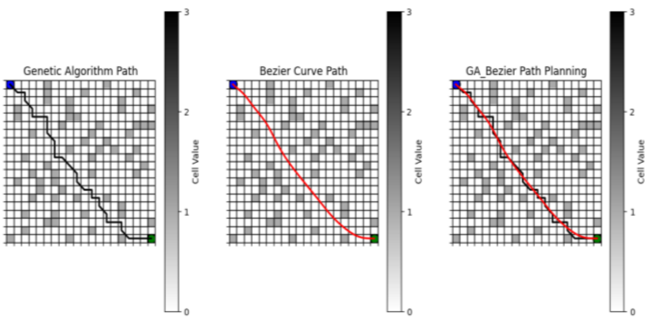

Fig. 18. Robot Performance in 15% Obstacles Occupying Workspace (PN = 100, GN = 150, and MR = 0.1)

In Fig. 17, when PN = 100, GN = 125, and MR = 0.1, the standard GA distance is 32.1421m. In Fig. 18, the GA path distance is 33.3137 m when PN = 100, GN = 150, and MR = 0.1. In both tests, the GA-BZ goes 27.6419m (55.2839 s) and 28.0543m (56.1086 s) less than the GA path. GA-BZ has a better route.

4.7. Optimal Path Obtained by AMR (15%): Mutation Rate (MR) is altered

When the mutation rate is varied from MR=0.1, 0.3, 0.5, and 0.7 accordingly, Fig. 19, Fig. 20, and Fig. 21 demonstrate the generated path that is obtained by both GA and GA-BZ. The population is going to be equal to 150 throughout the duration of this experiment, and the generation rate is also going to be equal to 100.

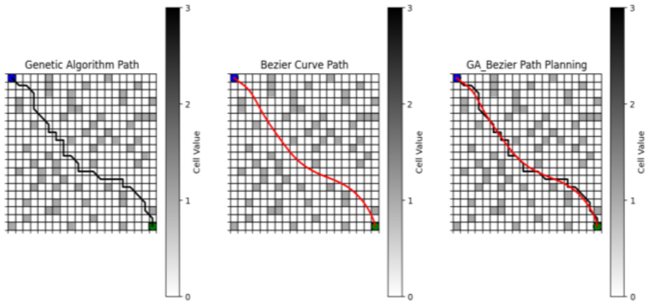

Fig. 19. Robot Performance in 15% Obstacles Occupying Workspace (PN = 150, GN = 100, and MR = 0.3)

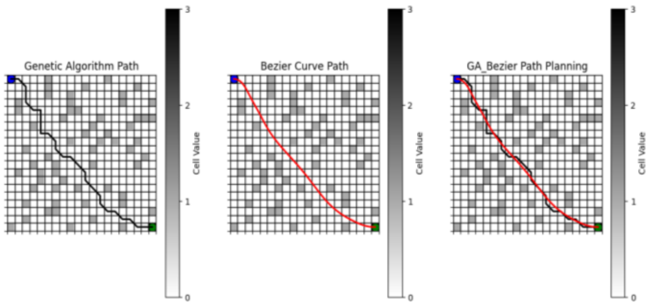

Fig. 20. Robot Performance in 15% Obstacles Occupying Workspace (PN = 150, GN = 100, and MR = 0.5)

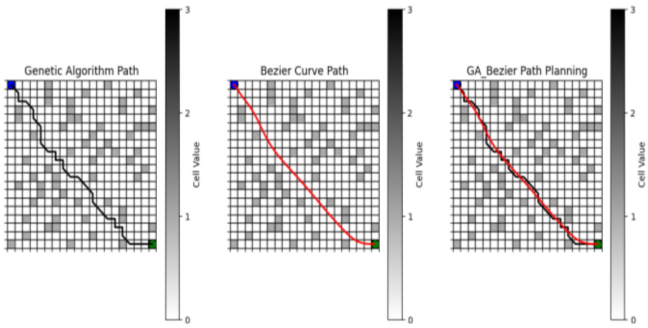

Fig. 21. Robot Performance in 15% Obstacles Occupying Workspace (PN = 150, GN = 100, and MR = 0.7)

To conduct the experiment depicted in Fig. 19, Fig. 20, Fig. 21, the mutation rate (MR) is varied from 0.3 to 0.5 to 0.7. Both the PN and GN are set to 150 and 100, respectively. The black line represents the conventional GA path. The AMR's route is shown in blue, beginning at coordinates (0, 0), with the destination shown in green at coordinates (19, 19). The Bezier path is made by extrapolating the control points from the original GA path. The proposed GA-BZ method combines regular GA with a Bezier curve, producing the red path shown. GA travels 32.7279m, 31.5563m, and 32.1421m when MR = 0.3, 0.5, and 0.7, respectively, while GA-BZ obtains a path length of 27.7749m, 27.5945m, and

27.6984m. The GA-BZ results in a route that is both smoother and more efficient. The shortest distance travelled by GA-BZ in this experiment was 27.5945m (within 55.1890s and cost RM 68.98).

4.8. Summarization of The Second Sub Experiment 1

The best GA-BZ road distance is 27.5655m, which takes 55.1312s and costs RM68.91 according to this 15% scale map occupied with barriers. This robot has a PN=100, GN=100, and MR=0.1 genetic makeup. The conventional GA's best distance is 30.9705m, 3.405m longer than the GA-BZ path. The AMR spends a total of RM77.42 and takes 61.9411s to reach its destinations through GA. We then experimented with various generation sizes for the genetic algorithms. The best pathways for GA were 30.9705m and for GA-BZ they were 27.5655m when PN=100, GN=100, and MR=0.1 were used. The GA-BZ takes less time (55.1312s) and costs less (RM68.91) than the GA (61.9411s and RM77.42), respectively. From the robot's performance, we may infer that decreasing the number of genetic populations and generations improves path optimisation in this context. When MR=0.5 (PN=150, GN=100) is employed to manage the mutation rate in an environment with 15% obstacles, reaching the targets takes 63.1126s and costs RM 78.89 with the typical GA best distance of 31.5563m. The proposed algorithms (GA-BZ) are more efficient and cost less money than the GA, covering a distance of 27.5945 m in 55.1890 s. The most effective outcomes were achieved with the robot's MR set to 0.1, the PN set to 100, and the GN set to 100, since this combination allows the shortest distance and time consumption, as well as the lowest cost, when the obstacles consumed 15% of the available workspace throughout the second sub-experiment 1.

In the context of the second sub experiment with barriers occupying approximately 15 percent of the workspace, it can be concluded that, as the number of populations and generations decreases, the better the performance of the robot using both GA and GA-BZ. Even with a higher mutation rate, AMR travel time and cost are unpredictable. The mutation operator makes random genetic changes to population members. Mutation is a chance process that can cause random changes and, sometimes, lead to better solutions. Last but not least, using the GA-BZ path that is generated, a more effective and efficient trajectory can be designed and optimised with greater obstacle avoidance compared to GA.

C. Performance of AMR in terms of Distances, Time Travel and Fare: 30% Obstacles

After running the models, the information about the distance traveled, the amount of time needed, and the fare is shown in Table III. These findings were acquired in an environment that featured around thirty per cent of the challenges.

Based on the data in the Table III, the optimal parameters for the third sub-analysis with a 30% obstacle are PN = 100, GN = 100, and MR = 0.1, resulting in a minimum trip distance of 30.9705 m. In comparison to this standard GA, the Genetic-Bezier method, GA-BZ, decreases the distance travelled to 27.2178 m and the time and cost from 61.9411 s to 54.4356 s and RM 77.42 to RM 68.04, respectively. The performance of robot with PN = 100 is considered the best compared to PN = 125 and PN = 150. Thus, in this scope, increasing the PN with fixed GN and MR will not guarantee the best distance travelled, time required, or fare of a robot; however, incorporating Bezier will enhance the outcome.

TABLE III. PERFORMANCE OF AMR: 30% OBSTACLES

			Classic Genetic Algorithms (GA)			Genetic Algorithms Combined with Bezier Curve (GA-BZ)		
PN	GN	MR	Distance Travel (m)	Time Taken (s)	Fare (RM)	Distance Travel (m)	Time Taken (s)	Fare (RM)
100	100	0.1	30.9705	61.9411	77.42	27.2178	54.4356	68.04
125	100	0.1	33.8994	67.7989	84.74	27.6902	55.3804	69.22
150	100	0.1	32.1421	64.2842	80.35	27.5701	55.1403	68.92
150	125	0.1	33.3137	66.6274	83.28	27.6213	55.2427	69.05
150	150	0.1	32.7279	65.4558	81.82	27.4138	54.8275	68.53
200	150	0.3	33.3137	66.6274	83.28	28.1896	56.3792	70.47
200	150	0.5	32.1421	64.2842	80.35	27.6182	55.2364	69.04
200	150	0.7	31.5563	63.1126	78.89	27.3564	54.7129	68.39

The investigation was resumed with PN = 150 and MR = 0.1 held constant, and the GN was altered. According to the research, the GA with GN = 125 takes 66.6274 s to reach the destination with a path distance of 33.3137 m and a fare of RM 83.28, whereas GN = 150 results in the fewest meters travelled (32.7279 m), the least amount of time spent (65.4558 s), and the lowest cost (RM 81.82). By incorporating Bezier into the research and selecting only the best standard GA result from the stated parameters, the distance travelled will be reduced from 32.7279m to 27.4138m, the time required will be reduced from 65.4558 s to 54.8275s, and the cost will be reduced from RM81.82 to RM68.53 (GN = 150).

The investigation is continued by increasing the mutation rates (MR) from 0.3 to 0.7 while holding PN and GN constant at 200 and 150, respectively. According to the data tabulation, increasing the mutation rate to MR = 0.7 for the standard GA will produce the best results, with the shortest distance travelled (31.5563 m), the fastest time (63.1126 s), and the cheapest cost (RM 78.89) compared to MR = 0.3 and MR = 0.5. The primary effect of optimizing the standard GA with Bezier is that the Bezier curve will generate a significantly more optimized and smoother route. Using GA-BZ with MR=0.7 reduces the distance the robot must travel to reach the finish line by 4.1999m, from 31.5563m (GA) to 27.3564 m (GA-BZ). The time required for the robot to reach its destination will decrease from 63.1126 s to 54.7129 s, and the cost will decrease from RM78.89 to RM68.39.

4.9. Optimal Path Obtained by AMR (30%): Population (PN) is altered

Fig. 22, Fig. 23, and Fig. 24 exhibit the paths traveled by AMR using GA and GA-BZ when the population is changed from PN=100 to PN=125 to PN=150, respectively. For this experiment, the number of generations is GN = 100, and the rate of mutation is MR = 0.1. Fig. 22, Fig. 23, and Fig. 24 show the progression of the experiment as the population size is increased from 100 to 150. The typical mutation rate in genetic algorithms is 0.1 for each generation, with 100 generations in total. The black route is the product of traditional GA. The AMR goes from the blue-highlighted starting point (0,0) to the green-highlighted final destination (19,19). The Bezier path is created from the core GA path's generated control points. The proposed GA-BZ method combines traditional GA with a Bezier curve, producing the red line. This results in a more direct and efficient route.

Fig. 22 shows that the GA-generated path is the shortest, with a distance of 30.9705m (61.9411 s), compared to the paths shown in Fig. 23 and Fig. 24, respectively, which have respective distances of 33.8994m and 32.1421m. The resulting GA-BZ path can be used to create an optimized path with better performance and obstacle avoidance. With optimal settings (PN = 100, GN = 100, and MR = 0.1), GA-BZ has the best distance travelled of 27.2178 m with travel time of 54.4356 s and an associated cost of RM 68.04. For PN = 125, the GA-BZ path is 27.6902 m and for PN = 150, GA-BZ distance is 27.5701 m.

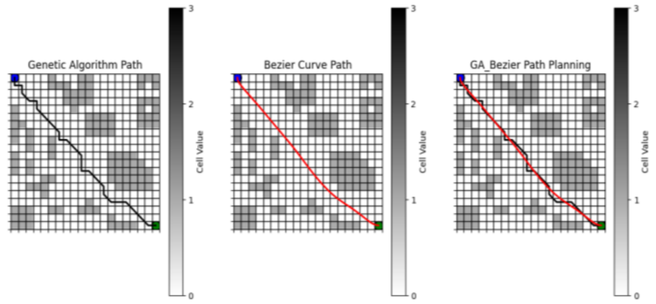

Fig. 22. Robot Performance in 30% Obstacles Occupying Workspace (PN = 100, GN = 100, and MR = 0.1)

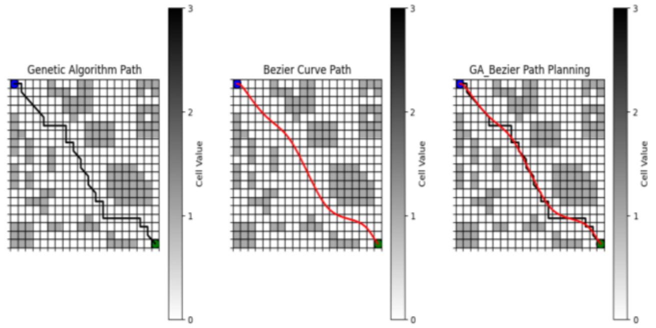

Fig. 23. Robot Performance in 30% Obstacles Occupying Workspace (PN = 125, GN = 100, and MR = 0.1)

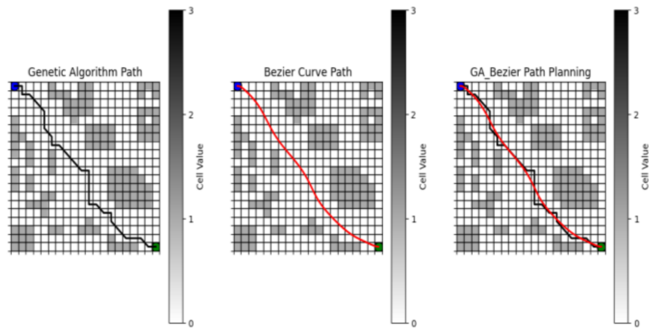

Fig. 24. Robot Performance in 30% Obstacles Occupying Workspace (PN = 150, GN = 100, and MR = 0.1)

4.10. Optimal Path Obtained by AMR (30%) : Generation (GN) is altered

The GA and GA-BZ pathways change from GN=125 to GN=150 in Fig. 25 and Fig. 26. For this experiment, the population is PN=150, and the mutation rate is MR=0.1. When PN is set to 150, GN is set to 125, and MR is set to 0.1, the standard GA distance in Fig. 25 is 33.3137 m. For the parameters shown in Fig. 26, the GA path distance is 32.7279 m for PN = 150, GN = 150, and MR = 0.1. The GA-BZ outperforms the GA path distances in both tests by an amount of 27.6213 m (55.2427 s) when GN = 125 and by 27.4138 m (54.8275 s) when GN = 150. The GA-BZ route dominates.

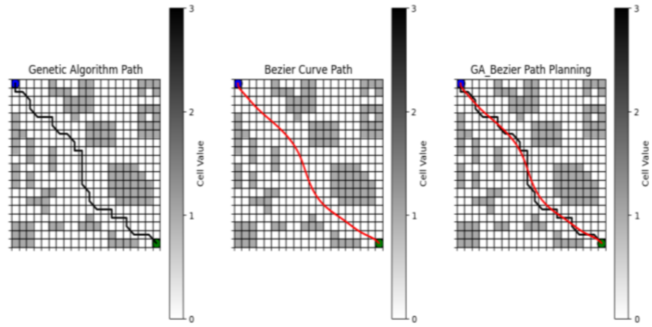

Fig. 25. Robot Performance in 30% Obstacles Occupying Workspace (PN = 150, GN = 125, and MR = 0.1)

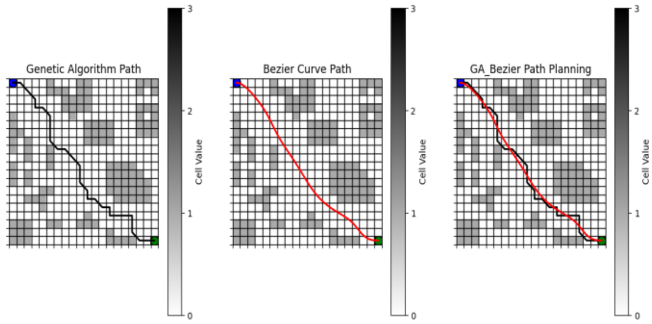

Fig. 26. Robot Performance in 30% Obstacles Occupying Workspace (PN = 150, GN = 150, and MR = 0.1)

4.11. Optimal Path Obtained by AMR (30%): Mutation Rate (MR) is altered

Fig. 27, Fig. 28 and Fig. 29 show the produced path acquired by both GA and GA-BZ when the mutation rate is adjusted from MR=0.1, 0.3, 0.5, and 0.7, respectively. Throughout the course of the experiment, the population will remain constant at 200, and the generation rate will remain constant at 150.

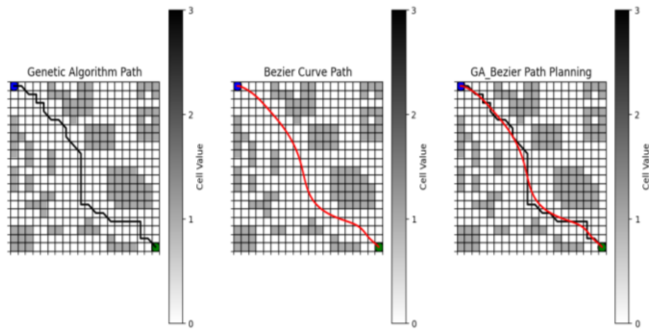

Fig. 27. Robot Performance in 30% Obstacles Occupying Workspace (PN = 200, GN = 150, and MR = 0.3)

The mutation rate (MR) is changed from 0.3 to 0.5 to 0.7 for the experiment shown in Fig. 27, Fig. 28 and Fig. 29. The PN and the GN are both set to 200 and 150, respectively. The black line shows the normal GA path. The AMR's path starts at (0, 0) and ends at (19, 19), which are shown in blue and green, respectively. The control points from the first GA path are used to make the Bezier path. The red path is what the suggested GA-BZ method makes by combining regular GA with a Bezier curve. When MR = 0.3, 0.5, and 0.7, respectively, GA moves 33.3137m, 32.1421m, and 31.5563m while GA-BZ moves 28.1896m, 27.6182m, and 27.3564m. Because of the GA-BZ, the road is both smoother and faster. In this experiment, the shortest distance travelled by GA-BZ is 27.3564m (MR = 0.7), which took 54.7129s and cost RM 68.39 as illustrated in Fig. 29.

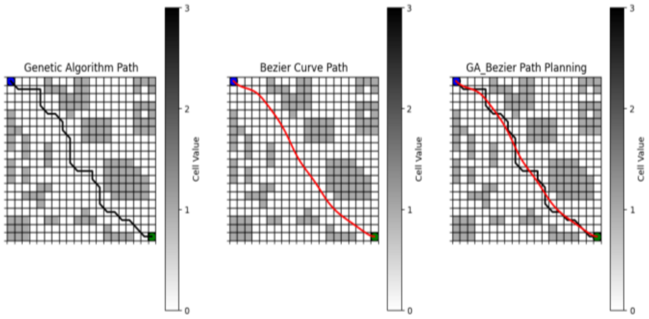

Fig. 28. Robot Performance in 30% Obstacles Occupying Workspace (PN = 200, GN = 150, and MR = 0.5)

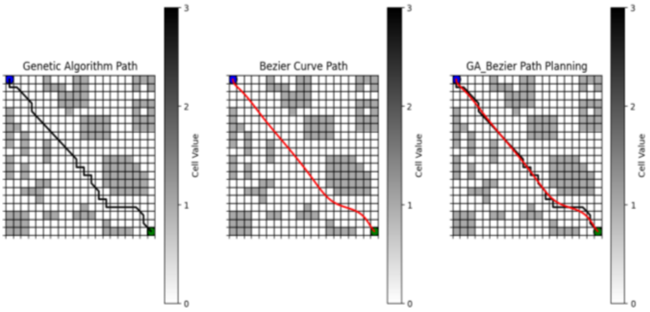

Fig. 29. Robot Performance in 30% Obstacles Occupying Workspace (PN = 200, GN = 150, and MR = 0.7)

4.12. Summarization of The Third Sub Experiment 1

According to this 30% scale barrier-filled map, the optimal GA-BZ road distance is 27.2178m, which takes 54.4356s and costs RM68.04. This robot has a genetic constitution of PN=100, GN=100, and MR=0.1. The most notable GA distance is 30.9705m, which is 3.7527m longer than the GA-BZ path. GA costs the AMR a total of RM77.42 and 61.9411 s to reach its destinations. Then, we conducted experiments with different generation sizes for genetic algorithms. When PN=150, GN=150, and MR=0.1 were used, the best paths for GA were 32.7279m and for GA-BZ they were 27.4138m. GA-BZ is faster (54.8275s) and less expensive (RM68.53) than GA (65.4558s) and RM81.82, respectively. When mutation rate is varied, MR=0.7 (PN=200, GN=150) achieves the best GA robot performance with a time of 63.1126s and a cost of RM 78.89. The average GA best distance is 31.5563m. The proposed algorithms are more economical and effective than the GA, covering the distance (27.3564 m) in 54.7129s and at a lower cost, RM 68.39. Based on the performance of the robot, we can conclude that increasing the mutation rate enhances path optimisation in this context.

GA-BZ improve routes as mutation rate increase in the third subenvironment with 30% obstacles. AMR travel duration and cost remain variable despite a higher mutation rate. Mutation operator alters population genetics randomly. Mutation can provide random changes and improved solutions. The produced GA-BZ path can be used to construct a more efficient and effective trajectory with better obstacle avoidance. The best results from this sub-experiment 1 were obtained when the robot's MR was set to 0.1, the PN was 100, and the GN was 100, with the obstacles occupying 30% of the workspace. GA-BZ travelled the shortest distance (27.2178m) and spent the least time (54.4356s) and money (RM68.04).

D. Second Experiment: Analyzing the Effectiveness of Various AMR Algorithms

The percentages of the difficulties in this study that were overcome are 25% and 50%, respectively. The 25% interval begins at (1,19) and terminates at (18,1). Each algorithm's output path is shown in black, and the barriers are represented by darkened square boxes.

The beginning points for the approximately half of the course that is free of obstacles is at (1,1), while the ending point is at (18,13). Both maps feature barriers, but their placement and layout are different. This is done to prove that the proposed method can be implemented successfully.

This study analyses the GA-BZ development with the following genetic parameters: PN = 150, GN = 150, MR = 0.5 (25%), and MR = 0.7 (50%).

4.13. Twenty-Five Obstacles Occupying Workspace

The performance of AMR in 25% obstacles filling workspace employing GA, GA-BZ, SA, A*, and DA is shown in Fig. 30, Fig. 31, Fig. 32, Fig. 33, Fig. 34 and Table IV.

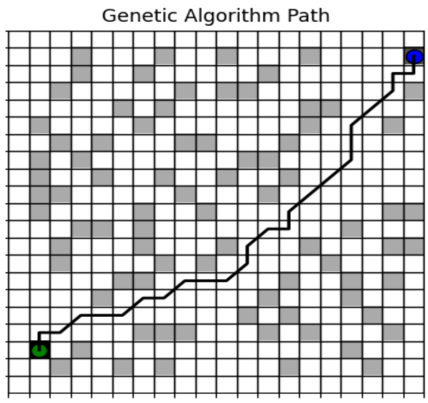

Fig. 30. Path Planning of Genetic Algorithms (25%)

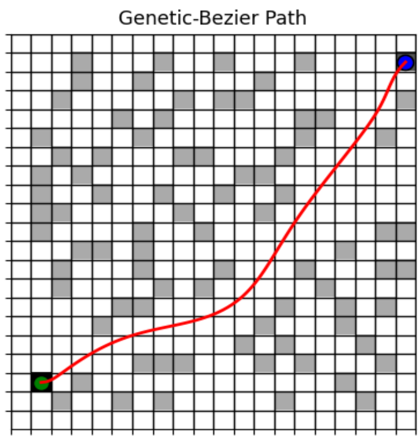

Fig. 31. Path Planning of Genetic-Bezier Algorithm (25%)

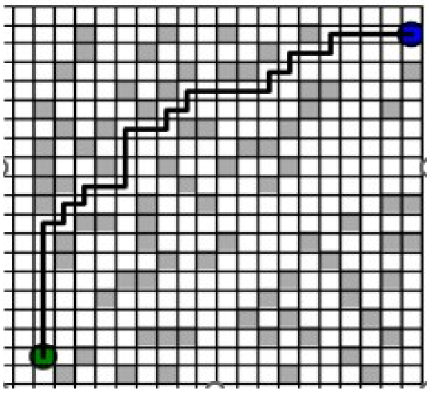

Fig. 32. Path Planning of Simulated Annealing Algorithms (25%)

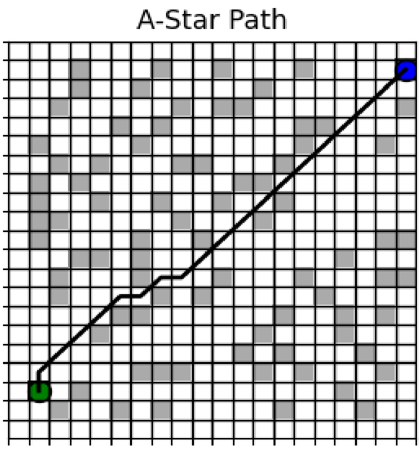

Fig. 33. Path Planning of A-Star Algorithms (25%)

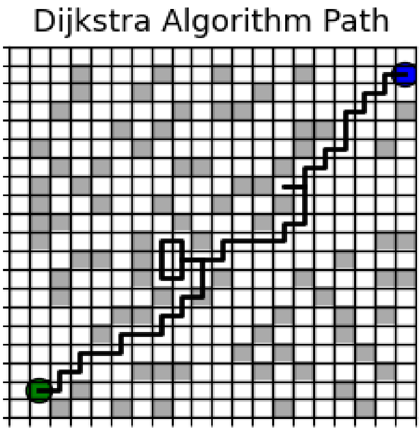

Fig. 34. Path Planning of Dijkstra's Algorithms (25%)

Fig. 30 to Fig. 34 and Table IV reveal the path length via 25% of the map's barriers. As shown in Fig. 30 to Fig. 34; GA, SA, A*, and DA each have the potential to produce a path with a length of either 32.8636 m, 33.4580 m, 25.6274 m, or 36.2251 m, respectively. Due to redundant nodes and infection spots, the GA, SA, and DA planning pathways are longer than the GA-BZ (25.6642m). GA-BZ's path planning performance is better than A*'s, and the robot's mobility security is guaranteed even though the path is somewhat longer. Fig. 30 and Fig. 31 show that the GA and GA-BZ paths have improved; the GA nodes reflect the control points of the curve, and the red line is the ideal smooth path. The GA-BZ yields better planned path lengths than other approaches. The updated method minimizes superfluous inflection points and nodes in path planning, making it smoother and shorter.

TABLE IV. PERFORMANCE OF AMR USING MULTIPLE ALGORITHMS (25%)

		Distance Travel (m)	Time Taken (s)	Fare (RM)
25%	Genetic Algorithms	32.8636	65.7273	82.15
	GA-BZ	25.6642	51.3285	64.16
	Simulated Annealing	33.4580	66.9160	83.64
	A-Star	25.6274	51.2548	64.06
	Dijkstra's Algorithms	36.2251	72.4502	90.56

Table IV shows that A-Star's simulation runtime is the quickest of all the algorithms evaluated at 51.2548 s. The path created by A-Star does not successfully avoid obstructions; hence, the results achieved are unsatisfactory. With a smoother and safer path for the AMR to attain the targets, the proposed GA-BZ approaches come in second place in terms of time with 51.3285 s, which has shorter time consumption compared to SA (66.9160 s), GA (65.7273 s), and DA (72.4502 s). This is due to the optimal selection, crossover, and mutation operators of the GA being incorporated into the GA-BZ's path planning mechanism.

In terms of fare, the base GA costs RM 82.15, whereas the GA-BZ costs only RM 64.16. By only incorporating the Bezier curve with obstacle avoidance tools in the standard GA, RM 17.99 can be saved. Other alternative algorithms demand a greater travel fee than GA-BZ. Therefore, the suggested method outperforms state-of-the-art algorithms in terms of path length, fare, and smoothness in low real-time contexts.

E. Fifty Percent Obstacles Occupying Workspace

The performance of AMR with GA, GA-BZ, SA, A*, and DA in a 50% obstacle-filled workspace is depicted in Fig. 35, Fig. 36, Fig. 37, Fig. 38, Fig. 39, and Table V.

Combining Fig. 35 to Fig. 39 and Table V yields the following data regarding the length of the path through fifty per cent of the obstacles on the map. As depicted in Fig. 35, Fig. 37, Fig. 38 and Fig. 39; GA, SA, A*, and DA can generate trajectories with respective lengths of 23.0897m, 29.0999m, 21.9750m, and 29.8753m. Normal GA, SA, and DA planning pathways are substantially longer than the GA-BZ (19.0072m) as a result of the additional nodes and infection spots. The revised path design algorithm reduces superfluous inflection points and nodes, resulting in a smoother, shorter path.

TABLE V. PERFORMANCE OF AMR USING MULTIPLE ALGORITHMS (50%)

		Distance Travel (m)	Time Taken (s)	Fare (RM)
50%	Genetic Algorithms	23.0897	46.1794	50%
	GA-BZ	19.0072	38.0144	64.16
	Simulated Annealing	29.0999	58.1998	83.64
	A-Star	21.9750	43.9500	64.06
	Dijkstra's Algorithms	29.8753	59.7506	90.56

The GA-BZ technique has the shortest simulation runtime, at 38.0144 s, as shown in Table V. The AMR was able to achieve its objectives in a less risky and better-coordinated fashion because of the GA-BZ approaches. The normal GA costs RM 57.72 (46.1794s), while GA-BZ costs RM 47.51 (38.0144s). Using the A-Star algorithm, the time and money spent on trip is calculated to be 43.9500 s and RM54.93, respectively. The time required for SA is calculated at 58.1998 s (RM72.74), while DA measures in at 59.7506 s (RM74.68). GA-BZ requires a shorter minimum travel distance than competing algorithms. Thus, GA-BZ provides more precise estimates of target path lengths, throughput, cost, and smoothness than alternative methods.

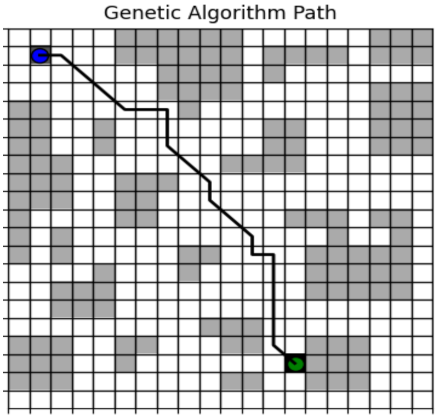

Fig. 35. Path Planning of Genetic Algorithms (50%)

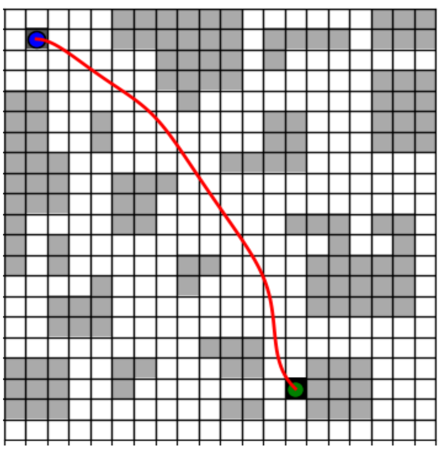

Fig. 36. Path Planning of Genetic-Bezier Algorithms (50%)

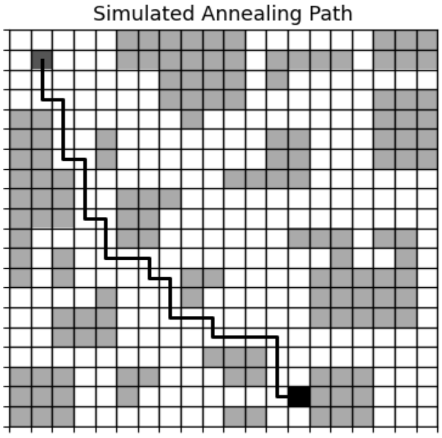

Fig. 37. Path Planning of Simulated Annealing Algorithms (50%)

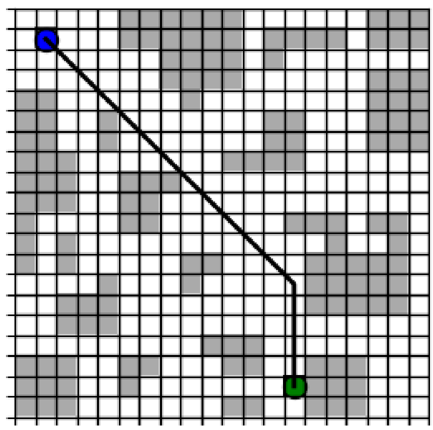

Fig. 38. Path Planning of A-Star Algorithms (50%)

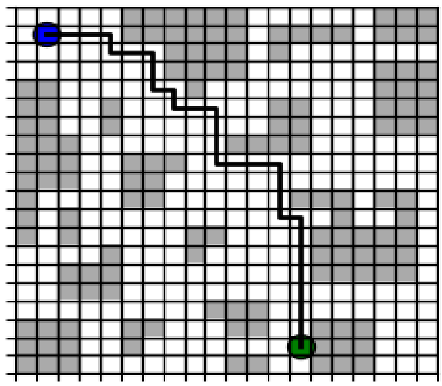

Fig. 39. Path Planning of Dijkstra's Algorithms (50%)

V. CONCLUSION

The goal of this research was to determine if and how a genetic algorithm with some modifications (GA-BZ) could be utilised to enhance the process of route planning for a mobile robot. Applying GA-BZ to the problem of route planning in a world full of obstacles always leads to the optimal answer. As was shown previously in this study, the GA-BZ has impressive potential to enhance the route planning algorithm and produce an ideal path in terms of path length. By incorporating specialised selection and crossover operations into the GA-BZ computation, we were able to speed up the process and reduce associated costs, ultimately producing a more effective strategy for travel planning. The performance of the robot's journey route is enhanced by the incorporation of a continuous Bezier Curve into the Genetic Algorithms.

Based on the configuration of the first sub environment with 15 percent obstacles, it can be concluded that as population and generation increase, both GA and GA-BZ generate smoother and superior routes. Even when the mutation rate is increased, the resulting duration and cost for an AMR to reach its destination are random. This is due to the fact that the mutation operator introduces random changes to the genetic material of population members. Mutation is a stochastic process that can introduce random perturbations while occasionally leading to solution enhancements. Using the GA-BZ path that is generated, a more effective and efficient trajectory can be designed and optimised with greater obstacle avoidance. The best results from sub-experiment 1 were obtained when the robot's MR was set to 0.5, the PN was set to 100, and the GN was set to 100, with the obstacles occupying 5% of the available workspace, as GA-BZ travels the shortest distance (27.1666m) and spends the least amount of time (54.3332s) and money travelling (RM67.92).

In the context of the second sub-experiment with barriers comprising approximately 15 percent of the workspace, it can be concluded that the performance of the robot using both GA and GA-BZ improves as the number of populations and generations decreases. Even with a higher mutation rate, the cost and duration of AMR travel are unpredictable. The mutation operator makes arbitrary genetic modifications to members of the population. Mutation is a random process that can result in arbitrary changes and occasionally produce superior solutions. The most effective outcomes were achieved with the robot's MR set to 0.1, the PN set to 100, and the GN set to 100 since this combination allows the shortest distance (27.5655 m) and time consumption (55.1312 s), as well as the lowest cost (RM68.91), when the obstacles consumed 15% of the available workspace throughout the second sub-experiment 1 using GA-BZ.

GA-BZ improves routes as the mutation rate increases in the third subenvironment with 30% obstacles. Despite a higher mutation rate, AMR travel time and expense remain variable. Randomly altering population genetics, a mutation operator. Mutation can result in arbitrary modifications and enhanced solutions. The generated GA-BZ path can be utilised to create a more efficient and effective trajectory with enhanced obstacle avoidance. This sub-experiment 1 yielded the greatest results when the robot's MR was set to 0.1, the PN was 100, and the GN was 100, and when obstacles occupied 30% of the workspace. GA-BZ travelled the minimum distance (27.2178 m) and spent the least amount of time (54.4356 s) and money (RM68.04).

Five distinct algorithms, GA, GA-BZ, SA, A*, and DA, are utilised to compare the performance of the AMR robot in the second primary test. In an environment where obstacles occupy 25% of the space, the shortest distance that effectively avoids obstacles is 25.6642m in 51.3285 s at a cost of RM 64.16. This robot performance was achieved with the help of the proposed algorithm, an enhanced Genetic Algorithm with Bezier Curve (GA-BZ). In addition, the shortest path, including time and cost, through a 50% obstacle coverage area is 19.0072m in 38.0144s at a fee of RM 47.51. The proposed algorithms, which combine an enhanced Genetic Algorithm and a Bezier curve, were used in the robot's performance.

The goals of this study have been met since an enhanced Genetic algorithm (GA-BZ) with variable population, generation, and mutation rates of GA was used to create an ideal path for an autonomous mobile robot (AMR). This study also verified the superiority of GA-BZ over traditional GA in terms of path planning performance, measuring the two types of algorithms across a range of metrics, including travel time, cost, and total distance travelled. Finally, the output from a comparison of GA, Simulated Annealing (SA), A-Star (A*), and Dijkstra's Algorithms (DA) with respect to path length (m), time (s), and cost (RM) demonstrates that the proposed GA-BZ is superior, as well as smoother and optimum.

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