

# Industry 4.0 with intelligent manufacturing 5G mobile robot based on genetic algorithm

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## ABSTRACT

A manufacturing fifth-generation (5G) mobile robot is a new development of industry 4.0 application, deploying an unmanned system. This study aims to implement a robot system for industrial applications in real-time with remote sensors to enable humans. Moreover, there is still some obstacle to cope with the better optimization solution for manufacturing 5G robot. This paper proposed a latency network algorithm for the manufacturing 5G mobile robot. An improved genetic algorithm (GA) by restructuring the genes is applied to plan a mobile robot path. The process of the robot path in a complex workspace is proposed, considering the node's collision-free constraint in the moving phase of a robot. The proposed scheme improves the robot path and delivery efficiency of the robot on average at 68% by moving on the industrial environment's shortest path and time average of the mobile robot reach its destination.

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## 1. INTRODUCTION

During the outbreak of the coronavirus pandemic, various companies and individuals involved in developing the robotics industry have been working on various projects related to the pandemic [1], [2]. In any project development, a robot must follow a path to safety, which is similar to the concept of industry 4.0. According to [3], the need for high-performance and long-term data storage has become more prevalent in the 5G mobile network that has been developed. A 5G mobile robot can adapt to an industrial environment's dynamic conditions that allow it to move seamlessly from one point to another.

On the other hand, an industrial internet of things (IIoT) is a new research area that focuses on developing a modern system industrial ecosystem. Since the number of data sources is growing and the heterogeneity of information collected, big data is defined not just by its volume but also by its sophistication [4]. Thus, we propose the 5G mobile robot to suit the IIoT terms for the advanced technology that will improve route planning efficiency and short time-consuming. Due to the complexity of the task and the high cost of these components, 4G networks cannot handle the demand. Compared to previous technology, 5G data return technology is more reliable. The main advantages of 5G are faster processing speeds and lower latency. The rise of the IoT technology has led to new processes and tools for factory automation. Since the concept of the IoT has not been implemented in current automobile models, it is not feasible to implement a real-time dynamic environment that can be used in self-driving cars, according to [5], [6].

Robotic path planning is a hot topic in robotics these days, particularly in robot navigation, which involves determining a collision-free and optimal path for a mobile robot from beginning to end [7], [8]. This

topic focuses on the advantages of hybrid navigation in autonomous vehicles that demonstrated in [9]. While these algorithms can solve the route planning problem, they all have drawbacks, such as the future field method's local minimum problem. As a result, much work is still to be done to create a more effective algorithm, according to [10], [11]. According to [12], the instability phenomena is intended. Due to the instability phenomena, robots are prone to wandering away from their goal places, leading to catastrophic harm. According to [13], a multi-robot that can exchange the sensing information data among the agents is proposed. In [14], a Voronoi-based strategy is used to minimize duplicated exploration areas. This method works by grouping different target locations into autonomous robots. According to [15], this paper proposes a multi-robot system that coordinates with a wall follower of a group of robots. It is designed to evaluate the reliability of the system. Mobile robot speed in a different scenario and speed control demonstrated in [16]-[18] is proposed.

## 2. ROBOT PATH PLANNING BASED ON GENETIC ALGORITHM

The proposed genetic algorithm (GA) for path planning effectively optimizes a robot navigation system's local and global planners, as demonstrated in [19]. The GA is a method of the quest for global optimization, and it can model the evolution cycle and its behaviour in nature. A promising algorithm known as the crossover operator in the GA has been implemented to increase the algorithm speed and accuracy, which align with the works done in [20]-[24]. A population comprises the entire set of chromosomes and is estimated based on the fitness function [25]-[26]. GA also implemented in network applications such as papers according to [27] used the algorithm to find the shortest path for a network by using a combination of Open shortest path first and genetic algorithm (OSGA). The algorithm can find a good set of values for the system's different parameters used in visible light communication, as shown in [28]. In [29], GA with local search method is proposed to uniform asymmetric multilevel inverter called USAMI. That removes the higher-order harmonics defined while maintaining the fundamental voltage needed. The goal of the GA is to transform the primary individuals into high-quality individuals. According to [30], GA has fast convergence towards global optimum rather than A\* algorithm for edge detection. The PSO algorithm has many shortcomings, such as its lack of global convergence guarantee and trapped in its local optimum, as mentioned in [31]. Furthermore, some academics are still looking into this topic to enhance the algorithm and find new approaches, and most of them have solved the best path in terms of a single objective.

It is assumed for the user to an interface that will manufacture the manufacturing 5G mobile robot based on the proposed route layout, which concentrating on the mobile robot's path that moves around inside the designated area designed. We investigate the shortest path of the robot movement and the average time taken by the robot. The optimization problem is considered by optimizing the network utility, and subsequently, the appropriate algorithm is presented. We construct the model using a 2-D grid-based map to visualize our environment for the mobile robot. Then, we apply the GA to the constructed model. The proposed GA is the improvised from paper [21] that uses GA to rearrange the genes for the new population by testing three different environments: irregular, maze and narrow winding environment. The GA was made according to the improvement factors mentioned above in this study. Finally, we analyze the performance and average time of the manufacturing 5G mobile robot based on the percentages differences of obstacles set. Unlike works in [21], we leverage the algorithm from [22]-[25] by adding three different percentages of semi-dynamic obstacles. Moreover, each set has six additional coordination consist of its existing obstruction.

This article is structured as follows; section 2 presents the manufacturing 5G mobile robot path planning, and section 3 uses the GA approach for the mobile robot. In section 4, we present several results obtained from the simulations. Finally, all the findings of the work are provided in section 5.

## 3. GENETIC ALGORITHM FOR 5G MOBILE ROBOT SCHEME

Through applying the GA, the steps to solve the problem are as follows: a chromosome coding system was developed; initial population fitness; fitness feature assessment for initial population fitness; discovery, crossover and mutation operator are chosen for the feasible solution. According to the theory of the fittest, the highest value of expectation is achieved by the global search. The manufacturing 5G mobile robot route planning intends to look for the shortest path across the working area. Route planning aims to guide the mobile robot to find its suitable route to complete its movement from the starting point to the destination point. Furthermore, using global route planning is used to build a collision-free path with restriction conditions. To ensure the journey of the mobile robot from point to point is complete, specific data is given to the mobile robot. Since the environment is a 2-D space, a grid-based space (where several obstacles are normal, known and stable) is used in this proposed algorithm to represent the environmental space, and decimal encoding is used according to [32]. In this article, the model's multi-layered representation is used to define the

environmental space. Two-dimensional planar graphics represent the mobile robot's direction region, and a circular list tracks the vertices  $(x,y)$  of the obstacle. The obstacle is set as an unspecified irregular polygon that is static, random and identified.

The workspace as illustrates in Figure 1 is modeled as a grid with an irregular shape obstacle, where each uniform cell points to a position.  $L$  represent the length of the grid. The red line represents the path of the robot to reach the destination. While symbol  $\times$  represents the best possible vertices of the robot path. Thus, the robot will find the optimal path to avoid the obstacle and safely arrive at the destination. Each area is split into rows and columns that form the structure of a regular grid. Each cell must be rectangular but not necessarily square in shape, the problem of complex environmental information is simple to solve and fewer resources are required as mentioned in [33]. In the route planning of a mobile robot, the grid-based model is typically used to show the workspace as it is simple to measure distances and represent obstacles. Let  $S_i$  ( $i = 1, 2, 3, \dots, n$ ) represents as the area of obstacles covered/ shaded region where  $n$  is the number of obstacles,  $L^2$  is the area of the grid space. We assume to have  $h$  the number of cells. The percentage of the shaded area which represents the obstacle is calculated as below:

$$\frac{S_i}{L^2} \times 100\% = O_h\% \tag{1}$$

Ordered numbered grids define the entire workspace, and the number of grids defines how many cells exist. Cells are defined by  $H$ , or  $H \in [1: h]$ , where a total number of cells,  $h = 20$ . Every cell is either considered to be empty or occupied. Obstacles  $O_h$  represents the total percentages of the obstacles. These imply that the cells occupied are off-limits for travel. Those obstacles are taken from the factory environment. The obstacles boundary is established by their exact boundary plus minimum safety distance. In practice, consideration of a mobile robot's size is 'one while 'moving. We assume that the percentage of the obstacle is calculated with each sum of the cell. The shaded region represents all the obstacles in the form of irregular shapes. Figure 2 illustrates the possible value for obstacle percentage and the allocation of number that defines the value of obstacle percentage which  $(0,1)$ . Step 1: the  $a$  represent the full area of the obstacle which can be defined as 1; Step 2: the  $b$  and  $c$  depict the small area of the obstacle area and non-covered area, respectively, which is defined as 0. The path optimization is based on the GA method to find an optimal path for the manufacturing 5G mobile robot. The optimization operator must analyse, choose, re-allocate, and perform other optimization processes to improve individual fitness and optimise the GA convergence rate based on individual gene characteristics and environmental factors that influencing individual genes.

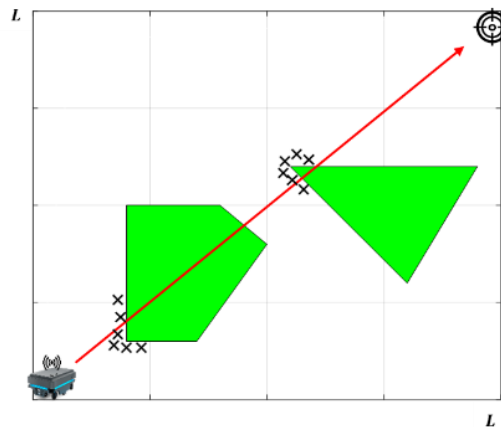


Figure 1. Path planning with 2-d grid-based space

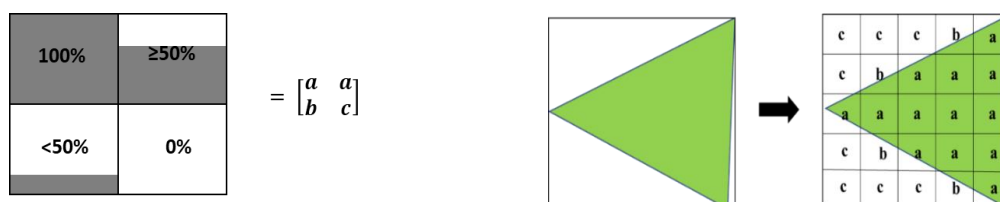


Figure 2. Possible value of each cell where  $a = 1$  and  $b = c = 0$

### 3.1. Genetic operator

#### 3.1.1. Selection operator

To select the best gene selection and inherit the next generation by using the fitness function. According to [26], the roulette method is used to ensure that the person who passes the obstacle is not selected.

#### 3.1.2. Crossover operator

A single point crossover method is used to ensure that a person crosses by generating random numbers. It produces an integer randomly within the range of genes as the intersection's starting point and randomly generates an integer as an element to be crossed between populations. If the  $i$ -th individual intersection is  $k$  and the cross object is the  $j$ -th individual.

#### 3.1.3. Mutation operator

Determine whether a randomly created number has mutated an individual. An integer within the range of the number of genes is generated randomly as a variance point to ensure the diversity of the population because of a minor change in chromosome position resulting in the formation of a new gene fragment. Algorithm 1 is the whole process of the manufacturing 5G mobile robot path planning. As the output of GA is  $K$  that denoted as the best fitness values of the coordination  $x$  and  $y$ .

### 3.2. Chromosome coding

In the encoding of chromosomes, true coding, binary coding, and tree coding are used, which will affect the usefulness of route planning. Here, the real number encoding method is used to express the coordinates of real points, while the path coordinates are encoded specifically. The robot's direction consists of multiple line segments, each represented by a line attached to the infinite starting point and endpoint node. We represent the symbol  $\mathcal{L}$  as a collection of intermediate nodes. Assume that there are  $n$  nodes overall, a point  $p_i$  ( $i = 1, 2, 3, \dots, n$ ) represents the  $i$ -th on the chromosome, that is  $\mathcal{L} = \{p_1, p_2, \dots, p_n\}$ . According to [25], in comparison to binary coding, there are several benefits of real coding: (1) Participate in the genetic process where actual numbers are used as chromosomes, instead of the time-consuming method of coding and decoding; (2) Removing the binary code 'hamming cliff issue'; (3) crossover and mutation operators are used for breeding new individuals, which enhances the algorithm's search efficiency. These points are then processed in a variety of ways to determine the best robot motion direction. Let  $l_c$  implied as total number of chromosome length.

Algorithm 1: The Main Function of GA	Algorithm 2: Population Initialization ( $x, y$ )	Algorithm 3: Selection Operator for Gene Selection using Fitness Function Value
Input: Environment setup Output: Optimal Path for Mobile Robot 1: Initialize: Crossover, Mutation, Population Size chromosome length, $x$ and $y$ limit) 2: for $i = 1: 1: N$ 3: do function in 3.1.1; 3.1.2; 3.1.3 4: if rand < 0.0 5: [ $x, y$ ] = optimization ( $x, y$ ) Function 6: end if 7: Calculate fitness Function (best $x, y$ ) 8: end for 9: for $i = 1: 1: \max(\text{size}(\text{best } x, y) - 1)$ 10: do (2) 11: end for 12: $K = \text{plot best } x, y$	Input: Population number of genes Output: Initial population 1: Initialize: $N_p, l_c, x_0, y_0, x_n, y_n$ 2: $i = 1$ ; for $j = 1: 1: N_p$ 3: while $i \leq l_c$ 4: if $i == 1$ 5: $x(j, i) = x_0; y(j, i) = y_0; i = i + 1$ 6: else if $i < l_c - 1$ 7: if rand < 0.5 8: else (2) 9: else if $i == l_c$ 10: $x(j, i) = x_n; y(j, i) = y_n; i = i + 1$ ; 11: end if 12: end while 13: $i = 1$ 14: end for	Input: Initial population adaptability Output: New population ( <i>new initial</i> ) 1: Initialize: new population for $x, y = \text{selection}(x, y, \text{fitness value})$ 2: $F = \sum_{v=1}^{10} F_v$ 3: $F_v = \sum_{i=1}^{10} F_{vi}$ 4: while $N_p \leq P_x$ 5: if $F_{vi} > 0$ 6: else if 7: $F_{vi} = F_{vi} + 1$ ; 8: end if 9: end while

### 3.3. Initialize population

The population must be initialized first to plan for the optimum direction for the mobile robot. Since the initial path is generated arbitrarily, the continuous domain contains the feasible path and the unreachable path. The genetic operator would inevitably find a direction that is close to ideal. Due to the unreachable direction, the utility search in the global search is reduced because where the chromosomes overlap, unreachable paths are likely to be generated by the two unreachable paths. Therefore, in the road's generation, this paper set an initial population to speed up the convergence rate to maintain the escape of obstacles and

deselect the path that encountered obstacles. A single production point is used for the initialization process, setting  $(x_0, y_0)$  as the starting point,  $(x_n, y_n)$  as the destination point, and meet  $x_n \geq x_0, y_n \geq y_0$ . The current position is  $i$ , while the  $i + 1$  point is produced, where  $R$  is a random function,  $[0,1]$ . The regulatory algorithm for the initial population is shown in Algorithm 2. Let  $N_p$  denoted as total number of new populations while  $P_x$  represents as number of matrices from small to large for the number of populations.

### 3.4. Fitness function

The fitness function is the assessment of the individual's environmental adaptability. Based on Figure 3, the fitness function is produced through the process of the population. There is a lower fitness of the individual who crosses the obstacle after the mutation and crossover. So, the person's fitness is set to 0 by the obstacle, and the fitness of the other individual is stated. As a result, there are two types of conditions for the adaptive operator: if the individual gets past the obstacles, it is possible to obtain fitness; while if the obstacles cannot pass, then compute the total number of fitness values given by:

$$F = \begin{cases} 0 & \text{if } O_h \text{ is } 0, \\ \frac{c}{\sum_{i=1}^{n-1} \sqrt{(x_{i+1}-x_i)^2 + (y_{i+1}-y_i)^2}} & \text{if } O_h \text{ is } 1. \end{cases} \quad (2)$$

Individual adaptability and fitness value are higher when  $C$  is any constant. More elevated fitness chromosomes are passed to the next generation, and if a healthy individual chromosome is found, this process continues. From (2),  $F$  denotes as best fitness for each population while  $F_{vi}$  is the total initial fitness values. Algorithm 3 shows the step for fitness and gene selection. In summary, the flow process of GA for mobile robot path planning is shown in Figure 3. The flowchart illustrates the overall GA optimization part used in this research.

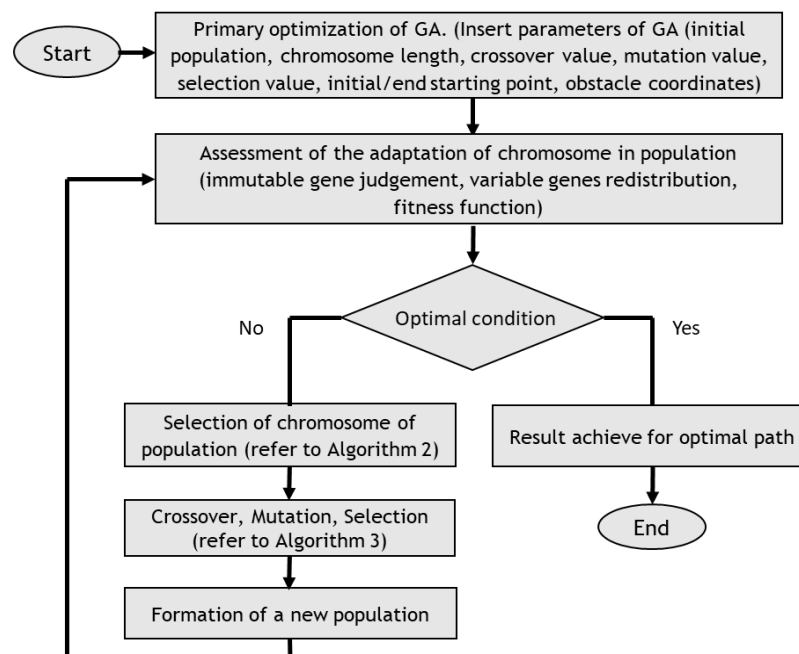


Figure 3. Flow chart of GA for mobile robot planning task

## 4. RESULTS AND DISCUSSION

To verify the effectiveness of the proposed algorithms, a simulation in one fair environment with different percentages of the obstacles: 50%, 70% and 90%. The shaded part of the initial configuration is made up of a coordination framework and an obstacle field. Table 1 shows the setting parameters of improved GA with obstacles implemented. The values are set considering the actual environment of the industry path. The fitness value is based on the GA parameters given to investigate the performance of fitness values. This value minimizes the GA process and optimizes and finds the robot's optimal path to reach the destination. The selection rate for the improved GA is 0 because the GA no need to choose a large number of chromosomes to be selected

and the process will take a shorter time to optimize. This research conducts three experiments which are using three different numbers of percentages. We proposed six environments for each experiment. For each experiment, the environment is provided with a possible value of obstacle coordination which means the obstacle is semi-dynamic for experiments 1, 2 and 3. We randomly move the position of the obstacle with the aid of the obstacle number provided. While Figure 4 shows the six possible environments of the obstacles for each experiment; Figure 4(a) 50% obstacle; Figure 4(b) 70% obstacle; and Figure 4(c) 90% obstacle.

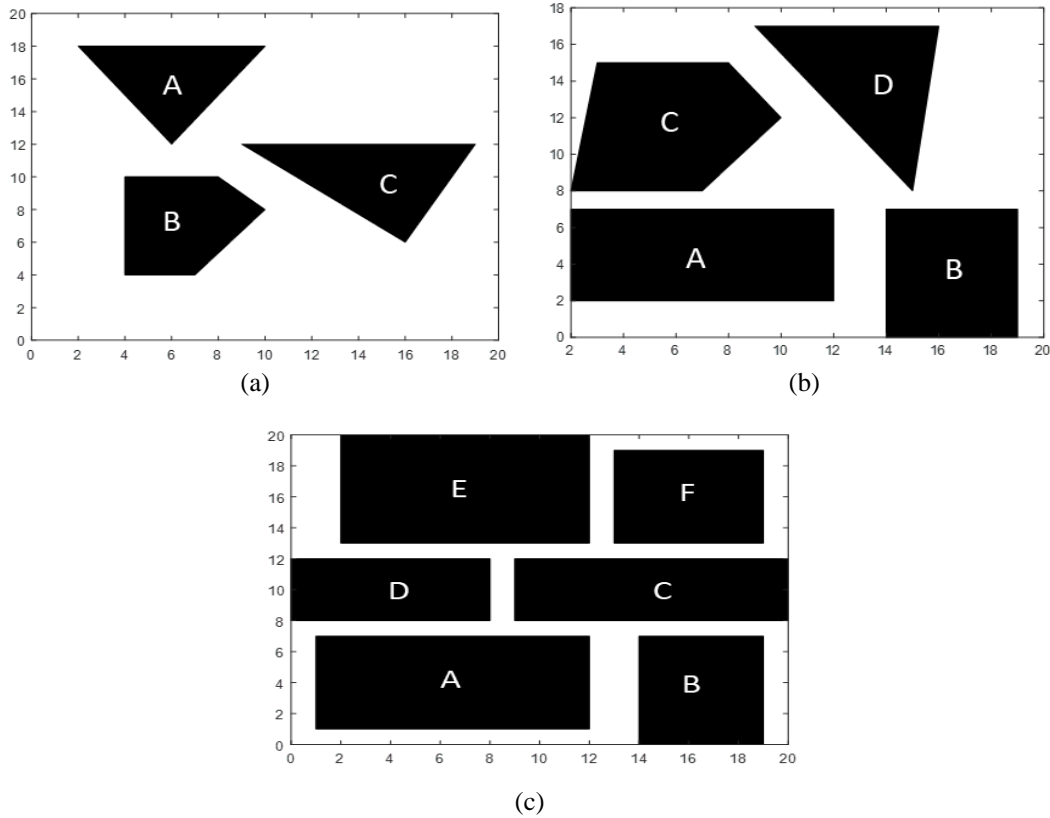


Figure 4. Proposed experiment for the various obstacle; (a) 50%; (b) 70%; (c) 90%

Table 1. GA parameters setting

Parameters	Proposed Values	Parameters	Proposed Values
Population Size, $N_p$	100	Selection Rate, $P_s$	0
Number of Genes	50	Crossover Rate, $P_c$	0.6
Maximum Number of Generation	100	Mutation Rate, $P_m$	0.01

The blocks are considered obstacles where the blocks' condition is to be semi-dynamic, which indicates that an obstacle is present in each region where the robot travels from its starting point to its destination point. The mobile robot starting position point is at (0,0), and the destination point is at (20,20). A minimum and maximum value of the path length is shown to optimise the result obtained from these three experiments. The robot path and the CDF value of the three minimum path lengths are illustrated in Figure 5(a)-(c) and Figure 6, respectively. The robot path represents in a red dotted line while the blue dots are the fitness value of the coordination to avoid the obstacle with GA operation involvement. Hence, the GA will optimize the path where the mobile robot is near the obstacle and make sure the path is smooth and shorter for the mobile robot to reach its destination.

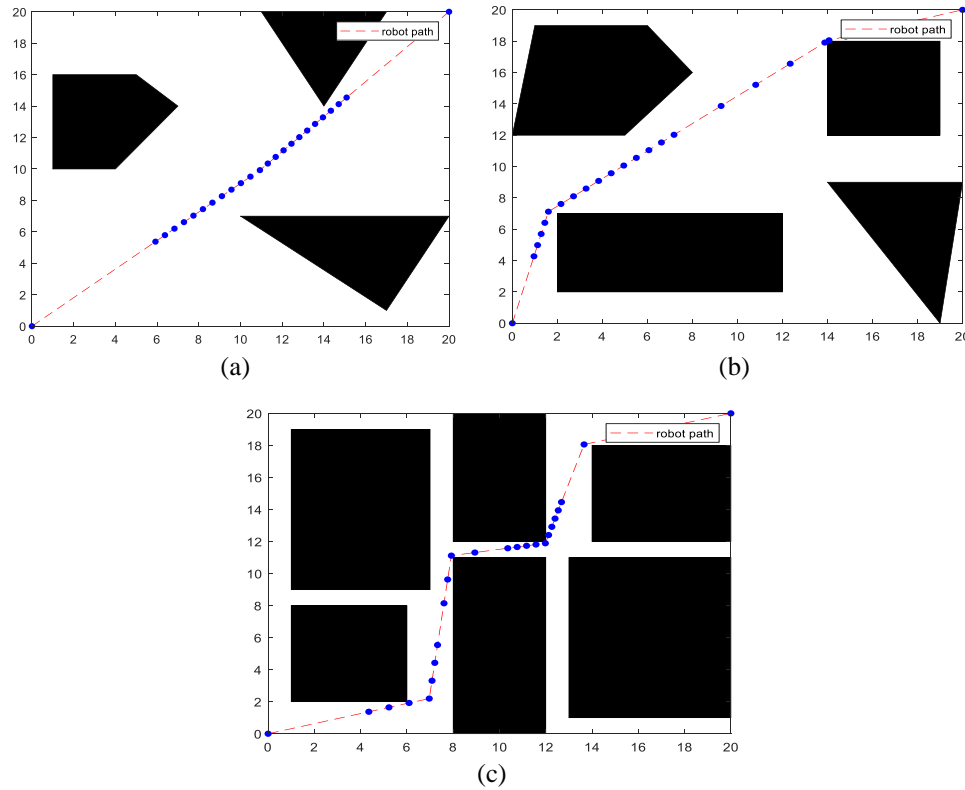


Figure 5. Mobile robot path with various percentages of obstacle; (a) 50%; (b) 70%; (c) 90%

Figure 6 (a) shows that the minimum path length for 50%, 70%, and 90% of obstacles are 28.32, 29.91 and 35.33 meters, respectively. As we know, the more complex the environment in the area, the longer time for the robot to get through the semi-dynamic obstacle. The robot path appears to be more consistent during the 50% obstacle parameter was made, where the others are erratic for the mobile robot path planning until the end of the 100 run times simulations. Based on Figure 6 (b), the mobile robot's maximum path length for 50%, 70%, and 90% of obstacles are 30.52, 32.06 and 35.58 meters, respectively. The robot path takes maximum length in all three experiments. As our observation, when simulations ended at 100, the robot path's length for maximum percentage implemented is recorded less value than the minimum set. The maximum percentage only recorded 45 meters while 50 meters for the minimum. The robot path can be the same as the simulations run until 100 times with the best individual genes and better fitness function production for each population.

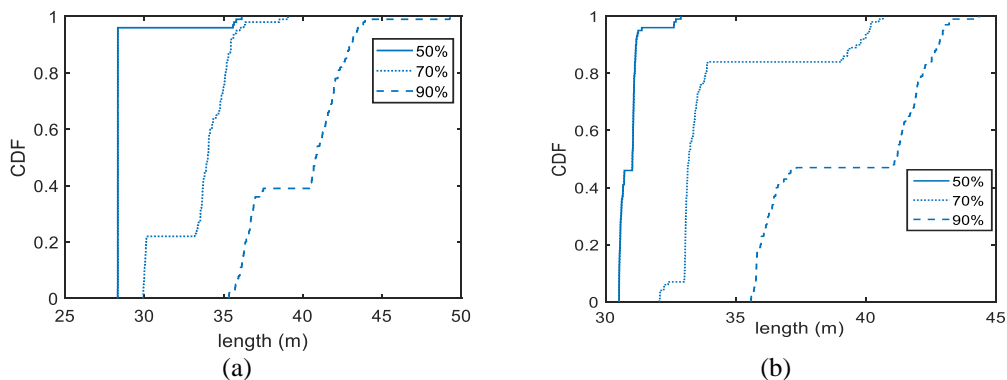


Figure 6. CDF; (a) minimum and (b) maximum total length for the various percentage of obstacle

In line with [19]–[20], the average speed for manufacturing a mobile robot is 0.5 with a maximum load of 1 kilogram. This setting is due to some limitations of the robot speed due to the safety in the industrial environment

and robot max payload. Table 2 shows the time average of the mobile robot with constant speed from start to end position based on the percentage of obstacles. The design of the mobile robot is considered for stability and consistent speed. Thus, the mobile robot can reach its destination on time with the presence of obstacles.

Table 2. Average time for various percentage of obstacle

Percentage of obstacle (%)	50	70	90
Minimum; Maximum total length time (sec)	60.498; 61.859	66.792; 67.964	79.585; 79.985

Moreover, the GA application functioned as a selection process that makes it possible to select good-quality solutions for mating in each generation and crossover activity that enables exchanging genetic information between two good-quality solutions to create better solutions generation. Crossover plays an important role in generating different gene combinations and has both potentials to explore and manipulate, thus improving the solution's quality. Our path optimization operator can be seen from the simulations, no matter how complicated or the higher the obstacles percentage of the environment is to shorten the path and reduce the length to improve the robot's protection. The convergence speed of the GA operator is improving the simulations before and after optimizations. As a result, the manufacturing 5G mobile robot gains the desired path length in a shorter distance. It reflects this study, which aims at the path optimization operator, which can speed up evolution and shorten path length in various environments using GA. While this is useful in improving the objective value, the search is probably pointless if the current solution is stuck in the optimum local area.

## 5. CONCLUSION

In this paper, industry 4.0 with intelligent manufacturing 5G, a mobile robot based on a GA, is proposed to optimize the mobile robot's path or route. According to the optimal path planning with different percentages of obstacles covered without collision, this improved GA is optimized to reduce the path length before and after optimization. The results of the experiments show that this strategy strengthens the ideal path even further. As the outcome suggests, path planning for manufacturing 5G mobile robots based on improved GA has developed better optimization than the previous GA. Future work improvement is proposed to develop a further GA-based scheme in terms of performance, such as energy consumption with 5G implementation and multi-robot involvements.

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