Reliability Analysis of Energy Efficient Mobile Robot Routing

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***Abstract*— Nowadays, mobile robots are used in many fields from industry to hobby, military to spacecraft. Industrial developments have enabled self-sufficient autonomous robots to be used more frequently in different tasks. Therefore, to achieve these tasks optimally, route planning should be performed by considering energy consumption, time, cost etc. In this study, first a routing problem is defined, and a mathematical model is formed. Then optimal routes considering energy consumption of the robot is achieved by using Genetic Algorithm (GA) and Cuckoo Search (CS), and the results are compared. Furthermore, details of the reliability analysis of the mobile robot among the optimal routes are given. The test results shown that the CS outperforms GA in terms of average objective function values and computational time.**

Keywords— Cuckoo Search, Genetic Algorithm, Mobile Robots, Reliability, Route Planning

I. INTRODUCTION

Robotic systems are used in various fields, especially in product transportation and storage, to increase efficiency and safety. As a result of rapidly developing technology, with the establishment of smart factories, autonomous robotic systems have started to come into prominence instead of the ones controlled by the operator or following the pre-defined routes. Since autonomous mobile robots are being used in repetitive and long-term transportation tasks in storage systems, long-term autonomous operations of robots and maintaining this autonomy becomes especially important.

Storage and transportation systems are mainly based upon route planning problems. Effective route planning is one of the important requirements for mobile robots to perform their tasks fertilely. This route planning can be defined as finding the most appropriate path from the starting point to the target point, by considering a specific performance index (shortest path, lowest cost, etc.). Therefore, it can be regarded as an optimization problem and can be solved with proper optimization algorithms.

Travelling Salesman Problem (TSP) and Vehicle Routing Problem (VRP), which can be considered as the main problem in transportation systems, take part in the basis of logistics route planning. In TSP, the shortest path, where a vehicle starts from an initial point and returns to same point after visiting each node at once, is searched. On the other hand, classical VRP, also known as Capacitated VRP (CVRP), seeks the optimal routes having the lowest travelling costs by considering the vehicle loading capacities [1]. VRP becomes a TSP when the vehicle capacity is taken as infinite [2]. TSP and VRP are NP-hard optimization problems that can be solved with mathematical methods for only small-scale problems, thus meta-heuristic algorithms are required for large-scale problems. In the literature, there are many studies on route planning via meta-heuristic algorithms are exist. In this manuscript, studies based on GA and CS are examined.

GA is well known optimization technique inspired by Darwin's theory of evolution. In the study [3], a route planning has been made with GA so that mobile robots avoid obstacles in the environment. This study is designed for robots with holonomic constraints, and the proposed algorithm has a lot of complexity. In the study [4], a mathematical model of CVRP was created for logistics and distribution operations and optimum route planning was achieved with GA. In the study [5], a method including GA is developed to solve the TSP. In this method, chromosomes were formed with a greedy approach structure, and they were inserted to the population. In the study [6], a mobile robot route planning is performed by using GA with variable length chromosomes and the routes were obtained where mobile robots avoid obstacles in both static and dynamic environments. In the study [7], a dynamic route planning based on GA was presented to navigate the mobile robot and avoid obstacles in an unknown environment and tests were performed in the VC ++ 6.0 simulation environment. Likewise, CS is another search algorithm which is based on brood parasitism, where the eggs are placed in the nest of other host birds (other species). In the study [2], a TSP is modelled and solved with CS regarding the collection of wastes in plastic waste containers located in 20 regions in Nis, Serbia. In the study [8], a hybrid CS method called CS-GRASP is proposed to solve VRP. In that study, it was observed that the proposed algorithm reached the optimal solution with a lower computational time compared to the other heuristic algorithms. In the study [9], to solve the TSP, a random key cuckoo search (RKCS) algorithm has been presented and the performance of the algorithm has been tested in the TSPLIB library. In the study [10], the application of the CS algorithm to the capacitated route planning problem was investigated and the algorithm was tested in the Augerat benchmark dataset. In the study [11], to solve the TSP an improved and discrete version of the CS (DCS) algorithm is presented. The experimental results showed that the proposed method performed very well for simple TSP, but it was stuck to the local optimum point in some problems. In the study [12], mobile robot route planning in a dynamic environment has been solved with the CS algorithm, and the size reduction process has been performed to overcome the computational complexity. In the study [13], the TSP was solved with the adaptation of CS and it was observed that CS outperformed GA in terms of not only optimal route distance values but also computational time. In the study [14], CS algorithm is applied to solve mobile robot route planning in an unknown or partially known environment filled with various static obstacles.

In complex systems such as industrial systems, it is expected that the reliability values of robots are known, and some decisions are made to maintain long-term operations. Reliability prediction is an important concept to minimize possible failures of robotic systems and thus to increase their success. A robot with low reliability can cause problems due to its higher maintenance costs and increased failure rate. Therefore, it is necessary to provide optimal routes and to calculate the reliabilities of the mobile robots to sustain the long-term autonomy in the smart factories. Studies on the reliability of mobile robots have started to gain importance in recent years. In the study [15], reliability-based task performance analysis was performed for multi-robot systems with the help of fuzzy logic. In the study [16], different reliability parameters of multi-robot systems are examined by using Real Coded Genetic Algorithm and Fuzzy Lambda-Tau methods. In the study [17], tasks are shared for multi-robot systems and the task completion probabilities for repairable robot teams were analytically estimated. In the study [18], a sample task performance analysis has been performed for robotic systems and the effects of the amount of loads carried by the robots and the temperature on the system reliability. In the study [19], reliability analysis of planetary exploration robots that will collect samples from planets has been accomplished. In the study [20], the user logs of CRASAR (Center for Robot-Assisted Search and Rescue) robot are examined and the most frequently repeated failure types and the frequency of these failures were analyzed. Furthermore, the failures in the subsystems of robots have been obtained by using statistical analysis methods, and the types and frequencies of these failures have been determined. Finally, the failure tree has been revealed by deducting the hazard rate of each failure. In the study [21], the reliability analysis of a mobile robot system over a 34-month period was performed using statistical modeling techniques. Most of the failure modes have been defined and descriptive statistics at the component level have been calculated. In the study [22], statistical calculations of failure and repair data were performed to analyze the reliability and sustainability of a robotic system of industrial applications. In the study [23], statistical techniques were applied to the failure data and reliability analysis was examined for an autonomous mobile robot system.

In this study, GA and CS methods have been applied to solve routing problem for mobile robots considering the lowest energy consumption and the obtained results have been compared in terms of solution quality and computational time. Finally, the reliability analysis of the mobile robot has been performed with the optimal routes. Paper organization as follows: the solution methods are explained in the second section, the tests results are given in the third section, and in the last section the obtained results are discussed, and future works are mentioned.

II. Mathematical Modelling

A. Energy Consumption Model

Energy consumption of a mobile robot can be given as the function of its speed and its total mass including the amount of load carried. For the movement between any two nodes, it is assumed that the mobile robot reaches the speed of vel_{max} in t_1 time after it leaves the node and travel with a constant speed of vel_{max} until t_2. At t_2, robot starts braking and stop at the next node. Since there is not any energy consumption on the braking phase, robot consumes energy only during the period of traction. The energy required to accelerate the robot up to speed vel_{max} from stationary state as given below:

$$e_{ij}^{(1)} = \frac{1}{2} \times m_{tot} \times (vel_{max})^2 \quad (1)$$

where m_{tot} is the sum of the mass of robot and the mass of the load carried by itself. Similarly, the energy required to overcome the surface friction during the traction period can be given as follows:

$$e_{ij}{}^{(2)} = k_f \times m_{tot} \times g \times d_{traction,ij} \quad (2)$$

In (2), k_f represents the friction coefficent of the surface and g represents the gravitational acceleration. Besides, $d_{traction,ij}$ is the distance that the robot travels during the traction period between i^{th} and j^{th} nodes. For a route segment between any two nodes, it is assumed that $d_{traction,ij}$ is equal to 95 percent of the length of this segment as given in (3).

$$d_{traction,ij} = 0.95 \times d_{ij} \quad (3)$$

Here d_{ij} represents the distance between i^{th} and j^{th} nodes. Therefore, the total energy consumption of the robot during its movement from node i to node j can be expressed as follows.

$$e_{ij}^{tot} = e_{ij}^{(1)} + e_{ij}{}^{(2)} \quad (4)$$

B. *Routing Problem Model*

The routing problem considered in this study consist of a single robot and can be modeled mathematically as follows.

$$min\ F_{obj} = \sum_{i\in A}\sum_{j\in A, i\neq j} x_{ij} e_{ij}^{tot} \quad (5)$$

subject to

$$\sum_{j\in N} x_{0j} - \sum_{i\in N} x_{i0} = 0 \quad (6)$$

$$\sum_{i\in N, i\neq j} x_{ij} = 1, \forall j \in N \quad (7)$$

$$\sum_{i\in N}\sum_{j\in N, j\neq 1} x_{ij} = node, \quad (8)$$

$$x_{ij}, \in \{0,1\},\ \forall i,j \in N \quad (9)$$

Here N are the sets that contain all nodes in the problem and $node$ is the number of nodes. The objective function to be minimized is given by (5). Equation (6) guarantees that robot return to the starting point after they completed the routes assigned to them. Equation (7) and (8) ensure that each node is visited once by the robot and all nodes will be visited. Equation (9) satisfies the upper and lower bounds for the binary decision variables. Binary decision variable x_{ij} can be expressed as follows.

$$x_{ij} = \begin{cases} 1, & if\ robot\ visits\ j^{th}\ node\ immediately\ after\ i^{th}\ node \\ 0, & otherwise \end{cases} \quad (10)$$

III. METHODOLOGY

Meta-heuristic methods are algorithms generally inspired by events in nature and designed for solving complex optimization problems that cannot be solved in a reasonable time with accurate solution methods. The purposes of these methods are to effectively search the solution space and quickly find the optimal or closest to optimal solutions. In this study, two different meta-heuristic algorithms, GA and CS, are applied separately to find the optimal route based on the lowest energy consumption.

A. *Genetic Algorithm*

GA is one of the well-known optimization techniques that use Darwin's principles of natural selection. In GA, the individual solutions to the problem are encoded as chromosomes, and these chromosomes creates a population. To perform the genetic operations such as reproduction, crossing-over and mutation, first fitness value of each chromosome should be calculated. As a result of genetic operations, chromosomes with better fitness values are survived and the population evolves. This process continues until the pre-determined stopping criteria are met.

Expressing any optimization problem by using a proper chromosome structure is one of the most important factors that effects the solution quality while GA is applied to solve it. In this manuscript, each chromosome consists of totally $node$ number of genes and each gene has a value between 0 and 1. Note that, genetic operations such as crossover, mutation etc. are performed on this chromosome structure. To evaluate fitness values, the route assigned to mobile robot should be decoded from the mentioned chromosome structure. First, the indices of the genes are sorted in an ascending order according to their values. Thus, a random sequence which consists of integers between 1 to $node$ is obtained. In this integer sequence, the indices create robot route. Once the routes are obtained, fitness values and the constraints can be easily evaluated.

Constraints of the routing problem given by (6) - (9) can be considered as mobile robot flow constraints and they are directly included to the solution with the proposed chromosome structure.

B. *Cuckoo Search Algorithm*

CS is an heuristic search algorithm based on the brood parasitism behavior of some cuckoo species. Each nest in the herd is represented by a vector in the multi-dimensional search space. The CS algorithm also determines how to update the position of the cuckoo eggs. Each cuckoo updates the position of the new egg according to the current step size with Lévy flights. There are three basic rules for the standard CS algorithm [24]:

- Each cuckoo lays only one egg at a time in a randomly chosen nest.
- Nests with quality eggs are passed on to the next generation.
- When the number of usable host nests become constant, the eggs laid by the cuckoo are discovered by the host bird with a probability of $(0 < p_a < 1)$ and thrown out the nest.

In the standard CS, first an initial environment and objective function are defined. Then, the initial population of *K* nests is produced. Until the stoping criteria is met, a cuckoo is chosen randomly with the Lévy flight and the best fitness value is calculated. A nest *r* is randomly selected from the available *K* nest. If the fitness value in nest *r* is lower than the initial one, then the route corresponding to nest *r* is determined as the best route and fitness value in nest *r* is taken as the new best fitness value of the problem. After this process is completed with the randomly selected nest, the nests that produce the best solution are kept and p_a of the total nests are left out. Then, these abandoned nests are replaced with randomly generated ones. At the end of each iteration, the solutions are sorted to find the best one. Note that, the routing problem is modelled by the same way as Genetic Algorithms while it was solving with CS.

IV. RELIABILITY ANALYSIS

Mathematically, reliability $R(t)$ can be defined as the probability of a system operating without a failure in time intervals between 0 and t and depends on the alteration on the hazard rate λ [25]. The hazard rate function specifies the aging rate of the system.

Although it is possible to use several kinds of distributions for hazard rate functions, exponential distribution function is the most commonly used in reliability analysis since it has a constant hazard rate. The relationship between the reliability function and the constant hazard rate is given in (11).

$$R(t) = e^{-\int_0^t h(x)\times dx} = e^{-\lambda t} \quad (11)$$

As it can be seen in (11), any alteration in hazard rate directly effects on the system reliability. In (11), λ is the constant hazard rate and it depends on the operation parameters such as amount of the load carried, temperature, pressure, humidity, etc. In this manuscript, the amount of the load carried by the robots is taken as the main factor on the hazard rate. The relationship between the hazard rate and the amount of load carried is given in Equation (12).

$$\lambda = \lambda_0 \times \left(\frac{Y_f}{Y_o}\right) \quad (12)$$

In (12), λ_0 represents current hazard rate, λ represents updated hazard rate. While Y_f gives the ratio of the total load carried by the robot to the total weight of the robot, Y_o is the ratio of the weight of the robot to the sum of the total load carried by the robot and the weight of the robot. Here Y_f/Y_o ratio can be defined as the load factor. With the updated hazard rate, the change of the reliability value is calculated as given in (13).

$$R(t) = R_0(t)\times e^{-\lambda t} \quad (13)$$

Here, R_0 represents current reliability, R represents updated reliability. As can be inferred from Equation (12) and (13), any change on the amount of load carried by the robot will result a variation on the robot's hazard rate, thereby change the reliability of the robot.

V. SIMULATION RESULTS

In this study, firstly a database was created for the robot and the environment. Then the routing problem with a single mobile robot was solved by considering minimum energy consumption as objective. Finally, the reliability analysis of the optimal routes was performed. The simulations were carried out for two different cases given below.

Case 1: Loads on nodes are determined randomly.

Case 2: One of the loads on the nodes is set as 177 kg, the others as 1 kg.

A. *The Test Environment and The Robot*

In order to perform the simulations, an environment of 200x200 meters was created. It is assumed that there is a single mobile robot exist. Besides, there are 11 nodes (SP and 10 load nodes) in the created environment and there is a path exist between any two nodes. The surface of the floor is considered to be a rubber on the concrete, so the friction coefficient is taken as 1. The gravitational acceleration of the environment is accepted as 9.81 m/s^2. The coordinates of each node and the amount of loads in these nodes in the test environment are given in Fig. 1 and Table 1.

TABLE I. NODES IN THE ENVIRONMENT AND LOADS IN NODES

Node ID	Coordinate (x,y) (m)	Load (kg)
0 (SP)	(0,0)	0
1	(25,152)	5
2	(4,148)	17
3	(58,149)	23
4	(63,21)	13
5	(131,136)	18
6	(192,93)	4
7	(188,42)	24
8	(92,19)	14
9	(48,165)	17
10	(153,35)	1

The parameters of the mobile robot that is used in the tests are given in Table 2.

The tests have been executed with MATLAB R2017b on a personal computer having Intel Core i7 7700 HQ 2.8 GHz processor and 16 GB RAM. In order to solve the considered routing problem, GA and CS algorithms have been applied 10 times. The parameters used for the algorithms are given in Table 3.

B. *Case 1*

In this case, all loads in the environment randomly determined. The solutions obtained among 10 trials for each objective are given in Table 4.

TABLE II. PARAMETERS OF THE MOBILE ROBOT

Parameter	Value
Speed	1 m/s
Load Carrying Capacity	250 kg
Mass	50 kg
Initial Hazard Rate	1e-006 failures/hour
Initial Reliability	1.00

TABLE III. PARAMETERS OF ALGORITHMS

Parameters of CS	**Parameters of GA**
Max. iteration = 500	Max. iteration = 500
Number of nest = 40	Population size = 40
Discovery rate (p_a) = 0.1	Elite chromosome = 8, Xover ratio = 0.925, Mutation ratio = 0.075

The problem addressed in Case 1 is solved for the lowest energy consumption. By applying CS, the optimal route is obtained as 0 → 2 → 1 → 3 → 9 → 5 → 6 → 7 → 10 → 8 → 4 → 0 in which the mobile robot has a minimum energy consumption of 676004.8469 joules. Likewise, GA is used once again to solve the same problem to have the route with a minimum energy consumption. In this case the optimal route found to be 0 → 2 → 1 → 9 → 3 → 5 → 6 → 7 → 10 → 8 → 4 → 0 where the robot consumes 656065.1716 joules among that route.

For the energy consumption objective is considered, it is observed that both GA and CS results similar routes where just only the nodes visited in the 3rd and 9th order are swapped. For the best solution obtained with CS, the total energy consumption and the corresponding distance travelled by the robot is calculated as 676004.8469 joules and 629.3784 meters, respectively. On the other hand, the total energy consumption and the corresponding distance travelled by the robot is calculated as 656065.1716 joules and 608.8901 meters, respectively for the best solution obtained with GA. In both solutions obtained by CS and GA, the total load carried by the robot was found to be 186 so all the loads in the nodes are completely carried by the robot without exceeding its capacity. It is observed that CS achieves optimal solutions with approximately 4 times lower average computational time compared to GA. Although CS outperforms GA by 10% for the average solutions among 10 trials, GA gives 3% lower energy consumption values for the best solution

TABLE IV. RESULTS OBTAINED AMONG 10 TRIALS FOR CASE 1

	CS	**GA**
$F_{fitness,worst}$	733762.0755 J	856152.0707 J
$F_{fitness,average}$	698957.3969 J	783200.4267 J
$F_{fitness,best}$	676004.8469 J	**656065.1716 J**
The best route	0-2-1-3-9-5-6-7-10-8-4-0	0-2-1-9-3-5-6-7-10-8-4-0
Avarage computational time	0.855291 sec	3.437378 sec

TABLE V. RESULTS OBTAINED AMONG 10 TRIALS FOR CASE 2

	CS	**GA**
$F_{fitness,worst}$	729483.5961 J	752334.1752 J
$F_{fitness,average}$	713674.1781 J	732741.7074 J
$F_{fitness,best}$	710965.0528 J	710965.0528 J
The best route	0-4-8-10-7-6-2-1-9-3-5-0	0-4-8-10-7-6-2-1-9-3-5-0
Avarage computation time	0.818364 sec	3.419173 sec

C. Case 2

In order to explain the effect of the load carried by the robot on the energy consumption, the amount of the load placed in node 5 is set to 177 kg with assuming that all remaining nodes have a load of 1 kg. Optimal results are given in Table 5.

When Table 5 is examined, it can be seen that CS and GA both achieves 710965.0528 joules as the best solutions among 10 trials, but CS achieves optimal solutions with approximately 4 times faster than GA. For the best solution, mobile robot follows the following route: 0 → 4 → 8 → 10 → 7 → 6 → 2 → 1 → 9 → 3 → 5 → 0. In the best solution, the total energy consumption and the corresponding distance travelled by the robot is calculated as 710965.0528 joules and 770.9143 meters, respectively. Besides, the total load carried by the robot was found to be 186 kg when the route was completed. In order to minimize the energy consumption among the route, the node with the heaviest load is visited in the last place and carried on a shorter interval. Therefore, it can be concluded that the energy consumption of the robot depends on not only the distance travelled but also the amount of load carried. Note that in all simulations, the mobile robot starts from SP (node 0), visits all nodes and again return to SP.

D. *Reliability Analysis of The Optimal Routes*

After the route selection, the reliability analysis of the mobile robot among the optimal routes was performed. In the reliability analysis, it is accepted that the hazard rate only depends on the distance travelled and the amount of load carried, thus the other factors were neglected. The change of both reliability and hazard rate values of the mobile robot among the optimal routes obtained with CS in Case 1 are given in Figure 1.

When the Figure 1 is analyzed, it can be observed that, the reliability values decreases from 1.00 to 0.999999597417178. It can be also seen that, when the mobile robot returns to SP after completing the route, it has higher reliability values in case of the lowest energy consumption objective is

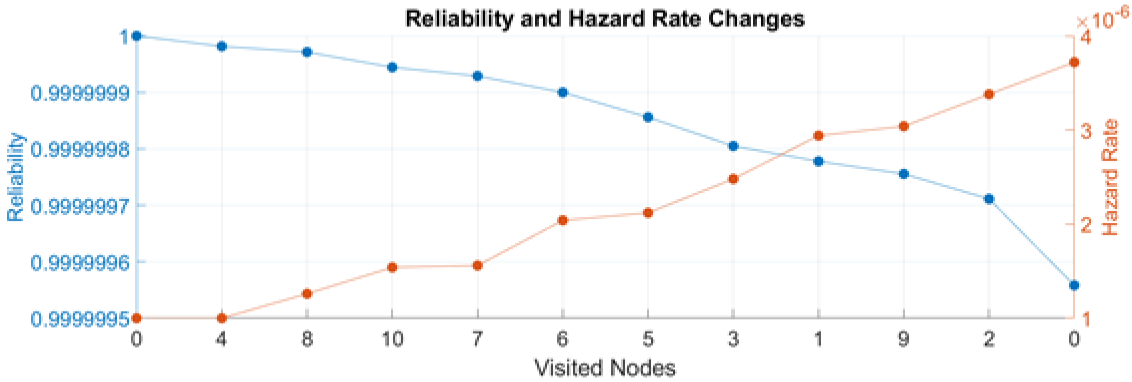

Fig. 1.*Changing the hazard rate and reliability values of the route by considering the lowest energy consumption.*

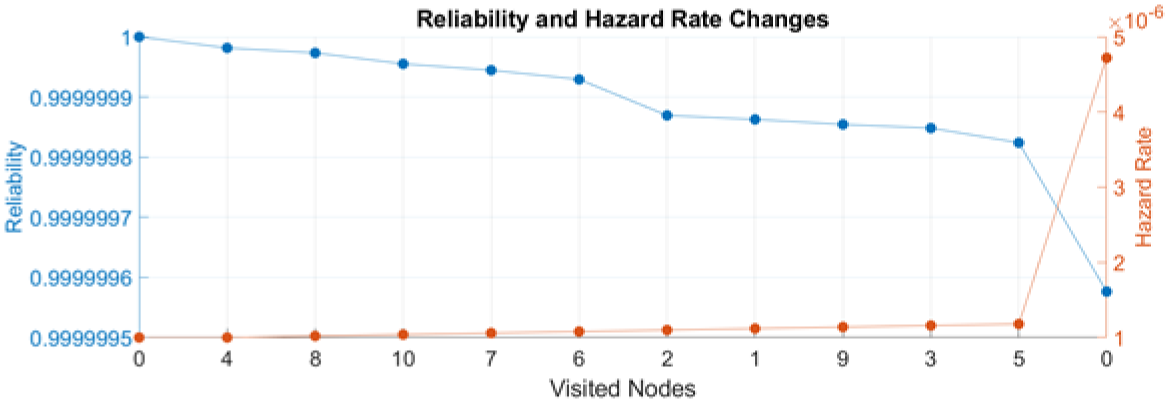

Fig. 2.*Changing the hazard rate and reliability values of the route followed by the lowest energy consumption*

considered. The reason for this situation is that the distance travelled and the amount of load carried are effective not only in the energy calculation but also the reliability. In order to better show the change of both reliability and hazard rate values of the mobile robot, the same reliability analysis performed for the optimal routes obtained with CS for Case 2. The result of the reliability analysis of the best route obtained in Case 2 is given in Figure 2.

As it can be observed from Figure 2, the reliability value decreased from 1.00 to 0.999999576411227. It is also obvious that the hazard rate suddenly increases, and accordingly, the reliability drops suddenly when the amount of the load carried by the mobile robot increased. When Figures 1 and 2 are examined together, even if the robot carries the same amount of total load, it does not have same reliability and hazard rate values since it travels on different routes.

VI. Conclusion And Future Works

The developments in the industry in recent years have brought up the idea of establishing smart factories. This situation led to the emergence of robotic systems that provide autonomous control instead of the previous systems where the robots were controlled by an operator and followed the pre-defined routes. The capability of the robots to perform the repetitive long-term tasks and to sustain the autonomy are essential for the industrial applications. In order to complete these tasks in an efficient way, the routes assigned to robots should be planned by considering the factors such as time, cost, energy, etc.

In this study, first a route planning for mobile robots were performed by solving a routing problem with both GA and CS methods for the lowest energy consumption objective. Then reliability analysis of the mobile robot among the optimal routes are performed. The results show that CS algorithm outperforms GA in terms of computational time and the average solution quality. Besides all constraints of the considered problem are satisfied in the solution points, thus the effectiveness of the proposed chromosome structure has been proven. It can be also concluded that the amount of load carried by the mobile robot considerably effects on the energy consumption and the hazard rate of the robot. Therefore, any increase on the load results an increase on the energy consumption and the hazard rate and a decrease on the reliability values.

In the future studies, route planning for repetitive tasks of multi-robot systems can be carried out in order to maximize the robots' reliability.

VII. Conflict Of Interest

No conflict of interest was declared by the authors.

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