International Journal of Technology and Engineering Studies
volume 4 issue 3 pp. 95-101 doi: https://dx.doi.org/10.20469/ijtes.4.10003-3

Ant Colony Optimization Solutions for Path Planning of Logistic Vehicle

Luo Jun-Qi *
Department of School of Electric and Information Engineering,
Qinzhou University, Guangxi, China

Wei Chien
Department of School of Electric and Information Engineering,
Qinzhou University, Guangxi, China

Xu Jia-Xin
Qinzhou University, Guangxi, China

Liang Xi-Qiu
Qinzhou University, Guangxi, China

Abstract: In recent years, online shopping has greatly promoted the development of the logistics industry. Logistics path planning has become a hot research topic among many researchers. Although path planning has been discussed by several previous studies, some real logistics conditions are not considered like obstacle and road slope. This paper presents a novel proposal to solve the problem of path planning for logistic vehicle based on Ant Colony Optimization (ACO) algorithm in the environment in which exists the obstacle. There are two kinds of environment in the path planner application, one is a single obstacle placed between the starting point and the terminal point in a known map which is recognized, then uses the ACO to find an optimal path with the capability to avoid impact with the obstacle for a logistics vehicle. The other works in the model with multi-obstacle and the same map as before to explore whether the best path solution can be found successfully by the ACO algorithm. Through experimental evaluations, the AOC can be verified to solve the path planning problem in the static, the grid and muti-obstacles environment model. Additionally, different from the common path planning algorithm, the size of the logistics vehicle is considered, the situation of touching the fringes of obstacles could be avoided, which is able to apply the logistic vehicle in the real environment.

Keywords: *Ant colony optimization, optimal path planning, logistic vehicle, obstacle avoidance*

Received: 23 April 2018; ***Accepted:*** 08 May 2018; ***Published:*** 25 June 2018

I. INTRODUCTION

In the informative society, automatic devices have replaced manual working. In order to meet the needs of all aspects, a variety of robots with different functions appears which is not only applied in manufacturing, family entertainment, military use, dangerous situations, unknown environment detection and medical care, but also in some difficult things that human can not reach, such as the UAV, automatic vehicles, automatic warehousing systems, patrol robots and so on. The invention of robots could help human avoid dangerous situation while working, which makes them become a high technology improving life equality in the future [1, 2, 3, 4]. There are quite a few papers mentioned in different ways to find the best path planning algorithm. For example, [5] proposed A* search algorithm(A-star) in 1985, he believed that A * search algorithm means the two evaluation functions h (n) and g (n) work together aiming to minimize the cost of all paths. Hence, A* search algorithm possesses the function of optimization path, but the low speed on searching. Dijkstra, which is the classical algorithm proposed by Edsger W. Dijkstra in 1959. The algorithm is used to obtain the shortest path from the starting point to all the other points. It adopts the greedy-choice strategy to seek the point which is the closest to the current point. However, it cannot be used to handle the negative edges. The high resources-consuming is also its another disadvantage [6]. [7] mentioned the genetic algorithm

*Correspondence concerning this article should be addressed to Luo Jun-Qi, Department of School of Electric and Information Engineering, Qinzhou University, Guangxi, China. E-mail: l.junqi@hotmail.com

in 1995, it is a parallel search which can get a global optimal solution. This algorithm mainly imitates natural selection that selects the better mother and exchanges genes in random, hoping to produce a better offspring. Although it could help to produce the most adaptable species by repeating performance, it has some disadvantages, like slowing computation time and convergence rate. The ant colony algorithm, proposed by [8] in 1992, has been discussed by many scholars. Actually, the ant colony optimization follows the example of the foraging behavior of real ants. Real ants can find the shortest path between the nest and the food without any obstacle because the former ants could leave pheromone and the later ones would follow the path with heavy pheromone, which could reach the goal on sharing experience on the path.

The first priority of path planning is to create a known map and establish an environmental knowledge base of the known map, and then it could update the position of the object on the known map and property on the known map from environment information provided by the sensor and the monitoring center of the logistics vehicles, which could make environmental knowledge base more palatable to dynamic information [9, 10, 11]. The path planning is an important research content in logistics car motion, that is, it could work out the best path from starting point to the ending point according to the algorithm in the environment with obstacles so that logistics vehicles could easily avoid all the obstacles on the path [12, 13].

This thesis focuses on studying an algorithm of the optimal path for logistics vehicle in the indoor navigation. It will find out the shortest path by ant colony algorithm with the construction of logistics vehicles positioning and navigation system and map, which could make this vehicle find the accurate and optimal path from starting point to the ending point without touching any obstacles. We herein investigated the feasibility of applying the grid environment model to solve the path planning problem. Also, the algorithm can be used by the logistics vehicle.

II. LITERATURE REVIEW

Path planning is the primary part for the navigation and motion control of logistics vehicles, which is a branch of NP-hard problems. The quality of the solutions will strongly impact the efficiency of logistics vehicles. Upon most occasions, the exact algorithm such as exhaustive search becomes inefficient when the scale of the NP-hard problem grows up [14]. Notably, the time for finding the optimal solution grows exponentially with the instance size n. Fortunately, Extensive work has been done in the area of metaheuristic, which is the combination of random algorithm and local search algorithm. Previous studies have indicated that the NP-hard problem can be solved by metaheuristic with high-quality solutions. Simulated Annealing (SA), which is a local search method, enlightened by the process of the physical annealing of solids. SA has been proved that the optimal solution can be found under some conditions but poorly global search capability [15]. Tabu Search (TS), an optimization algorithm can avoid getting stuck in a local optimal solution by the tabu list, but easy influence by initial solution selection of neighbor solution [16, 17]. Another algorithm with attracting great attention is the Genetic Algorithm (GA), an optimal algorithm inspired by the theory of natural selection. By comparing other optimal algorithms, GA has the ability to generate good-quality solutions in a short time through genetic operators such as mutation, crossover, and selection. Yet, it is liable to appear premature convergence and stagnation behavior [18]. ACO, the algorithm we applied in this paper, is able to use the foraging behavior of artificial ants to find the optimal solution. Benefit from the characteristic positive feedback and distributed computation, ACO can obtain the optimal solution with high efficiency, but sensitive to the parameters setting. Moreover, ACO tends to get sub-optimal solution cause of the characteristics of ant colony [1]. In order to improve ACO, some scholars propose some creative strategies, for example, the Elitist Ant System (EAS), which provides robust extra strengthening to the arcs belonging to the best line found so far [19]. Another improvement is the rank-based ant system(ASrank), the core idea is each ant deposits an amount of pheromone that decreases with its rank. As in EAS, it is an additional strategy for reinforcing the positive feedback [20].

In past few years, the relevant literature demonstrates that algorithm fusion can be substantially improved the algorithm performance. Fidanova proposed local research mix the ACO can restrain premature and accelerate the convergence rate [21]. Alajlan and Chaari presented an efficient method to fuse GA and ACO so that it can ameliorate the global optimized search capability and reduced search time [22].

III. PROPOSED METHOD

This method applies ant colony optimization to deal with the path planning of logistics vehicle. It will obtain the environmental map information first and then make it realize gridding. Then, the obstacles and feasible paths can be distinguished by different kinds of lattice points, so the ants cannot touch the obstacles when walking. When the path is planned, all the pheromones on accessible paths can be initialized to a fixed value and will also change over time.

The computational flow chart of Ant colony algorithm is shown in Figure 1.

Step 1: Environment map definition. We need to know the size of the map, the position of the starting and ending points and position of each obstacle.

Step 2: All ants start moving from the starting point, and the algorithm would work out the next points that are accessible.

Step 3: According to formula (1)(2), the algorithm calculates the probability of each selected accessible point $P_{ij}^{k}(t)$.

$$= \{ \frac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum_{s\varepsilon allowed_k} \tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)} \quad j \ \varepsilon \ allowed_k \tag{1}$$

$$\eta_{ij} = 1/\frac{0}{\sqrt{(x_j - x_E)^2 + (y_j - y_E)^2}} \tag{2}$$

Where $P_{ij}^{k}(t)$ is the probability that k-th ant k chooses to move from city i to city j; allowed$_k$ is the set of cities that ants have not visited yet; α and β influence the importance of heuristic coefficient; $\tau_{ij}(t)$ represents the residual pheromone concentration on the path connecting city i and city j at time t, $\eta_{ij}(t)$ represents the heuristic information is the end of the path planningexpressed as $1/d(j,E)$where E is the end of the path planning, and $d(j,E)$ means the distance between j and E_0.

Step 4: The ant moves to the next point and the point that has passed is removed from the list of all available points to prevent the ant from forming a loop on the path.

Step 5: Determine whether the ants reach the end and repeat steps 3 and 4 until all ants arrive at the end.

Step 6: Record the walking path and length of each ant and update the pheromone field. Paths through formula (3) to evaporate and increase pheromone. The pheromones of all paths are reduced, and some paths add some pheromones to the places where the ants traveled. (3) (4) where p is the pheromone volatilization coefficient and $\rho\varepsilon[0,1)$, $\Delta\tau_{ij}(t)$ is the pheromone increment which remains in the path (i,j), Q is the concentration of pheromoneLk is the path length of the k-th ant in this cycle.

$$\tau_{ij} = (1-\rho)\tau_{ij} + \Delta\tau_{ij}^{k} \tag{3}$$

$$\Delta\tau_{ij}^{k}(t) = \frac{Q}{L_k} \tag{4}$$

Step 7: Repeat Step 2 to Step 6 until the number of iterations satisfies the end condition and the error of result from the first 50 generations must be equal to zero.

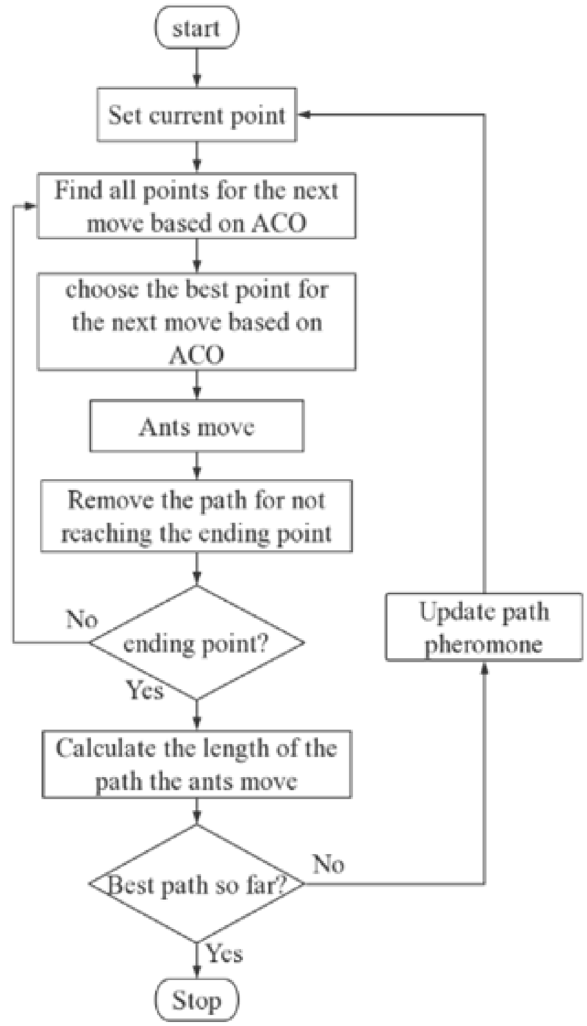

Fig. 1. Computational flow chart of ACO

The optimal path rule definition. In a known indoor environment which contains several obstacles. The logistics vehicle moves from the starting point to the ending point, and the process of movement cannot collide with any obstacle. In order to make logistics vehicle complete the task successfully, the article defines three conditions rules on the best path.

1. Environmental information is known, including the size of the map, the position, shape of obstacles, and the positions of starting and ending.

2. There are a variety of routes between the starting and the ending points, and the logistics car must complete the mission without obstacles.

3. The running result must be the shortest path between the starting point and the ending point within a short time.

Build environment map. This thesis mainly aims at the best path planning in the known environment. In order to write the adaptive function program in the algorithm and find out the best path smoothly, to find out the best path and obtain the necessary environmental information is the first priority. According to the simulation requirements, this paper first builds a 20mx20m environment map, adding two 4mx8m obstacles, starting at (0.5, 19.5) blue dots and ending at (19.5, 0.5) red dots, the known environmental map information as shown in Figure 2.

After the environmental map and obstacle information are set up, it is necessary to consider that the size of the logistics car itself may cause a collision with obstacles during exercise. It is necessary to exclude the situation that the planned route will pass through the edge of obstacles.

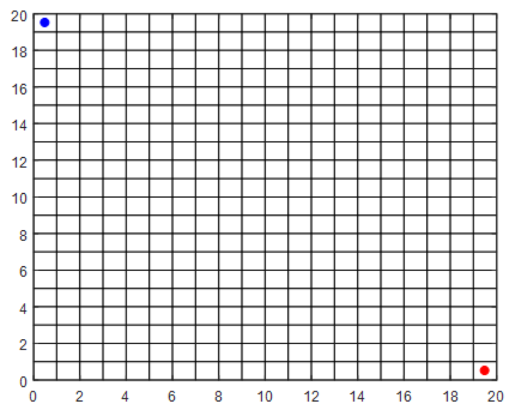

Fig. 2. The 20m×20m grid network

Adaptability function. It can use the coordinate of path connected by the starting point and the ending point to identify whether it is a valid path, and the coordinate point is the shortest path. Three rules are defined according to the problem of path planning.

Rule 1: The coordinate point of path is not allowed to fall on the obstacle.

Rule 2: The coordinate point of path is not allowed to fall on the repeated coordinate point.

Rule 3: the line which is connected by any two adjacent coordinates is not allowed to touch the obstacles.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In the simulation, a simple environment is established, which contains two obstacles in the center of the grid network, the parameters are initialized, which $\alpha = 1$, $\beta = 7.5$, $\rho = 0.3$, $Q = 1$. The simulation result of the optimal path is shown in Figure 3. The result of Convergence tendency is shown in Figure 4, which shows the convergence curve converges on the 33rd generation, and the final convergent path length is 30.38m.

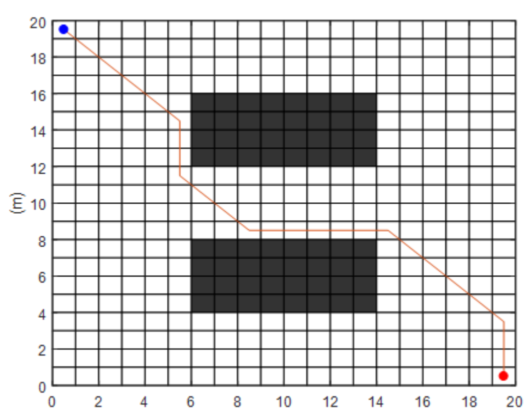

Fig. 3. The optimal path found by ACO in simple environment

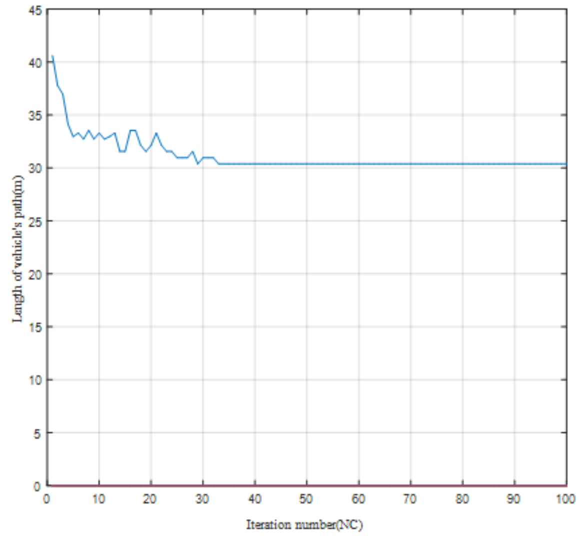

Fig. 4. Convergence tendency of the ACO algorithm with two obstacles

Figure 5 demonstrates another simulation with multi-obstacle environment, the parameters are set to $\alpha = 1$, $\beta = 7$, $\rho = 0.3$ and Q = 1. The simulation results are shown in Figure 5 and Figure 6, the convergence curve converges on the 37th generation, and the final convergent path length is 32.73m.

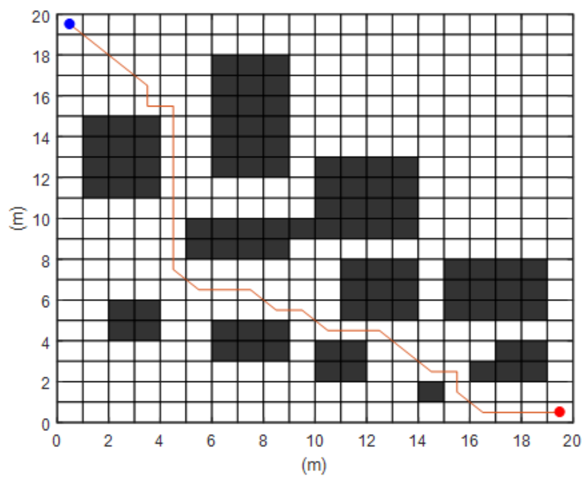

Fig. 5. The optimal path found by ACO in complex environment

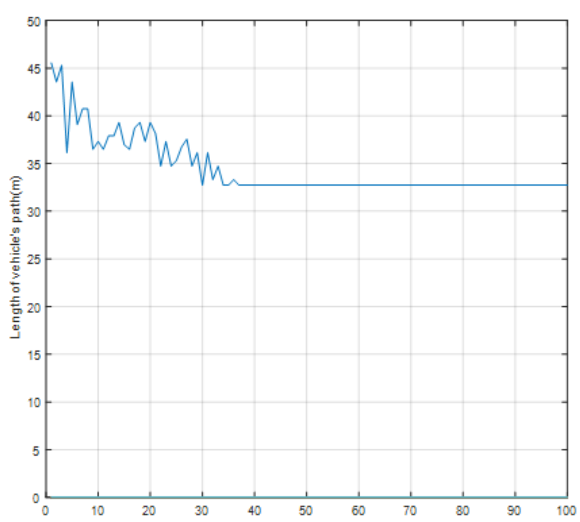

Fig. 6. Convergence tendency of the ACO algorithm in complex environment

According to the previous report, we chose the parameters as $\alpha = 1$, $\beta = 7$, $\rho = 0.3$ and $Q = 1$. After initialization the parameters, the ants will be randomly selected the next visiting point because the concentrations of all the accessible points are equivalent. It is noteworthy that ants tend to choose the points which are closer to the ending. This bias depends on the value of β: the high value had the higher tendency. The algorithm possesses both excellent exploration capability and convergence rate when the value of β is set as 7 or 7.5. Figure 3 and Figure 5 showed that the line of path length decline with oscillation before convergence. This is because as the number of iterations increases, shorter paths leave more pheromones than longer ones, and the ants tend to choose shorter ones. Respectively, after 33 and 37 iterations, the gap of pheromones will become extremely big. In contrast to the shorter path, the pheromone level of the longer paths remains only very rarely, or never, receive more pheromone. In this case, the probability that the ants choose the shorter one unlimited approach 100%. As expected, the result has been converged, and a horizontal line has been observed in Figure 4 and Figure 6.

Figure 3 and Figure 5 also ascertain that the algorithm can find the optimal solution in both the simple static environment and the complex static environment.

V. CONCLUSION

The results of the computer simulation experiment indicate that the ant colony algorithm can implement optimal path planning in the grid and complex environment model. Taking into account that the logistics vehicle itself could obstruct the obstacles, therefore, it should avoid the situation of planning the path from the edge of obstacles. Our findings provide evidence that the algorithm plays a key role in the practical application of logistics vehicle. As with the common ACO, we also found that the parameters choosing can greatly influence the quality of solutions. Besides, the method that we discussed in this paper is not fully verified yet for the real-time obstacles environment. So in the paper, we limit our discussion to the method of optimal path planning is based on known environments and static obstacles. In the future, further research is needed to verify the dynamic obstacles in the grid environment model can be solved by the ACO.

ACKNOWLEDGMENT

This research is supported by the director of project (2017KY0803) and the project (IOT2018C01), The Key Laboratory for Advanced Technology To Internet of Things ,Qinzhou ,535011,China.

REFERENCES

[1] K. M. Yu, M. G. Lee, and S. S. Chi, "Dynamic path planning based on adaptable ant colony optimization algorithm," in *Sixth International Conference on Future Generation Communication Technologies,* Dublin, Ireland, 2017.

[2] F. Dragomir, O. E. Dragomir, M. E. Ivan, S. S. Iliescu and I. Stanescu, "Optimal embedded system for two-axis tracking pv panels," *Journal of Applied and Physical Sciences*, vol. 3, no. 1, pp. 1–16, 2017. doi: 10.20474/japs-3.1.1

[3] K. Punaiyah and H. Singh, "Biped robot for walking and turning motion using raspberry pi and arduino," *International Journal of Technology and Engineering Studies*, vol. 3, no. 2, pp. 49–58, 2017. doi: 10.20469/ijtes.3.40002-2

[4] O. T. F. Gongor and S. Colak, "Development and implementation of a sit-to-stand motion algorithm for humanoid robots," *Journal of Advances in Technology and Engineering Research*, vol. 6, no. 6, pp. 245–256, 2017. doi: 10.20474/jater-3.6.4

[5] R. Dechter and J. Pearl, "Generalized best-first search strategies and the optimality," *Journal of the ACM*, vol. 32, no. 3, pp. 505–536, 1985. doi: 10.1145/3828.3830

[6] J. Jiang, H. W. Huang, J. H. Liao, and S. Y. Chen, "Extending dijkstra's shortest path algorithm for software defined networking," in *16th Asia-Pacific Network Operations and Management Symposium, Chiao Tung, Tiwan*, 2014.

[7] I. Ashiru and C. Czarnecki, "Optimal motion planning for mobile robots using genetic algorithms," in *International Conference on Industrial Automation and Control,* Hyderabad, India, 1995.

[8] M. Dorigo, "Optimization, learning and natural algorithms," Phd thesis, Politecnico di Milan, Milan, Italy, 1992.

[9] J. Liu, J. Yang, H. Liu, X. Tian, and M. Gao, "An improved ant colony algorithm for robot path planning," *Soft Computing*, vol. 21, no. 19, pp. 5829–5839, 2017. doi: 10.3724/sp.j.1087.2008.02877

[10] J. Zhao, D. Cheng, and C. Hao, "An improved ant colony algorithm for solving the path planning problem of the omnidirectional mobile vehicle," *Mathematical Problems in Engineering*, vol. 3, no. 13, pp. 1–10, 2016. doi: 10.1155/2016/7672839

[11] P. Wongsai and W. Pawgasame, "Analysis of a crime scene getaway vehicles escaping path," *International Journal of Technology and Engineer-*

ing Studies, vol. 2, no. 5, pp. 134–139, 2016. doi: 10.20469/ijtes.2.40002-5

[12] P. Yang, Y. Yang, H. Chen, X. Quo, and Z. Wang, "A study of path planning algorithm of mobile robot," in *Fifth World Congress on Intelligent Control and Automation,* Hangzhou, China, 2004.

[13] C. Alexopoulos and P. M. Griffin, "Path planning for a mobile robot," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 22, no. 2, pp. 318–322, 1992.

[14] G. Panchal and D. Panchal, "Solving np hard problems using genetic algorithm," *Transportation*, vol. 106, pp. 6–2, 2015.

[15] S. McCammon and G. A. Hollinger, "Planning non-entangling paths for tethered underwater robots using simulated annealing," *Robot Learning and Planning*, vol. 1, no. 5, pp. 45–56, 2016. doi: 10.1109/icra.2017.7989349

[16] S. Belhaiza, P. Hansen, and G. Laporte, "A hybrid variable neighborhood tabu search heuristic for the vehicle routing problem with multiple time windows," *Computers & Operations Research*, vol. 52, pp. 269–281, 2014. doi: 10.1109/cec.2017.7969457

[17] L. T. D. Ha and K. M. T. Tsai, "Numerical study on optimization of wooden-steel hybrid beams base on shape factor of steel component," *International Journal of Technology and Engineering Studies*, vol. 1, no. 2, pp. 53–62, 2015. doi: 10.20469/ijtes.40004-2

[18] B. Patle, D. Parhi, A. Jagadeesh, and S. K. Kashyap, "Matrix-binary codes based genetic algorithm for path planning of mobile robot," *Computers & Electrical Engineering*, vol. 67, pp. 708–728, 2018. doi: 10.1016/j.compeleceng.2017.12.011

[19] M. Yousefikhoshbakht, F. Didehvar, and F. Rahmati, "An efficient solution for the vrp by using a hybrid elite ant system," *International Journal of Computers Communications & Control*, vol. 9, no. 3, pp. 340–347, 2014. doi: 10.15837/ijccc.2014.3.161

[20] M. Yousefikhoshbakht, F. Didehvar, F. Rahmati, "An effective rank based ant system algorithm for solving the balanced vehicle routing problem," *International Journal of Industrial Engineering*, vol. 22, no. 3, pp. 330–340, 2016.

[21] S. Fidanova and P. Pop, "An improved hybrid ant-local search algorithm for the partition graph coloring problem," *Journal of Computational and Applied Mathematics*, vol. 293, no. 5, pp. 55–61, 2016. doi: 10.1016/j.cam.2015.04.030

[22] M. Alajlan, I. Chaari, A. Koubaa, H. Bennaceur, A. Ammar, and H. Youssef, "Global robot path planning using ga for large grid maps: Modelling, performance and experimentation," *International Journal of Robotics and Automation*, vol. 31, no. 6, pp. 1–12, 2016. doi: 10.2316/journal.206.2016.6.206-4602