Optimal A* Path Planning with Ant Colony Optimization on Multi-Robot Task Allocation for Manufacturing Model

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***Abstract*—This paper presents the optimal path planning by using A* with ant colony optimization based on the multi-robot systems. The purpose of this research is to design an appropriate path planning model for manufacturing. The safety path and the processing time are the priority of the manufacturing. The main contribution of this study is the A* for path planning with the ant colony optimization for the lowest risk of collision (RC) searching. The 5 robots condition is the best condition for the minimum RC and the minimum processing time. The simulation results represent the suitable path planning prediction model for manufacturing systems.**

Keywords-optimal path planning; A*; ant colony; multi-robot task allocation; manufacturing

I. INTRODUCTION

Path planning in the multi-robot system is very complicated. The complexity of an algorithm is needed. The multi-robot system is a dynamic environment which it is quite hard to control. Seagate Technology (Thailand) Ltd. is the one of the multi-robot in the manufacturing systems. This research starts on the model development based on the layout of Seagate Technology (Thailand) Ltd and starts on the survey of scholarly knowledge on robotics path planning, and multi-robot systems. Many researchers have proposed the algorithm for robotics path planning. In [1], Yan L. and Lingyun W. presents an improved A* algorithm for the optimal routes of the multimodal transportation networks and the results show the good performance based on the real GPS data. Tao Z. et al.[2] improved A* algorithm by adding the angle cost function and their results show faster path searching with the good optimal path. In [3], they select A* for valet parking. They can improve the runtime up to 40%. In restaurant service, the A* algorithm has been selected to find the best optimal restaurant service robot path. This algorithm shows the high efficiency in dynamic environments of restaurant [4]. For robotics model, Tongtong J et al. studied the model optimization for the storage chosen point of robot. Their results represent the better performance [5]. Ilya M. et al. in [6] designed the model of crawler robot and verified in worst condition. In [7], they designed the route planning for smart cars with the real- time condition. The best path finding algorithm from their experiment is A* because of the best suitable path length on appropriate operation time.

For optimal path finding, [8] is the optimal path finding by using the modified of ant colony optimization (MGACO) and the results show shorter path than ACO. Zhao H., Lei C., and Jiang N. proposed the dynamic recursive ant colony algorithm for the shortest path searching [9]. Zhang Y. et al. developed the ant colony algorithm for multiple industrial mobile robots with dynamic environments [10]. Their model can represent the good performance for industrial application. In [11], the researcher studied the comparison of Dijkstra and Dijkstra with ant colony optimization. The Dijkstra with ACO has better performance. Shao X. et al. improved the ant colony algorithm by using the adaptive adjustment heuristic function and the results illustrate the faster path search [12]. Ran Xu, Ge Fen, and Zhang Qi selected the ant colony algorithm for path planning and they observed an improvement on the total path length [13]. Hong Z. designed the optimal path planning by using ant colony algorithm in [14] and the results show that the shortest distance and shortest time. In [15], the ant colony optimization has been selected for robot path planning. They verified the results for both simulation and experiment. The results show the effectiveness and feasibility of their algorithm.

To sum up, the A* algorithm and ant colony optimization algorithm are widely used in variant robotics path planning applications. Many researchers modified these algorithms for the shortest path searching only. The new contribution of this research is to find the safety path searching in the multi-robot systems for manufacturing. The purposed method of this research is to calculate the appropriate starting point and ending point by using A*. Then, the ant colony optimization starts on the safety path searching in multi-robot systems. The new RC function of this research is the risk of collision function for the objective function in the ant colony optimization process. The best value from the ant colony searching represents the best safety path or the low risk of collision. The conflict checking loop is to avoid the robot crashing when the RC is high. The simulation results show the best safety path searching with suitable processing time in multi-robot systems of manufacturing model.

II. CONSTRAINT IN MANUFACTURING

In manufacturing, this paper designs the model based on the Seagate Technology (Thailand) Ltd environment. The 1st priority for manufacturing is safety path. 0% collision rate is

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the main goal in manufacturing systems. The processing time is the 2nd priority for the fastest processing time.

Fig. 1 illustrates the manufacturing environment of Seagate Technology (Thailand) Ltd. The 3 rectangle boxes on top layout are the loading station, and unloading station. Other boxes are the operation test station. The environment in manufacturing is the multi-robot systems. All robots can move together with the different tasks.

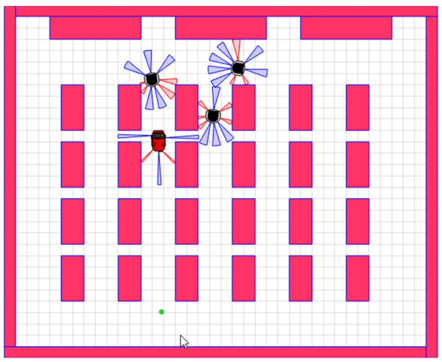

Figure 1. Manufacturing environment

III. A* PATH PLANNING

A* path planning is the searching algorithm for the shortest path of the starting point and the goal point. Equation (1) is the total distance calculation in A* algorithm. g(n) is the distance from the starting point to the current point. h(n) is the heuristic value. It is the estimated distance from the current point to the goal point.

$$f(n) = g(n) + h(n) \tag{1}$$

The A* algorithm starts on the g(n) calculation and h(n) estimation. Then, the best path for A* selection is the minimum of total distance. For the heuristic value h (n), there are 3 heuristic calculations for estimated distance.

1) Manhattan distance

Manhattan distance in (2) is the sum of absolute values between the differences of the current point (x_c,y_c) and the goal point (x_g,y_g).

$$h(n) = |x_c - x_g| + |y_c - y_g| \tag{2}$$

2) Diagonal distance

Diagonal distance in (3) is the maximum of sum of absolute values between the differences of the current point (x_c,y_c) and the goal point (x_g,y_g).

$$h(n) = \max(|x_c - x_g| + |y_c - y_g|) \tag{3}$$

3) Euclidean distance

Euclidean distance in (4) is distance values between the current point (x_c,y_c) and the goal point (x_g,y_g).

$$h(n) = \mathrm{sqrt}((x_c - x_g)^2 + (y_c - y_g)^2) \tag{4}$$

IV. ANT COLONY OPTIMIZATION (ACO)

Ant colony optimization is the popular probabilistic technique for finding the optimal paths. This optimization algorithm was introduced by Macro Dorigo in 1992. It is introduced the behavior of an ant for seeking the source food from their colony. Ants are the social insects that live in the colonies. Ant's behavior is depending on the food around their colonies. The best walking path for ant is the high quantity of the food or high quality of the food. During moving, the ants will drop the high pheromone along the walking path when the ants found the best walking path. Other ants can smell the pheromone and follow the high pheromone path. Then, the pheromone on the path will increase from more ants. $\tau^k_{i,j}$ is the pheromone at the edge i,j of k^{th} ant. It will be equal to the sum of pheromone deposited the edge i,j of k^{th} ant ($\sum\Delta\tau^k_{i,j}$) during without vaporization condition. With vaporization condition, the high rate of pheromone evaporation (ρ) impacts the lower pheromone value ($\tau^k_{i,j}$) in (5). ρ is in range 0 to 1 ($0 < \rho < 1$). From the literature review, many researcher use $\rho = 0.5$ to represent 50% rate of pheromone evaporation in the model.

$$\tau^k_{i,j} = (1-\rho)\,\tau_{i,j} + \sum\Delta\tau^k_{i,j} \tag{5}$$

$\Delta\tau^k_{i,j}$ is the pheromone deposited at the edge i,j of k^{th} ant. The pheromone deposited condition is shown in table I. L_k is the total distance of k^{th} ant from the starting point to the colonies by Euclidean distance calculation. If k^{th} ant can move along the edge i,j and distance (L_k) is the lowest value, the pheromone deposited at the edge i,j ($\Delta\tau^k_{i,j}$) will be the highest value.

TABLE I. PHEROMONE DEPOSITED CONDITION

No.	Condition	$\Delta\tau^k_{i,j}$
1	k^{th} ant travels along the edge i,j	$\Delta\tau^k_{i,j} = 1/L_k$
2	Otherwise	$\Delta\tau^k_{i,j} = 0$

The last step is to calculate probabilities for each k^{th} ant path. The probabilities calculation is in (6) where $\tau_{i,j}$ is pheromone of the path, α is the pheromone coefficient, $\eta_{i,j}$ is heuristic information ($\eta_{i,j} = 1/L_{i,j}$), and β is the heuristic information parameter.

$$P_{i,j} = ((\tau_{i,j})^\alpha (\eta_{i,j})^\beta) / \sum ((\tau_{i,j})^\alpha (\eta_{i,j})^\beta) \tag{6}$$

The highest probability is the best path selection. If $\alpha = 0$, only heuristic information is utilized. If $\beta = 0$, only pheromone value is utilized.

V. PURPOSED METHOD

The purposed method of this research is to design the appropriate path planning model for manufacturing. Firstly, this research designs the model from manufacturing

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requirements. The model is the multi-robot systems with the loading station, the unloading station and the operation test station. The robot tasks in manufacturing are the multi-tasks. One robot has many tasks assignment. All robots in the map can move together with the different tasks. The obstacle avoidance and the processing time are very important for manufacturing. This research designs the robotics path planning model for manufacturing by using the A* for path planning and the ant colony optimization for the best safety path searching. This research selects the Manhattan distance for heuristic calculation in A* path planning. It works well in many applications from literature review.

The new contribution of this research is the new design of the risk of collision equation. Many researcher use the distance function for L_k in ant colony optimization. This paper presents the RC function for L_k in ACO. RC is the risk of collision function. The high RC means the high risk of a collision. $RC_{i,j}$ in (7) is the risk of collision equation. δ is the risk of collision factor (0 < δ < 1). $D_{i,j}$ is the distance from robot to other robot at the edge i,j. $\sum D_{i,j}$ is sum of $D_{i,j}$ in all probability choice.

$$RC_{i,j} = \max(1-\delta(D_{i,j})/ \sum D_{i,j} \ , 0) \qquad (7)$$

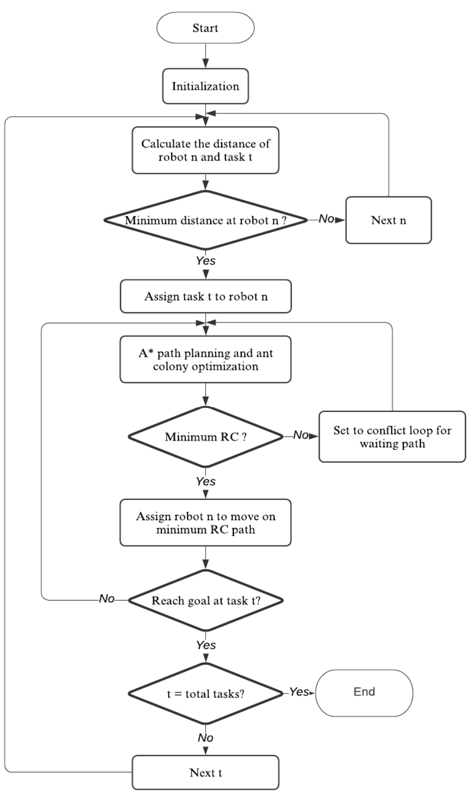

Figure 2. Purposed method flowchart.

Fig 2. is the purposed method flowchart of this research. Firstly, the total robots and total tasks are defined in the initialization phase. Then, this model starts on the robot assignment tasks process and A* path planning. During ant colony searching, the robot path with the minimum RC value will be selected for the next path. If the RC value is high, the robot state will be changed to the conflict loop. The process is completed when all tasks can be done by the robot.

Table II shows the risk of collision condition. RC value is close to 1 when the condition is the high risk of collision. The low risk of collision is when RC is close to 0.

TABLE II. RISK OF COLLISION CONDITION

No.	Condition	$(D_{i,j})/ \sum D_{i,j}$	$RC_{i,j}$
1	High risk of collision	$(D_{i,j})/ \sum D_{i,j} \rightarrow 0$	$RC_{i,j} \rightarrow 1$
2	Low risk of collision	$(D_{i,j})/ \sum D_{i,j} \rightarrow 1$	$RC_{i,j} \rightarrow 0$

Table II shows the risk of collision condition. RC value is close to 1 when the condition is the high risk of collision. The low risk of collision is when RC is close to 0.

VI. RESULTS

The result of this research represents the safety path in dynamic environments and the processing time for each condition. This research starts the simulation test on 2, 3, 4, 5, and 6 robots in the model. A total task input in this model is 30 tasks. The risk of collision factor is 0.8. Fig 3. illustrates the risk of collision (RC) value between the model without RC searching and the model with RC searching. The ant colony optimization can search the minimum RC value as fast as possible. For the without RC model, it has a risk of collision all the time.

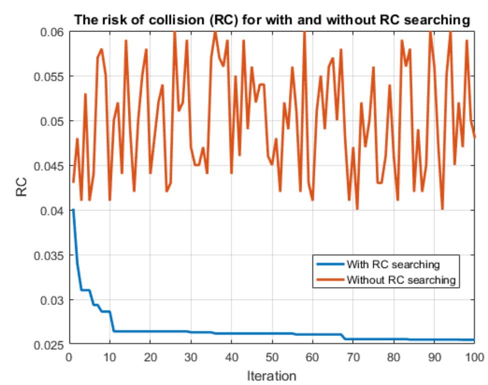

Figure 3. The risk of collision (RC): with and without RC searching

In Fig.4, the 2 robots can move without any waiting path. Each robot can perform their tasks as well. The processing time for 2 robots in this model is 174.654875 seconds. The total movement step is 1096.

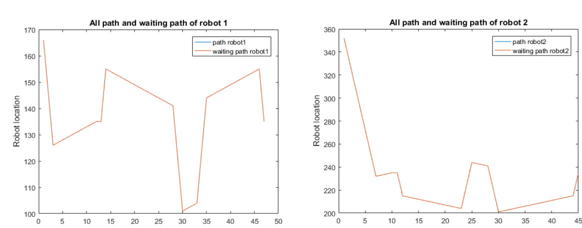

Figure 4.Path and waiting path in 2 robots condition

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In Fig.5, the 3 robots condition shows the waiting path in robot no.2. The robot no.2 found the conflict condition in the model. It will stop at that location to avoid the collision. Then, it will continue to move through the path again. The red line and the blue line of robot no.2 in Fig.5 illustrate the different path of robot planning path and waiting path. The processing time for 3 robots in this model is 118.555342 seconds. The total movement step is 1132.

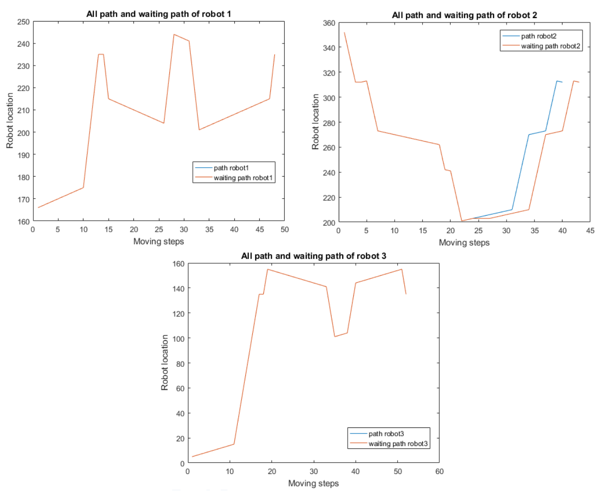

Figure 5. Path and waiting path in 3 robots condition

The 4 robots condition in Fig.6 shows the waiting path in robot no.4. The processing time for 4 robots in this model is 106.094368 seconds. The total movement step is 1227.

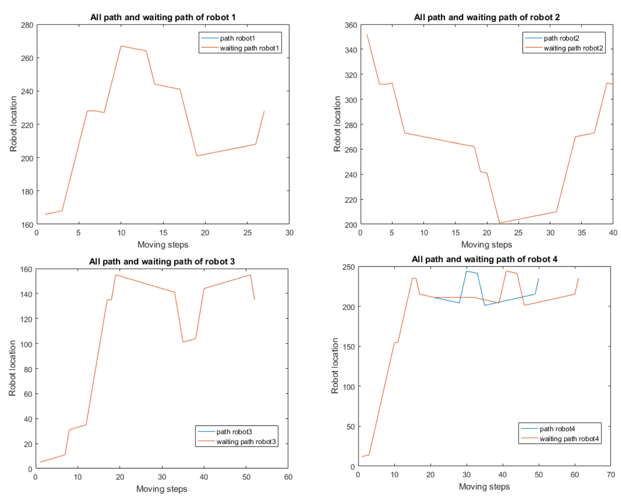

Figure 6.Path and waiting path in 4 robots condition

In Fig.7, the 5 robots condition shows the waiting path in robot no.4. The processing time for 5 robots in this model is only 99.838161 seconds. The total movement step is 1228.

For 6 robots, the robot cannot complete all tasks because all robot move into the conflict loop. Then, all robots stop to avoid the collision. Based on the manufacturing layout on this research, the maximum no. of robot on this layout is 5 robots. The minimum RC value in 5 robots condition is 0.031838 with the fastest processing time. For the model prediction in manufacturing, the model of this research shows an appropriate model prediction for manufacturing in term of the safety path searching and the suitable processing time.

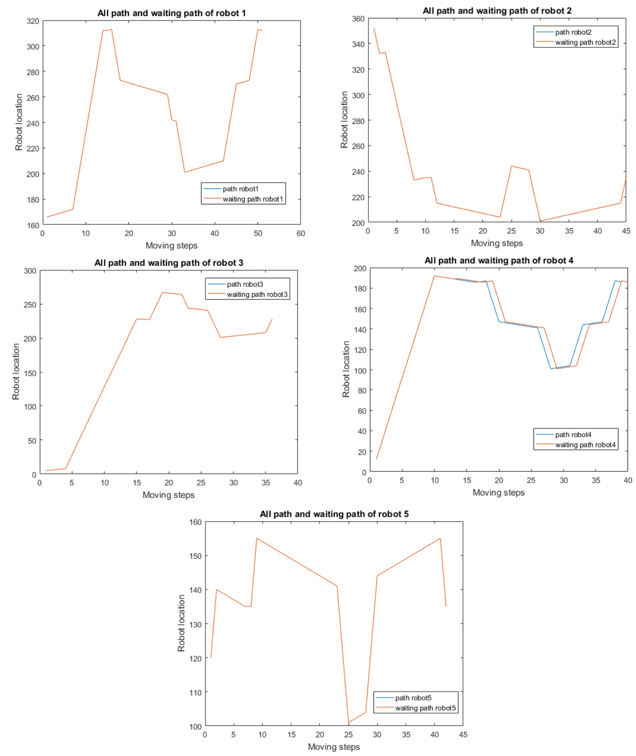

Figure 7. Path and waiting path in 5 robots condition

VII. CONCLUSION

In this paper, the A* path planning with ant colony optimization is proposed for robotics model of manufacturing. In this model, the A* for path planning is to plan the robot path but the ant colony is for safety path searching. This research designs the risk of collision function and modifies the ant colony optimization for minimum risk of collision (RC) searching. The model without RC searching shows the high RC for all the time. The high RC is not suitable for manufacturing. From the results of this research, the best RC value is 0.031838 and the best processing time is 99.838161 seconds in 5 robots condition. The simulation results of proposed method represent the good prediction model for manufacturing systems.

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