ICIC Express Letters
Part B: Applications
Volume **12**, Number **3**, March **2021**

ICIC International ©2021 ISSN 2185-2766
pp. **223–229**

OPTIMAL PATH PLANNING WITH A-STAR OPTIMIZATION AND MULTI-ROBOT TASK ALLOCATION IN HARD DISK DRIVE MANUFACTURING LAYOUT

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Received September 2020; accepted November 2020

Abstract. *Hard Disk Drive Manufacturing is the manufacturing industry in electronics components. The automation processes for process capability improvement, process control improvement, and process stability improvement are important. A robotics system in this manufacturing is Multi-Robot System. The new development for Multi-Robot System depends on manufacturing requirements. This research is focused on the Optimal Path Planning for Multi-Robot Systems with Multi-Robot Task Allocation. A-star searching has been selected for path planning and modified for manufacturing requirements. The simulation model of this research has been developed by using Matlab R2016b as program based. Error built-in has been integrated in this simulation mode for validation. The simulation results for optimal path planning with modified A-star optimization and Multi-Robot Task Allocation can help to predict the suitable completion tasks/hour for Hard Disk Drive Manufacturing.*
Keywords: Optimal path planning, Multi-Robot System, A-star, Multi-Robot Task Allocation, Hard Disk Drive Manufacturing

1. **Introduction.** This research is studied about the optimal path planning for robotics systems based on Hard Disk Drive Manufacturing layout. Seagate Technology (Thailand) is the electronic industry in Hard Disk Drive Manufacturing which is required the development of Multi-Robot Systems support to an improvement on manufacturing process. Completion task per hour is the key requirement for manufacturing process because number of robot planning, tasks planning, and area control are very important. The major contributions and significance of this research is the optimal path planning with safety constraint on Multi-Robot Systems of Hard Disk Drive Manufacturing layout. Devaurs et al. studied about RRT method for path planning by RRT and T-RRT combination. The result is shown the good results on complex problem [1]. Wan et al. developed the GPR-based (Gaussian Process Regression) prediction for optimal path planning. They can perform high accuracy from both simulation and experiments [2]. Many researchers selected A-star for path planning and this method can represent good performance on variant problem. In [3], Votion and Cao studied new navigation algorithms on Multi-Robots by using A-star and the result is shown good performance on some examples. It should be better on systems reliability. For path planning on cooperative robot, key matrix is not only the path planning. The task allocation is also important for task arrangement of each robot. Huang et al. studied on Multi-Robot Task Allocation. They focused on the robot to target distance. In addition, they have checked model and their model can represent effectiveness [4]. In manufacturing, the key matrix for path planning is not only the shortest path. The obstacle avoidance for safety path is very important in

DOI: 10.24507/icicelb.12.03.223

manufacturing. In [5], new development of path planning has been developed for shortest path and safety path for manufacturing with good performance but the results are in 1 mobile robot only. For Multi-Robot Systems (MRS), the Multi-Robot Task Allocation (MRTA) is the one of the key matrices for systems. All tasks must be completed by robot tasks arrangement. Farouq et al. developed bundle algorithm with Ant Colony on Multi-Robot Task Allocation algorithm and it shows good performance results [6]. In [7], Chen et al. developed the 3-PRS ankle for force/position control by using the combination of position control and impedance control. Their purposed method can represent the effectiveness of flexible control. Solyman et al. studied about the robot task planning for pick-and-place task. Their purposed method shows the effectiveness for robot task planning in unstructured environments [8]. Yazeed studied the locomotion mechanism on small robot. He developed the hybrid locomotion mechanism with the highly effective results [9]. In [10], Watanuki et al. developed the deep reinforcement learning in multi-robot environment for obstacle avoidance based on the image. After learning, the performance looks better. Some researcher studied about the robot on human posture. In [11], the effect of exoskeleton robot has been studied during manual lifting task. The result can represent the exoskeleton robot can help users for the correct posture. From the literature review, many researchers developed the optimal path planning for the shortest path searching only. This research has developed the new modified A-star algorithm for safety path planning as a first priority and shortest path planning as a second priority. In addition, this research has developed this concept in the Multi-Robot Systems based on the Hard Disk Drive Manufacturing layout.

In this research, the manufacturing requirement is shown in the first section. The layout and manufacturing process were built in the model. Then, the path planning algorithm has been developed by the modified A-star algorithm. After that, the condition for Multi-Robot System needs to develop and add in the model. The output of this simulation is the completion tasks per hour between conventional method and purposed method with error built-in.

2. **Layout.** In the model of this research, layout and manufacturing requirements have been integrated for optimal path planning model creation. The concept of robotic path in manufacturing is to have the loading station for incoming part load, unloading station for outgoing part, and testing station for incoming part testing and outgoing part checking with data. Robots need to perform task to support the manufacturing process in layout as plan.

In Figure 1, 4 robots are moving in parallel and 3 boxes at the top of layout are the loading station and unloading station. The testing stations are 24 boxes in which it can perform both testing and checking condition in electrical testing of hard disk drive components. The material will be loaded from loading station and transferred from loading station to testing station by using robot and planning algorithm. After that, the next process is to load the tested material from the testing station to the unloading station. The path planning algorithm must perform each robot task for waiting time reduction. Then, the capability will be increased or we can get high completion task/hour.

3. **A-Star Path Planning.** One of popular algorithms for path planning is A-star which is the method to find the shortest path. Key concept is to calculate distance from starting point to any point and distance from any point to goal. Based on the concept, program can calculate the distance from starting point to any point but the distance from any point to goal needs to be estimated. The prediction model is required. The A-star uses the heuristic function for distance estimation from any point to goal to support starting point to goal point calculation. Equation (1) is the objective function of A-star algorithm. The minimum objective function will be selected for next robot path. $g(n)$ is the distance

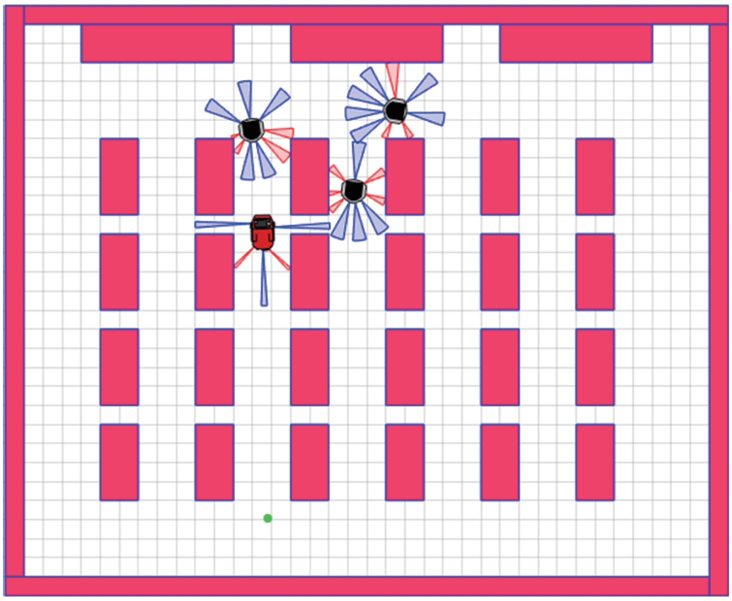

Figure 1. Hard Disk Drive Manufacturing layout and robots

from starting point to any node n. $h(n)$ is the estimated distance from any node n to goal. $f(n)$ is the sum of $g(n)$ and $h(n)$ to represent distance from starting point to goal based on the actual distance and estimated distance.

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

For estimated distance, the heuristic function $(h(n))$ is the calculation of sum of difference of x and difference of y between two locations. For path planning, two locations are the location n (x_n, y_n) and goal (x_g, y_g) where location n is any point and goal is goal point in Equation (2).

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

4. **Purposed Method for Optimal Path Planning.** This research designed new A-star function by modified A-star function with safety path constraint. The new method is ASOA in Equation (3). The purpose is to find the optimal path planning for manufacturing layout and manufacturing constraint.

$$f(n) = g(n) + h(n) + OA(n) \tag{3}$$

From Equation (3), the objective function will be combined between the path planning for shortest path function and safety path function. The minimum value is required. Sum of these functions is required minimum value selection during searching to support optimal path planning also.

Obstacle avoidance function is OA function in [11]. From Equation (4), OA is obstacle avoidance function, α is safety factor, d is distance between robot and obstacle, R is radius of obstacle region and r is radius of robot region. If the OA value is close to 1, it will be the high risk condition of crashing between robots to any obstacle. If the OA value is close to 0, it will be the low risk of crashing or safety zone for robot path.

$$OA = \max\left(1 - \alpha * \frac{d}{R + r}, 0\right) \tag{4}$$

For Multi-Robot Systems, the Multi-Robot Task Allocation or MRTA is the robot task assignment where R is set of robot and T is set of tasks.

In general problem, the single task is good enough for task allocation. The system will have robot with task in pairs as Equation (5). One robot will get one task for this case.

$$(r_1, t_1), (r_2, t_2), (r_3, t_3), \ldots, (r_k, t_k) \tag{5}$$

For complex tasks, the task allocation will be in group assignment as tasks of the bundles which are the sum of costs of individual tasks.

$$b_r(G) = \sum_{k=1}^{f} b_r(t_k) \quad \{t_k \in G\} \tag{6}$$

where G is the bundle, f is the number of tasks of bundle, b is the cost of tasks, and t is the tasks.

The robot is assigned to group assignment by the cost of individual tasks. This research selected the bundle task and designed new algorithm for optimal path planning on Multi-Robot Systems. The first step of this research is the reviewing process with the requirements of the Hard Disk Drive Manufacturing first which are the completion task/hour must be more than the conventional method with 0% robot crashing and robot can move within space constraint in specific layout from manufacturing plan. The A* has been selected for path planning because of effectiveness of A* method on many path planning research from literature review.

In Figure 2, the purposed method of this research is to start on whole task defining. Then, the model will start on distance calculation of each robot with all tasks. After that, it will select the minimum distance as 1st task for each robot and continue the A* path planning process. During the path planning process, it will have path conflict checking

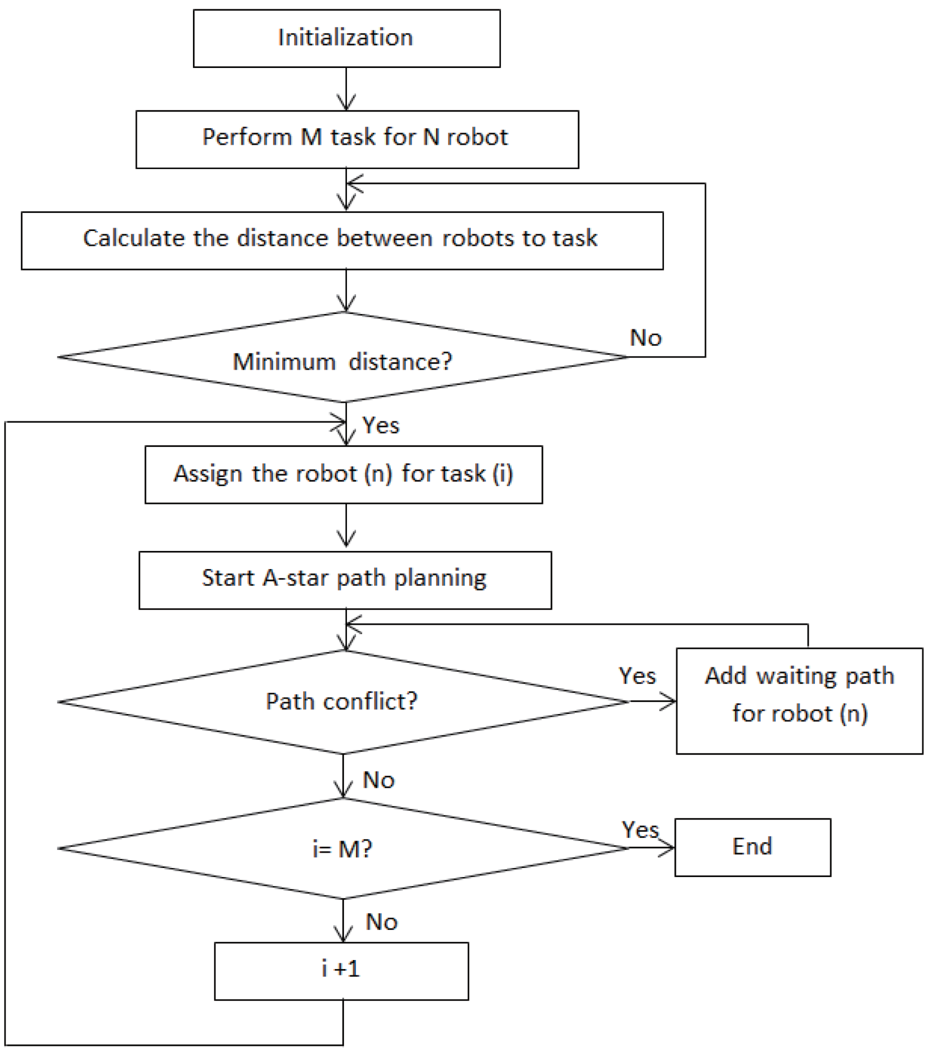

Figure 2. Purposed method of optimal path planning and Multi-Robot Task Allocation

between robots due to cooperative robot working at the same time. If the path conflict = true, the waiting path process will start on that robot until conflict = false. Finally, the process will continue as this in continuous loop until all tasks have been completed.

Conditions for conflict path checking are

- Check conflict path between 2 robot paths;
- Current point of robot$_a$ (x_i, y_i) is not equal to the next point of robot$_b$ (x_{i+1}, y_{i+1});
- For not equal condition, continue the process as normal;
- For equal condition, add waiting time on the robot$_b$ in 1 second and compare the robot point again in continuous loop.

5. **Simulation Results.** The simulation results show that the maximum robot for this model is 5 robots during maximum 30 tasks. If the robot number is more than 6, the simulation program will wait without stopping. The reason is the waiting path process on purposed method that it has limitation to support this model.

From Table 1, the longest processing time is 2 robots condition but the total step movement is smaller than 3, 4, 5 robots because robot can be managed the task in queue from 2 robots selection only. Shortest path will be the 1st priority when systems found only 2 robots. However, 5 robots can be shown the fastest processing time because program can share task for more robots but the total step movement may be increased to allow alternative robots movement path with safety constraint.

Table 1. Simulation results

No. of robots	Processing time (min)	Total step movement
2	2.49.02	1081
3	1.58.06	1129
4	1.43.19	1245
5	1.23.54	1216
6	Infinity	Cannot identify

During 6 robots test, program cannot continue until the end of process because of waiting path. All robots move in to waiting path loop at the same time and cannot find the solution by themselves.

In addition, this research has built the error on systems for checking model performance. 4 built-in error models are constant in Equation (7), proportional in Equation (8), and exponential in Equation (9) where f is objective function and y is the output after built-in error inside.

$$y = f + ae \tag{7}$$

$$y = f + b|f|e \tag{8}$$

$$y = f * \exp(ae) \tag{9}$$

From Table 2, no. of robots = 5 cannot be tested during random error built-in. Robot will stop at waiting path process as same as the results of no. of robots = 6 in Table 1. Maximum robot test on simulation is 4 robots condition.

Table 2. Simulation results with random error built-in at no. of robots = 4

Built-in error	Processing time (min)	Total step movement
Constant	1.50.28	1236
Proportional	1.50.38	1329
Exponential	2.01.15	1378

After built-in error in model, we can see the higher processing time and the higher trend of total step movement. The worst case a result is when error built-in is "exponential". Processing time will be 2.01.15 minutes. It means that the completion tasks per hour will be around 895 tasks/hour for worst case of 4 robots condition.

The completion tasks/hour calculation is in Equation (10) where Ta = count of total tasks, t is time in minute and 60 is the constant value for time converting from minute to hour.

$$Completion\ tasks/hour = \frac{Ta}{t} \times 60 \tag{10}$$

From Figure 3, the completion tasks/hour is reduced after built-in error in models by using $Ta = 30$ tasks. The best completion tasks/hour is the model without built-in error that it can reach to 1258 completion tasks/hour but it might not be accurate for actual condition. The 2nd is model with constant error built-in that it can be 1200 completion tasks/hour. The 3rd is model with proportional error built-in and the 4th is the model with exponential error built-in. From these results, the worst case completion tasks/hour is 895 tasks/hour. It is higher than the conventional method which is equal to 800 tasks/hour.

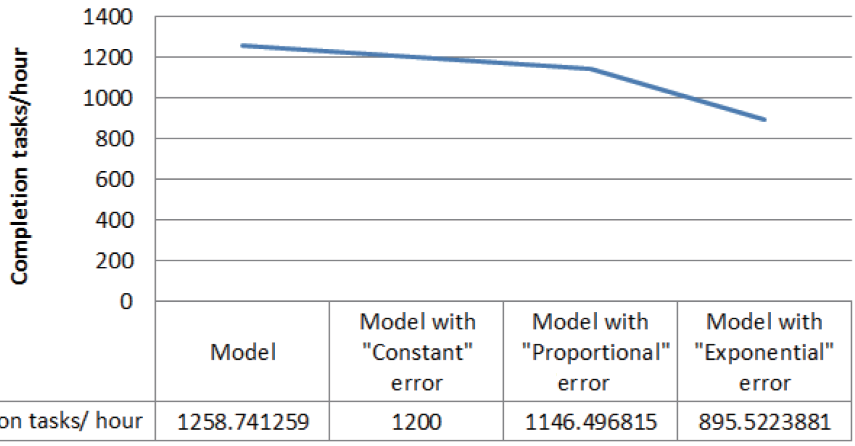

Figure 3. Completion tasks/hour during 4 robots running in the model

6. **Conclusions.** This research contributes new purposed method for optimal path planning based on Hard Disk Drive Manufacturing layout by using the combination of A-star path finding and safety path constraint with Multi-Robot Task Allocation. The conventional method by using Genetic Algorithm (GA) shows 800 tasks/hour. With the same condition, the purposed method results can represent 5 robots/30 tasks with 1.23.54 minutes which are the simulation results without error built-in. With 3 built-in errors in the model, it cannot run in 5 robots condition due to waiting time loop constraint. The best case for simulation test is 4 robots and worst case completion tasks/hour is 895 tasks/hour which is more than 800 tasks/hour. This result can help to support Hard Disk Drive Manufacturing for prediction and planning and this model can be applied for future development of the multi-robot path planning on manufacturing as well.

Acknowledgment. This research was supported by RRi and Seagate Technology (Thailand) Ltd. under Grant No. PHD59I0059.

REFERENCES

[1] D. Devaurs, T. Siméon and J. Cortés, Optimal path planning in complex cost spaces with sampling based algorithms, *IEEE Trans. Automation Science and Engineering*, vol.13, no.2, pp.415-424, 2016.

[2] A. Wan, J. Xu, H. Chen, S. Zhang and K. Chen, Optimal path planning and control of assembly robots for hard-measuring easy-deformation assemblies, *IEEE/ASME Trans. Mechatronics*, vol.22, no.4, pp.1600-1609, 2017.

[3] J. Votion and Y. Cao, Diversity-based cooperative multi-vehicle path planning for risk management in costmap environments, *IEEE Trans. Industrial Electronics*, vol.66, 2019.

[4] Y. Huang, Y. Zhang and H. Xiao, Multi-robot system task allocation mechanism for smart factory, *IEEE the 8th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*, China, 2019.

[5] R. Praserttaweelap, S. Kaitwanidvilai and H. Aoyama, Safety path planning with obstacle avoidance using particle swarm optimization for AGV in manufacturing layout, *International Journal of Innovative Computing, Information and Control*, vol.15, no.1, pp.351-368, 2019.

[6] Z. Farouq, H. Saad and M. Ramdane, A distributed approach to the multi-robot task allocation problem using the consensus-based bundle algorithm and ant colony system, *IEEE Access*, vol.8, no.2, pp.27479-27494, 2020.

[7] G. Chen, H. Zhou and P. Yang, Force/position control strategy of 3-PRS ankle rehabilitation robot, *International Journal of Innovative Computing, Information and Control*, vol.16, no.2, pp.481-494, 2020.

[8] A. E. Solyman, K. M. Ibrahem, M. R. Atia, H. I. Saleh and M. R. Roman, Perceptive augmented reality-based interface for robot task planning and visualization, *International Journal of Innovative Computing, Information and Control*, vol.16, no.5, pp.1769-1785, 2020.

[9] Y. Ghadi, A novel hybrid locomotion mechanism for small mobile robot, *ICIC Express Letters, Part B: Applications*, vol.10, no.11, pp.1031-1036, 2019.

[10] R. Watanuki, T. Horiuchi and T. Aodai, Vision-based behavior acquisition by deep reinforcement learning in multi-robot environment, *ICIC Express Letters, Part B: Applications*, vol.11, no.3, pp.237-244, 2020.

[11] M. Hussain, J. Park, N. Kim, H. K. Kim, J. Lee and J. Lee, Effects of exoskeleton robot on human posture and lumbar pressure during manual lifting tasks, *ICIC Express Letters, Part B: Applications*, vol.11, no.5, pp.439-445, 2020.