Optimal Path planning on Multi-Robot Task Allocation for Manufacturing with Artificial Bee Colony Algorithm

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Abstract

This research presents the optimal path planning for manufacturing. The new contribution is the safety path searching by using artificial bee colony algorithm in multi-robot systems. The new RC function was introduced in this paper to represent the risk of collision path. The best safety path searching is the low risk of collision path from automatic searching on RC function. This research designs the artificial bee colony algorithm for the safety path searching based on the manufacturing environment. The proposed is to find the optimal safety path with fast convergence. With the built-in error, the simulation results illustrate the effectiveness of the optimal path planning in multi-robot systems for manufacturing.

Keywords
Safety path planning, Artificial Bee Colony Algorithm, Multi-Robot Systems, Manufacturing

1. Introduction

Nowadays, the multi-robot system in manufacturing is the key process for the capabilities and the reliabilities. In dynamic environments, the multi-robot movement is the complex systems. The new development for multi-robot path planning is required. Seagate Technology (Thailand) Ltd. is the one of the multi-robot manufacturing in the electronics industry. This research designs the optimal path planning in multi-robot systems based on the manufacturing layout of Seagate Technology (Thailand) Ltd. Many researchers studied the path planning with the different condition. An Wan et al. (2017) designed the GPR-based deformation compensation method for the assembly robots. Both simulation results and experimental prototype illustrate the good performance on their proposed method. Johnathan V. and Yongcan C. (2019) proposed the new path planning algorithm by using A*. The comparison results show the effectiveness of the modified A* (Johnathan and Yongcan 2019). Rong-Jong Wai et al. (2019) designed the optimal path planning and adaptive neural network for energy consumption prediction. This combination algorithm represents the efficiency UAV surveillance systems. Shuai D. H. et al.(2020) proposed new multi-robot path planning algorithm by using DDM. The results show good performance at high levels with the optimum quality. Jiankun Wang et al.(2020) created the neural RRT* for optimal path planning. The results show better performance than RRT in term of the convergence speed.

About the algorithm for path planning, Guozun Tian et al.(2018) improved the artificial bee colony algorithm for the faster convergence in Multi-UAV systems. The results represent the better efficiency. Xiangmin Li et al.(2018) improved the artificial bee colony algorithm for robot path planning. The results illustrate the faster optimal path searching. Necmettin et al.(2018) designed the optimal path planning by using artificial bee colony algorithm and probabilistic roadmap. The results show good performance in simulation only. Fateh B. and Beyza G.(2018) selected the artificial bee colony for robotic path planning and they compared the performance with the genetic programming. X. Bai et al. (2019) proposed the hybrid algorithm between the artificial bee colony algorithm and A* for Multi-UAV systems. The hybrid performance illustrate the better results than A* algorithm. Chengfang W. et al.(2020) selected the artificial bee colony algorithm for the aerial vehicle path planning. Their simulation results represent the faster convergence than the conventional method. About the multiple vehicle research, Kiwon Y. (2020) developed the monitoring mobile sensors of multiple vehicles. He presented the new arrangement technique to support the particle matters in the urban street. His results represent the correlation of the particulate matters and metrological parameters.

From literature review, many researchers studied the robotic systems and designed the smart algorithm for complex problem solving. The path planning concept from previous research are the shortest path searching. The popular algorithm is the A* and artificial bee colony algorithm. The goodness of the artificial bee colony algorithm is the good effectiveness for fast convergence and this algorithm still performs the accuracy for optimal search.
This paper presents the new safety path searching for manufacturing in multi-robot environment. At first, this research designs the model from the manufacturing layout. The path planning for this research is A* path planning. The new contribution is the new risk of collision function (RC) for the safety path searching. However, the safety path searching concept can impact the higher processing time. From this problem, this research proposes the artificial bee colony for the fast convergence of optimal safety path searching. The results show a good prediction model for manufacturing.

2. Manufacturing

This research studied the manufacturing layout of Seagate Technology (Thailand) Ltd. Figure 1 shows the 3 rectangle boxes which are the loading station and unloading station. The 24 rectangle boxes are the operation test station. In automation process, the robotic system of this manufacturing is the multi-robot systems. The robotics path planning algorithm is very important for manufacturing capabilities with 0% collision.

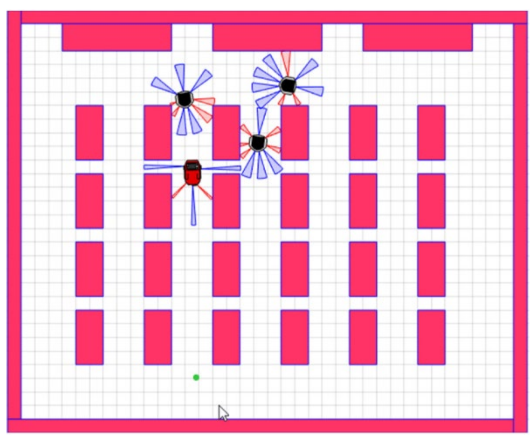

Figure 1. Manufacturing layout

3. A* Path planning

The A* path planning is the algorithm to search the shortest path. The distance between the starting point and the goal point $f(n)$ in (1) is the A* path planning function where $g(n)$ is the distance between starting point and current point and $h(n)$ is the estimated distance between current point and goal point.

$$f(n) = g(n) + h(n) \quad (1)$$

The distance calculation of $g(n)$ is the Euclidean distance in (2) where (x_s,y_s) is the starting point and (x_c,y_c) is the current point.

$$g(n) = \sqrt{(x_s - x_c)^2 + (y_s - y_c)^2} \tag{2}$$

At the current point, the distance between the current point to the goal point is the estimated distance in the heuristic value ($h(n)$). There are 3 types of heuristic calculations where (x_c,y_c) is the current point and (x_g,y_g) is the goal point.

3.1 Manhattan distance

Manhattan distance for $h(n)$ in (3) is the sum of the absolute value between the current point and the goal point.

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

3.2 Diagonal distance

Diagonal distance for $h(n)$ in (4) is the max value of Manhattan distance.

$$h(n) = \max(\left|x_c - x_g\right| + \left|y_c - y_g\right|) \tag{4}$$

3.3 Euclidean distance

Euclidean distance for $h(n)$ in (5) is the distance calculation between the current point and the goal point.

$$h(n) = \sqrt{(x_c - x_g)^2 + (y_c - y_g)^2} \tag{5}$$

4. Artificial Bee Colony Algorithm

Artificial bee colony algorithm is an optimization algorithm based on the behavior of honey bee swarm. The bee colony has three groups of bees. The 1st group is the employed bees. The 2nd group is the onlookers and the 3rd group is the scouts. The unemployed bees are the onlookers and the scouts. Firstly, the employed bees start on the specific sources of food. Then, the onlooker bees observe the dance of employed bees within the hive. The dance of employed bees can represent the food source. For the scout bees, they search the random food source and they can find all food source locations.

In artificial bee colony algorithm, the food source position represents the solution quality. The algorithm process is as follows.

4.1 Initialization phase

Firstly, the initialization phase is to initiate the population of food source and population of scout bees with control parameters. The optimization process is to minimize the fitness function. The minimum fitness function represents the best food source. The population of food source is in (6) where l_i is the lower bound of X_{mi} , u_i is the upper bound of X_{mi} , and $rand(0,1)$ is random value between 0 to 1. The index m is the population of bees and i is an optimization variable.

$$X_{mi} = l_i + rand(0,1) * (u_i - l_i) \tag{6}$$

4.2 Employed bees phase

The employed bees search the high nectar in the neighbor food source. The neighbor food source in (7) is the new food source (V_{mi}) where ϕ_{mi} is random number within [-a, a] and X_{ki} is a random food source.

$$V_{mi} = X_{mi} + \phi_{mi}(X_{mi} - X_{ki}) \tag{7}$$

The fitness of the solution is shown in (8) and (9) where $f_m(X_m)$ is the objective function value of X_m .

$$fit_m(X_m) = \frac{1}{1 + f_m(X_m)};\ if\ \ f_m(X_m) \geq 0 \tag{8}$$

$$fit_m(X_m) = 1 + abs(f_m(X_m));\ if\ \ f_m(X_m) < 0 \tag{9}$$

4.3 Onlooker bees phase

The onlooker bees get the food source information from employed bees. Then, the onlooker bees choose their food sources based on the probability value of the fitness values from the employed bees. The probability value calculation is in (10).

$$P_m = \frac{fit_m(X_m)}{\sum_{m=1}^{M} fit_m(X_m)} \tag{10}$$

4.4 Scout bees phase

The scout bees choose the food source randomly. The employed bees become the scout bees when the solution is in hard limit criteria.

4.5 Final solution phase

The final solution phase is to select the best solution after the repeating process. The hard limit of repeating process is the maximum cycle number.

5. Proposed method

The proposed method of this research is to design the optimal path planning for manufacturing. Firstly, this research designs the manufacturing model as manufacturing layout from Seagate Technology (Thailand) Ltd. Based on the manufacturing requirements, the 0% collision is very important for manufacturing in multi-robot systems environment. This research proposes a new safety path by using the artificial bee colony algorithm for fast convergence. The lowest risk of collision path is the final solution of the proposed method. Nowadays, many researchers design the shortest path for the best path planning. The safety path planning with fast convergence is the new contribution of this research.

The risk of collision function or RC function is in (11) where γ is the safety factor, d_{ij} is the maximum distance of robot i (r_i) to each robot, and $\sum_{i=1}^{n} d_{ij}$ is sum of maximum distance of robot i (r_i) to each robot.

$$RC_{ij}(r_i) = \max(1-\gamma(d_{ij}) / \sum_{i=1}^{n} d_{ij}, 0) \tag{11}$$

The minimum RC value is the low risk of collision path. This research applies the RC function in the artificial bee colony algorithm. The new fitness function in artificial bee colony algorithm of each robot i is shown in (12).

$$fit_{ij}(r_i) = \frac{1}{1+RC_{ij}(r_i)}; \ \ if \ \ RC_{ij}(r_i) \geq 0 \tag{12}$$

The best safety path is the minimum RC value or the maximum fitness function in artificial bee colony algorithm. The maximum fitness function represents the highest probability for onlooker bees.

The proposed method process is as follows.

1. Initialization process
2. Calculate the Euclidean distance of robot n and task t
3. Assign the task t for robot n from minimum distance
4. Start A* path planning searching
5. Start the safety path searching by using artificial bee colony algorithm
   Case 1: Best safety path
   Continue the next process
   Case 2: Conflict path
   Conflict loop process (waiting path)
6. Repeat the process until it reaches criteria

The end of process criteria is the completed tasks or out of the processing time limit.

6. Results

From the simulation results, the without RC searching shows the high risk of collision. With RC searching, the result shows the low risk of collision. Figure 2 shows the RC value of with and without RC searching from 100 iterations. The RC searching algorithm reduces the risk of collision value during the iteration process

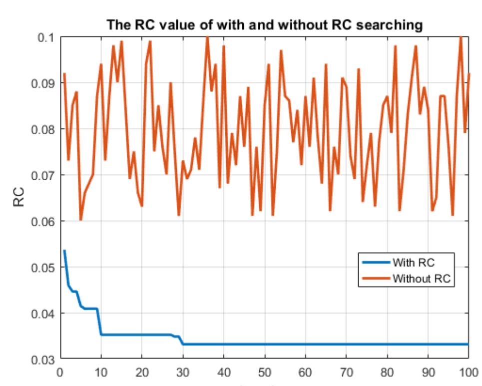

Figure 2. RC value of with and without RC searching

This research assigns 30 tasks for this simulation. The simulation conditions are 2 to 6 robots with a built-in error. Figure 3 is the location of 30 tasks.

In 6 robots condition, the model cannot complete the process. All robots stop because of the conflict loop in case 2 of process step 5.

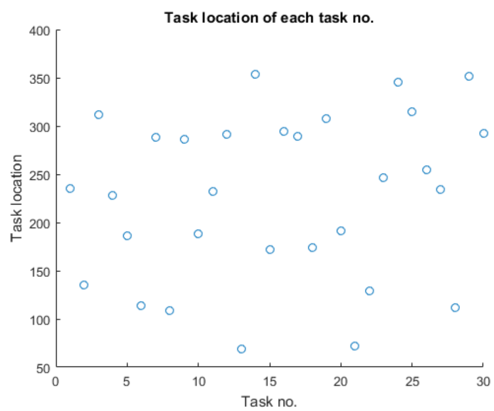

Figure 3. Task location of each task no.

For the model validation, this research built the error in the model on each condition. The built-in errors in this model are the constant, the proportional, and the exponential.

1. Built-in error: Constant

   For the constant, the output of built-in error (y_{out}) in (13) is the sum of the desired function ($f_{desired}$) and the random error value (c).

$$y_{out} = f_{desired} + c \tag{13}$$

2. Built-in error: Proportional

   For the proportional, the output of built-in error (y_{out}) in (14) is the sum of the desired function ($f_{desired}$) and the multiplication of the desired function and the absolute of the random error value (c).

$$y_{out} = f_{desired} + |c| f_{desired} \tag{14}$$

3. Built-in error: Exponential

   For the exponential, the output of built-in error (y_{out}) in (15) is the multiplication of the desired function ($f_{desired}$) and the exponential function.

$$y_{out} = f_{desired} * \exp(ce) \tag{15}$$

Figure 4 is the result of 2 robots condition. Without error in the model shows the lowest moving step. The exponential built-in error shows the highest moving step. The lowest moving step is the without error.

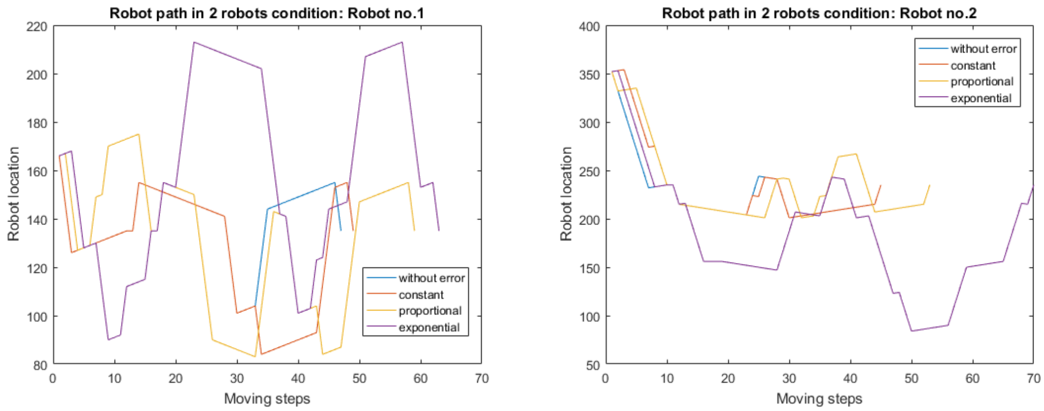

Figure 4. Robot path in 2 robots condition

With the built-in error, the moving step is higher than the without error. The reason is the built-in error in the heuristic value for the prediction variation simulation. The heuristic value in the A* path planning is the prediction of the robot path from the current point to the goal point. The next robot path can change along the time from the built-in error.

Figure 5 is the results of 3 robots condition. The last robot location for without error and built-in error show the same location. The robot steps show the over traveling in built-in error. The worst case is the exponential error. Without error is the best case. The maximum moving step is 74 steps in robot no.3 with an exponential error. The maximum processing time is 1.595712 minutes.

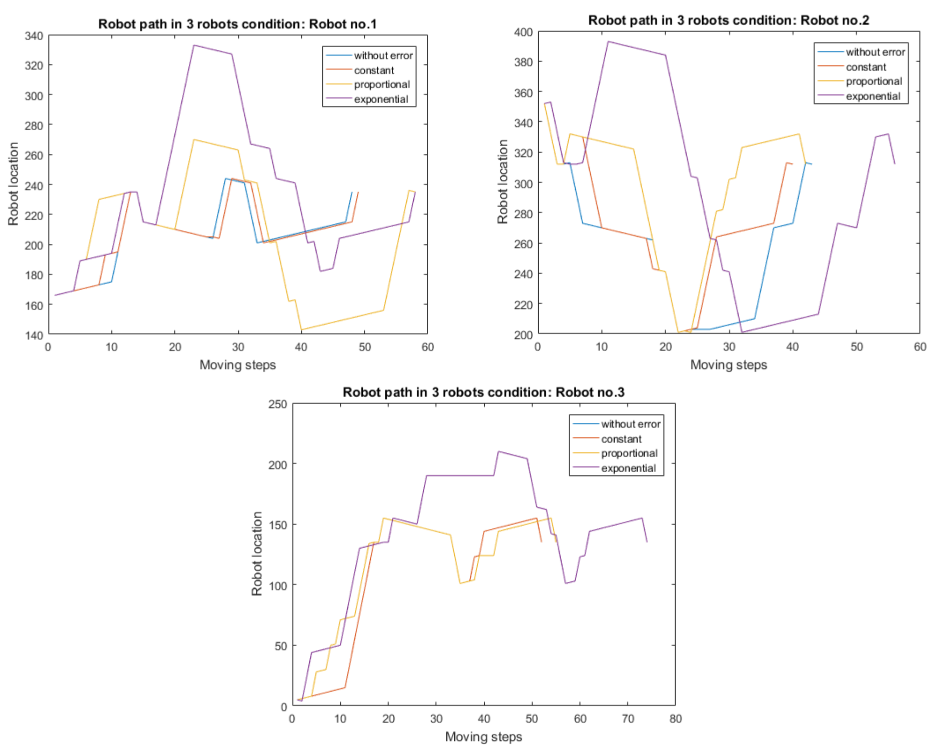

Figure 5. Robot path in 3 robots condition

Figure 6 is the results of 4 robots condition. The results are similar to 3 robots condition. The maximum moving step is 68 steps in robot no.4. The maximum processing time is 1.963558 minutes.

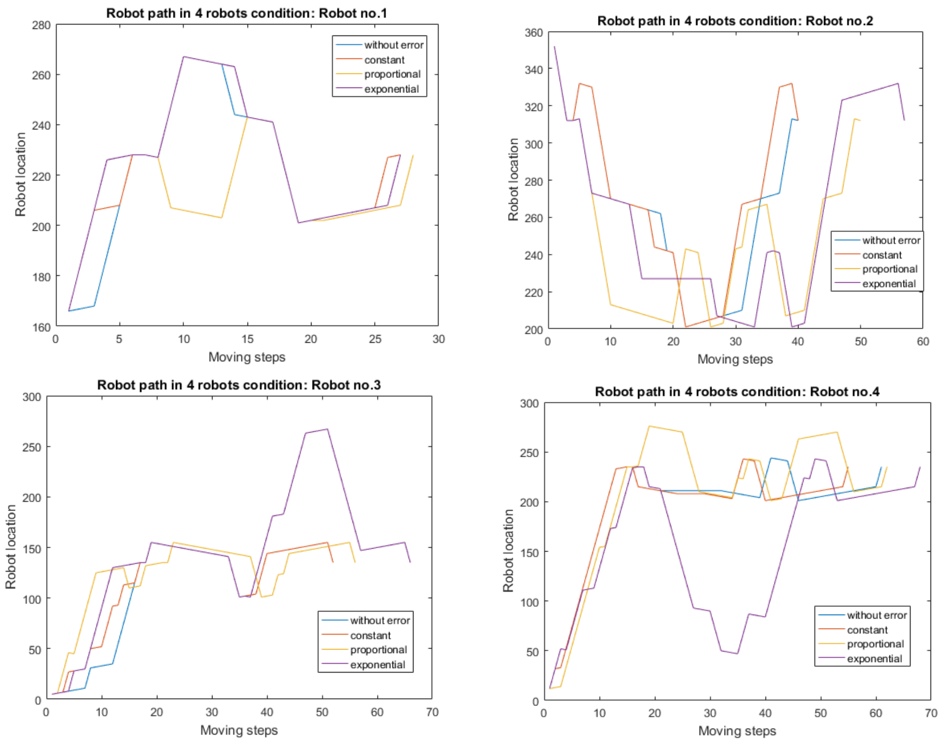

Figure 6. Robot path in 4 robots condition

In 5 robots condition, the result is shown in Figure 7. The results are similar to 3 robots condition and 4 robots condition. The maximum moving step is 57 steps in robot no.1. The maximum processing time is 2.645825 minutes. The increasing of robot no. in manufacturing layout reduces the moving step of each robot but the processing time is higher. The reason is the conflict loop process for safety path searching.

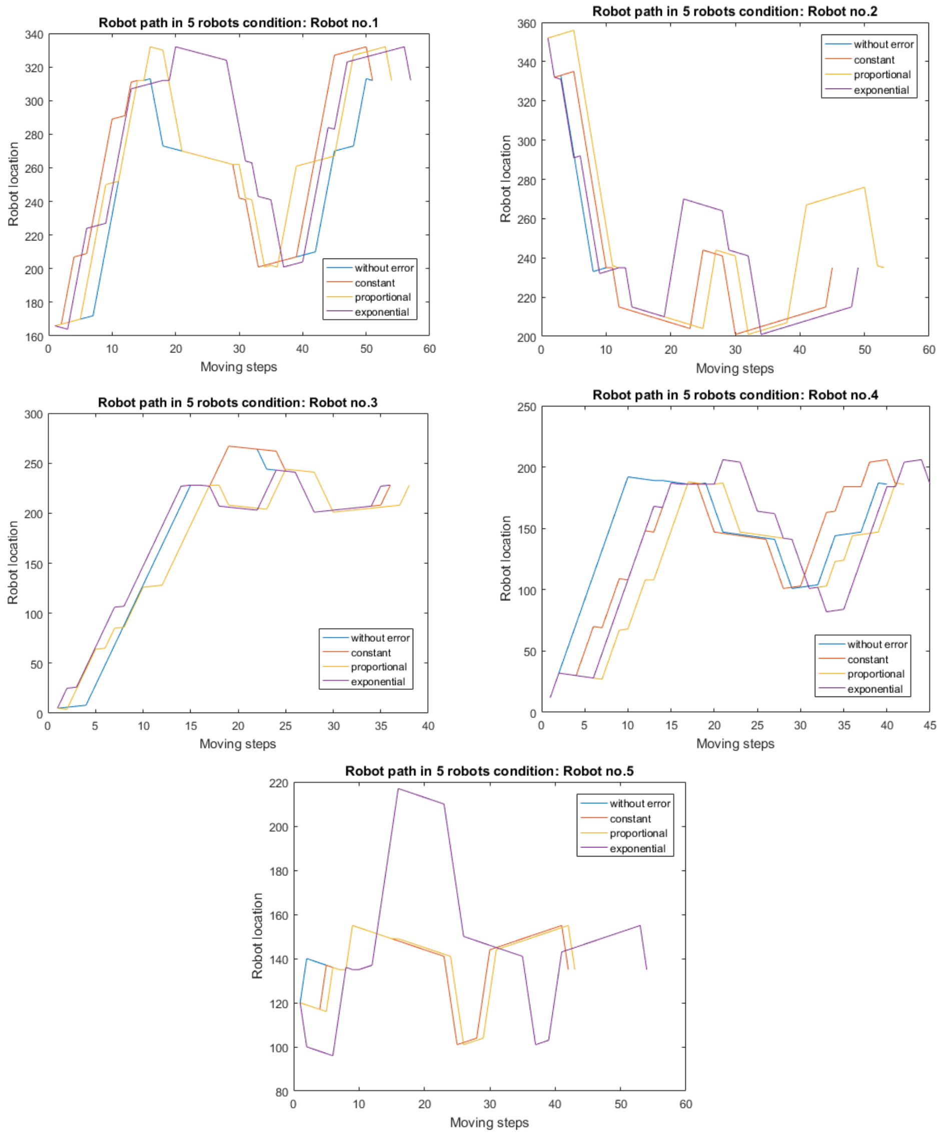

Figure 7. Robot path in 5 robots condition

Figure 8 is the processing time in a minute of each condition. The minimum processing time is the 2 robots condition and the maximum processing time is the 5 robots condition.

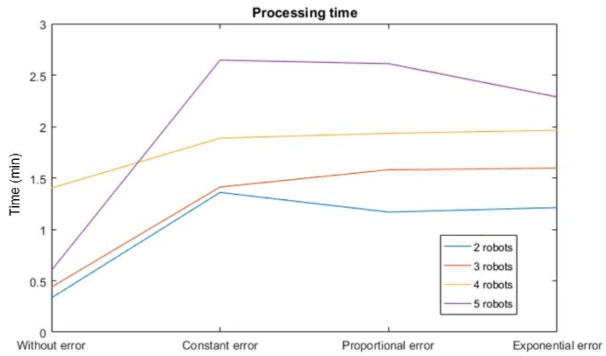

Figure 8. Processing time of each condition

Figure 9 is the maximum RC value of each condition. The minimum RC value is the 2 robots condition and the maximum RC value is the 5 robots condition.

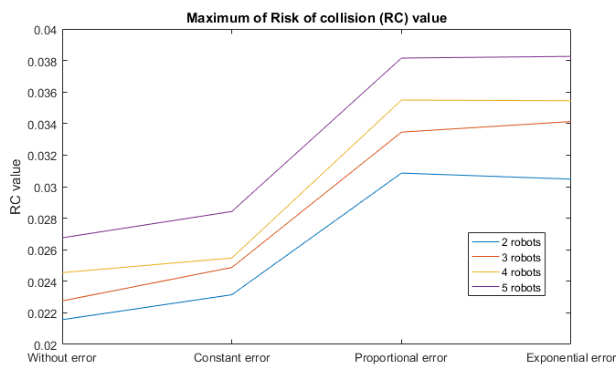

Figure 9. The maximum RC value of each condition

From the results, the best safety path searching is the 2 robots condition because of the lowest risk of collision and the fastest processing time. The optimal path planning in manufacturing is for 0% of collision with less impact on capability. The proposed method of this paper illustrates a good prediction model for manufacturing.

7. Conclusion

The proposed method of this research is to design the new optimal path planning for manufacturing. The environment in manufacturing is the multi-robot systems. The safety path is the 1st priority. The shortest path for fast processing time is the 2nd priority. This research presents the new safety path searching with fast convergence on the optimal value. The best condition is 2 robots condition for this manufacturing layout. The maximum risk of collision is only 0.0304789 and the maximum processing time is 1.358885 minutes. The results show the effectiveness of a prediction model for multi-robot systems in manufacturing.

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References

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.

J. Votion, and Y. Cao, Diversity-Based Cooperative Multivehicle Path Planning for Risk Management in Costmap Environments, *IEEE Transactions on Industrial Electronics*, vol. 66, no.8, pp.6117-6127, 2019.

R-Jong Wai, and A. S. Prasetia, Adaptive Neural Network Control and Optimal Path Planning of UAV Surveillance System With Energy Consumption Prediction, *IEEE Access*, vol. 7, pp. 126137-126153, Aug 2019.

S. D. Han, and J. Yu, DDM: Fast Near-Optimal Multi-Robot Path Planning Using Diversified-Path and Optimal Sub-Problem Solution Database Heuristics, *IEEE Robotics and Automation Letters*, vol.5, no.2, pp.1350-1357, 2020.

J. Wang, W. Chi, C. Li, C. Wang, and M.Q.-H. Meng, Neural RRT*: Learning-Based Optimal Path Planning, *IEEE Transactions on Automation Science and Engineering*, vol.17, no.4, pp.1748-1758, Mar 2020.

G. Tian, L. Zhang, X. Bai, and B. Wang, Real-time Dynamic Track Planning of Multi-UAV Formation Based on Improved Artificial Bee Colony Algorithm, *37th Chinese Control Conference (CCC)*, China, 2018, pp. 1934-1768.

X. Li, Y. Huang, Y. Zhou, and X. Zhu, Robot Path Planning Using Improved Artificial Bee Colony Algorithm, IEEE *3rd Advanced Information Technology*, Electronic and Automation Control Conference (IAEAC), China, 2018.

N. Alpkiray, Y. Torun, and O. Kaynar , Probabilistic Roadmap and Artificial Bee Colony Algorithm Cooperation For Path Planning, *International Conference on Artificial Intelligence and Data Processing (IDAP)*, Turkey, 2018.

F. Boudardara, and B. Gorkemli, Application of Artificial Bee Colony Programming to Two Trails of the Artificial Ant Problem, *2nd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*, Turkey, 2018.

X. Bai, P. Wang, Z. Wang, and L. Zhang, 3D Multi-UAV Collaboration Based on the Hybrid Algorithm of Artificial Bee Colony and A*, *Chinese Control Conference*, China, 2019.

C. Wu, X. Huang, Y. Luo, and S. Leng, An Improved Fast Convergent Artificial Bee Colony Algorithm for Unmanned Aerial Vehicle Path Planning in Battlefield Environment, *IEEE 16th International Conference on Control & Automation (ICCA)*, Singapore, 2020.

K. Yeom, Real-Time Particle Matters Monitoring Based on Mobile Sensors from Multiple Vehicles in Urban Street, Daejeon-City, South Korea, *International Journal of Electrical and Electronics Engineering & Telecommunications*, vol.9, no. 1, 2020.

Biographies

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