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SAFETY PATH PLANNING WITH OBSTACLE AVOIDANCE USING PARTICLE SWARM OPTIMIZATION FOR AGV IN MANUFACTURING LAYOUT

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Abstract. *In robotic systems, path planning is the one of important processes for robot motion. The best path planning is required for shortest path searching that can make fast movement of robot. However, the real environment is not only the path from point to point but it has obstacles which are the one of constraints for best path searching. The obstacle avoidance is concerned to avoid the crashing between robot and obstacle under environment. In Hard Disk Drive manufacturing, the first priority is safety constraint for non-collision and second priority is shortest path for processing time saving. This research designed the algorithm for path planning and obstacle avoidance for AGV in Hard Disk Drive Manufacturing of Seagate Technology (Thailand) Ltd by using particle swarm optimization. The fitness function on particle swarm optimization process for particle searching has been integrated with obstacle avoidance function to find the best path for robot without collision and total distance to find the shortest path. This algorithm is applied to verifying the model performance. The simulation results of this research are done by MATLAB 2016b and illustrate the good performance on different cases with controlled parameter.*

Keywords: Path planning, Particle swarm optimization, Obstacle avoidance, Hard disk drive, Safety constraint

1. **Introduction.** Currently, robotic system is the one of popular systems for manufacturing. Many factories apply the robotic system to increasing manufacturing performance such as unit per hour, accuracy, and reliability. One of robotic types is AGV which is the automated guided vehicle. Normally, it has been used for transferring process because it can move faster than people and it can work all the time without rest. In addition, the robotic system can be controlled and designed easier than people. There is the main reason why the robotic system is very popular in manufacturing. Hard Disk Drive factory is one manufacturing that applied the robotics for manufacturing process. Their purpose is to transfer the object from station to target point. Path planning is an important section to make robot movement in manufacturing layout. In addition, the obstacle avoidance is

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the key feature because it is related with safety requirement. Seagate Technology (Thailand) Ltd is the Hard Disk Drive manufacturing. This factory designs the robot system with path planning in manufacturing layout. Due to constraint on the total space, the width of robot pathway in layout is not a large width. The robot cannot move through robot pathway easier. In term of safety requirement in this factory, the minimum width of robot pathway must be more than 20% of robot's safety region radius. The robot can move along the path without crashing. When the crashing problem occurred, the transfer object (product) and robot can be damaged. It will impact the factory on rework cost and timeline commitment to customer. Safety path is the first priority for robot movement on this factory. This research focuses on algorithms for the best safety path of robot movement based on the layout on this factory. The layout of this factory is provided by industrial engineer in Seagate Technology (Thailand) Ltd. From Figure 1, it is the estimated layout of storage shelf. All of rectangles in Figure 1 are the storage shelf (obstacles) and AGV station. The small circle is the AGV. The comparing size of distance between the edge of obstacle (gap) are shown in Figure 1. The AGV station and AGV operation zone are created from model of factory floor. 2 AGV stations are the AGV parking zone before operation. It will be the start point of AGV in the model. AGV station 1 will be used to support AGV operation left zone (left dash line rectangle) and AGV station 2 will be used to support AGV operation right zone (right dash line rectangle). The concept of this design is to reduce the path of AGV to make high capability on process. The AGV size is shown in Figure 2. a is $a = \frac{6}{5}r$ and gap b is $b = \frac{9}{5}r$ where r is radius of AGV region.

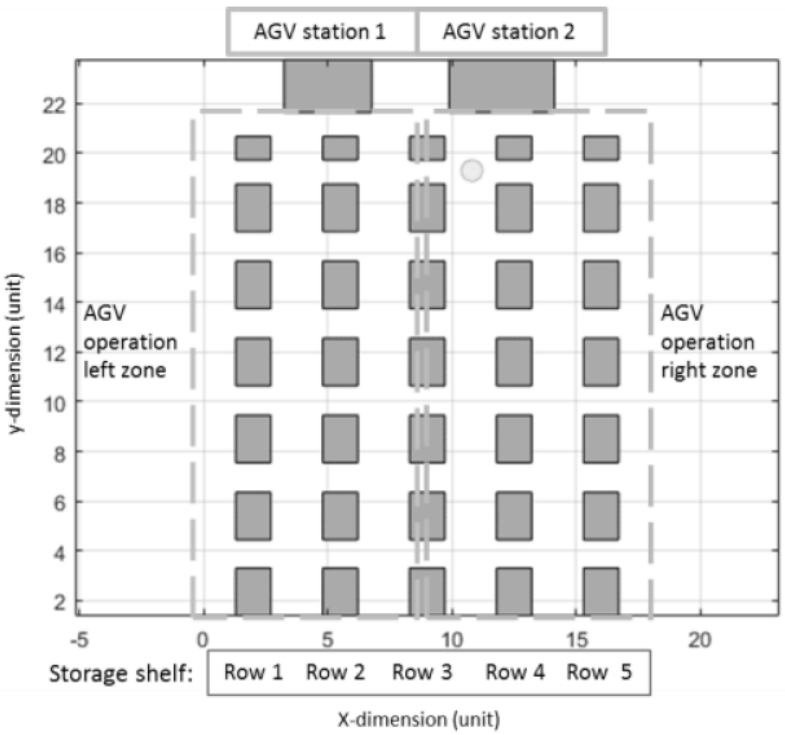

FIGURE 1. Estimated layout in production with AGV

Figure 3 shows the 2 wheels AGV inside the circle. Radius (r) is calculated from width and length of AGV by using Pythagoras theorem. The circle zone in Figure 3 represents the AGV region. This research used the simulation model as Figures 1-3 based on nonholonomic robot. The constraint on the model is the narrow gap (a) that is close to AGV region. In term of algorithm, many researchers studied the algorithm for robot movement. Probabilistic concept was applied in [1]. P. Alexandros et al. combined the

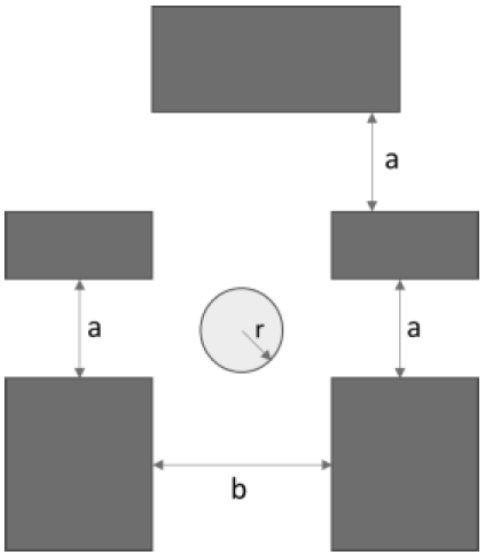

FIGURE 2. Distance between the edge of obstacle (gap) and AGV size

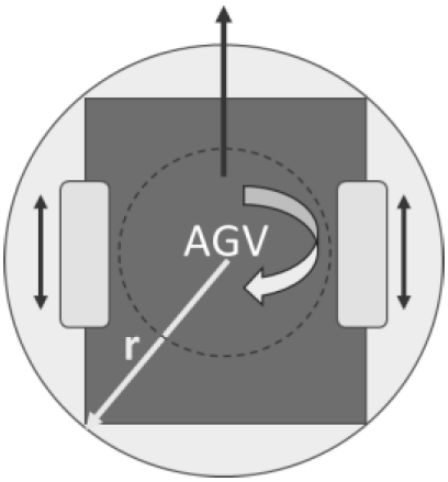

FIGURE 3. Circle and AGV

probabilistic movement primitives and Bayesian task prioritization but they still need to expand the evaluations on more complex real-word scenarios. In [2], G. Han et al. studied the probabilistic neighborhood location-point for data collection latency optimization and obstacle avoidance. The simulation shows better performance than the other existing underwater data collection algorithms. C. Evers and P. A. Naylor derive the framework in general for GEM-SLAM which is Probability Hypothesis Density (PHD)-based in SLAM algorithm. The simulation shows good on model-specific by using range-bearing sensors [3]. In [4], the obstacle avoidance is main objective by using Nonlinear Model Predictive Control (NMPC) in real time which represents good performance in various situations. A. K. Kar et al. presented the navigation techniques on 2 different environments which are normal and artificial potential function. Recalculated path is required for optimal path to avoid the obstacle which shows high risk to effect high processing time [5]. For motion path planning with additional tool, the aerial videography was selected in [6]. The purpose is to avoid the obstacle in real time but the constraint is the position and framing by user only. About the path planning algorithm, the algorithm for optimal path planning is popular because of the various environments. D. Devaurs et al. combined the

principle of RRT and T-RRT. This method is faster than the RRT on complex problem [7]. A. Wan et al. presented a GPR-based (Gaussian Process Regression) prediction of deformation and method of compensation for robot motion accuracy improvement. They can achieve at high accuracy on both simulation and experimental prototype [8]. Furthermore, development phase for path planning by using integrated circuits was developed in [9]. Reconfigurable Analog Very Large Scale Integrated (AVLSI) circuits are Application Specific Integrated Circuits (ASICs) for path planning. The algorithm for mapping robot's environment needs to be loaded onto Field-Programmable Analog Arrays (FPAAs). They tested the proposed method on 24 environment scenarios. This is one of good studies about the path planning. P. Grosch and F. Thomas studied the geometric path planning for nonholonomic robots to find smooth paths but it is an open-loop method. The noise and errors on the systems still need to consider for next improvement [10]. One of techniques that many researchers selected for robotics system is Particle Swarm Optimization (PSO) but the fitness function is different because it is dependent on the design concept for each researcher. S. Yeasmin et al. proposed the point-to-point motion and planned the trajectory for robot arm using the Enhanced Particle Swarm Optimization (EPSO). The simulation results illustrate the optimal trajectory for different conditions of robot arm [11]. In [12], N. Setyawan et al. developed adaptive Gaussian parameter particle swarm optimization because of difficulties balancing on basic PSO algorithm. The simulation results show the better processing time with smooth path planning. In term of application, hybrid of particle swarm optimization with Tabu Search (TABU) were developed in [13] for mobile robot. The results show the best performance on hybrid PSO-TABU. In addition, PSO is widely used for multi optimal objectives. In [14], A. D. Falehi and M. Rafiee studied about the harmonic mitigation optimization and they applied the PSO on algorithm with multi-objective for low THD and harmonic elimination pulse width modulation. However, the results can represent good performance on desired situation only. In multiple robot systems, A. Ayari and S. Bouamama studied the advanced artificial intelligence. A new Dynamic Distributed Particle Swarm Optimization (D2PSO) is the main concept of their research. The results of proposed method perform better performance than normal [15]. L. Liao et al. improved the path planning on complex environment by Dynamic Double Mutation Particle Swarm Optimization (DDPSO) algorithm but it is not simulation results from various situations [16]. N. Mizuno and C. H. Nguyen used PSO to estimate parameters for high accuracy tracking control. Their concept is validated by several trajectories with good performance [17]. M. K. Rath and B. B. V. L. Deepak studied the path planning for mobile robot by using particle swarm optimization. The purpose is the obstacle avoidance with shortest path but the environment on simulation is not complex [18]. In [19], Z. Nie et al. combined the particle swarm optimization with annealing algorithm. The incremental work is required. Y. Guo et al. designed the path planning for robot for collision-free path by using fuzzy neural network on obstacle avoidance strategy and improved fuzzy parameters by particle swarm optimization. Verification phase shows the effectiveness from proposed method [20]. In addition, many researchers studied about the Spline for smooth path planning. Z. Wang et al. combined the Astar and B-Spline for path planning on autonomous underwater vehicle. Their purpose is to generate fit path based on the motion constraint. However, their concept works on low-dimension only. New method is required for high-dimension environments [21]. A. Khan et al. designed the coverage path planning for mobile robots by using rational quadratic Spline. They focus on smoothing of coverage path which is created by rational quadratic spline. The results show good on simulation only [22]. Y. Wang et al. used Spline interpolation to map 2D dubins path for 3D multi-vehicle path planning. They proposed to design the system to support multiple targets. Simulation

results show shortest dubins with small probability of collision [23]. D. Lee et al. designed the optimal path planning by using the Spline-RRT in 3-D environments of UAVs. Simulation results show good for their systems [24]. K. Yang et al. presented the optimal spline-based RRT path planning by using probabilistic map. RRT is good for quick path but it is not good for quality path. Spline-based RRT is their concept to get the feasible path. Simulation results illustrated feasibility for optimal path on system [25]. N. Arana-Daniel et al. designed smooth path planning by particle swarm optimization, radial basis function, Splines, and B'ezier curves. The results from their experiments show good on complex environments [26]. M. Neubauer and A. Müller designed the smooth path planning with Quaternions using B-Splines. They compared the angular velocities between standard method (SLERP) and smooth path generation. The appropriate method for continuity of motor torque on robotic manipulator is required. Smooth path by Splines can support their purpose [27]. S. Zhang et al. presented the smooth path planning using η^3-splines for home service robot. Known maps with static obstacles are created. They used 2 steps in algorithm which are MAKLINK graph for shortest linear path and the smoothly connected path using η^3-splines. Simulation and experiments results show good performance [28]. D. Lee and D. H. Shim used the Spline-RRT for optimal path planning of Fixed-Wing UAVs flights. Simulation results show that their concept can be utilized [29]. From many researches, the new algorithm for path planning optimization and obstacle avoidance are the important topics for robotics systems due to the various constraints such as robot specifications, robot performance, and environments.

In this research, the purpose is to design the new algorithm for path planning and obstacle avoidance to support AGV in Hard Disk Drive manufacturing. Normally, the main purpose to apply the robotics system in manufacturing is for replacing human workers because they can reduce high labor cost in operation. In addition, the static obstacles on factory are the normal condition that it will have more than one obstacle as station to support process operation in process. Non-collision system is main key of this research to avoid the accidents. This research is focused on the real layout of Hard Disk Drive in Seagate Technology (Thailand) Ltd, where AGV is working in factory operation. Moreover, the path planning searching is the one of main processes. W. Ojenge et al. studied about the Particle Swarm Optimization and Genetic Algorithm (GA) on mobile traffic jam times prediction. Their results indicated the better performance on PSO than GA in case of model prediction performance [30]. C.-C. Chiu et al. compared the PSO and GA in an urban area for the path loss reduction. They used GA and PSO for excitation voltage optimization on high order nonlinear optimization problem. The results show that the PSO is better than GA in term of performance in reduction of path loss [31]. V. Kachitvichyanukul studied the differences of Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Differential Evolution (DE). The results show that GA is appropriate for discrete but PSO and DE are appropriate for continuous optimization system. PSO shows better performance in terms of tendency for premature convergence and influence of best solution on population. In addition, the performances without local search to reach good solution and homogeneous sub-grouping convergence improvement are the one of good points from PSO also [32]. This main reason why this research selects the PSO is the good point and good performance from previous study on many researchers such as the performance to find the one of the best solutions and premature convergence trends. However, the path planning and obstacle avoidance algorithm cannot finish by using only the total distance along the path for PSO processing. It required the additional condition for obstacle avoidance. The fitness function inside PSO is modified on this research to support the shortest path without collision condition.

2. **Particle Swarm Optimization.** Particle Swarm Optimization (PSO) algorithm is introduced by Dr. Eberhart and Dr. Kennedy [1995] [15]. It is the one of optimization techniques which used nature bird convergence concept. The particle randomly moves through the space at each iteration. The objective is to search the best solution which can be defined by objective function. The properties of each particle are position (x_i) and velocity (v_i). Swarm is the set of particles. p_i (P_{Best}) is best fitness value so far and g_i (G_{Best}) is best value so far from population. The velocity and position are calculated by Equation (1) and (2) respectively.

$$v_{ij}^{t+1} = wv_{ij}^{t} + r_1^t c_1 \left(p_{ij}^t - x_{ij}^t\right) + r_2^t c_2 \left(g_{ij}^t - x_{ij}^t\right) \tag{1}$$

$$x_{ij}^{t+1} = x_{ij}^{t} + v_{ij}^{t+1} \tag{2}$$

where w is inertia, r_1 and r_2 are positive number in random, and c_1 and c_2 are acceleration coefficients. The inertia weight is decreasing function in linearity.

The PSO algorithm process flow is shown in Figure 4. The process starts from parameter initialization. The position, velocity, particle, swarm, dimensions, swarm size and number of iterations have been set in initial phase. The position number (r) has been run in random condition between 0 to 1. Then, the PSO process will start calculation on Equation (1) and Equation (2) until it meets criteria. The fitness function or objective function is calculated to check the best value before continuing to the next process. All of PSO process will be stopped when it reaches the stopping criteria.

The vector of PSO calculation on Figure 5 is related with Equation (1) and (2). The positive number (r) and acceleration coefficient (c) are the important parameters on PSO process because there are the multiplication factors on Equation (1). The weight of vector will be changed by these parameters. It means that the next particle position will be changed also.

3. **Obstacle Avoidance with PSO.** One of key processes of this research is the obstacle avoidance and the obstacle avoidance function is designed by this research. In addition, this research combined the PSO method and obstacle avoidance function to find the best solution. Equation (3) is an equation for distance calculation between AGV's position (x_r, y_r) and obstacle's position (x_o, y_o).

$$d = \sqrt{(x_r - x_o)^2 + (y_r - y_o)^2} \tag{3}$$

Figure 6 shows the safety region between AGV and obstacle from Equation (3) but it is calculated from the center point of AGV and obstacle only. This condition is enough for model calculation in point to point but it cannot represent the real condition of robot in the real environment.

The equation for real gap calculation is shown in Equation (4) where R is the radius of obstacle region and r is radius of AGV region from Pythagoras theorem.

$$d_r = d - R - r \tag{4}$$

where $R = \sqrt{\left[\frac{w_o}{2}\right]^2 + \left[\frac{l_o}{2}\right]^2}$, $r = \sqrt{\left[\frac{w_r}{2}\right]^2 + \left[\frac{l_r}{2}\right]^2}$, w_o is width of obstacle, l_o is length of obstacle, w_r is width of AGV, and l_r is length of AGV.

Obstacle Avoidance function (OA) is shown in Equation (5) where α is positive number in range $(1, 2)$.

$$OA = \max\left(1 - \alpha * \frac{d}{R + r}, 0\right) \tag{5}$$

From Table 1, the OA value is convergent to 1 on high risk for crashing condition. When the OA value is convergent to 0, it is the low risk for crashing condition. However, the best condition is the condition that OA value shows 0 but it is only normal condition

on empty area. The OA value on area with obstacle will converge to 0. On this research, the results from obstacle avoidance function will be taken into account for fitness function calculation on PSO.

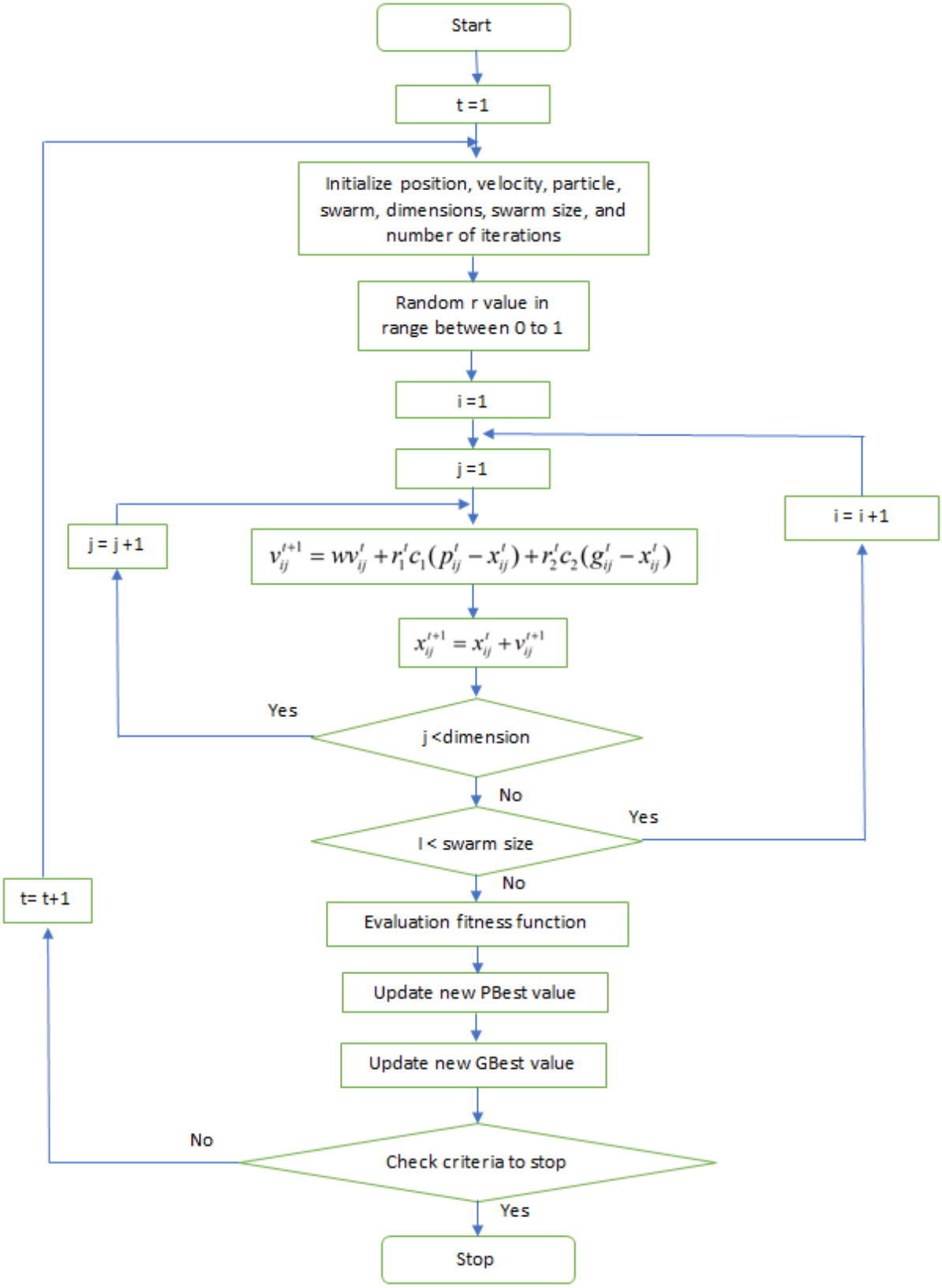

FIGURE 4. PSO algorithm process flow

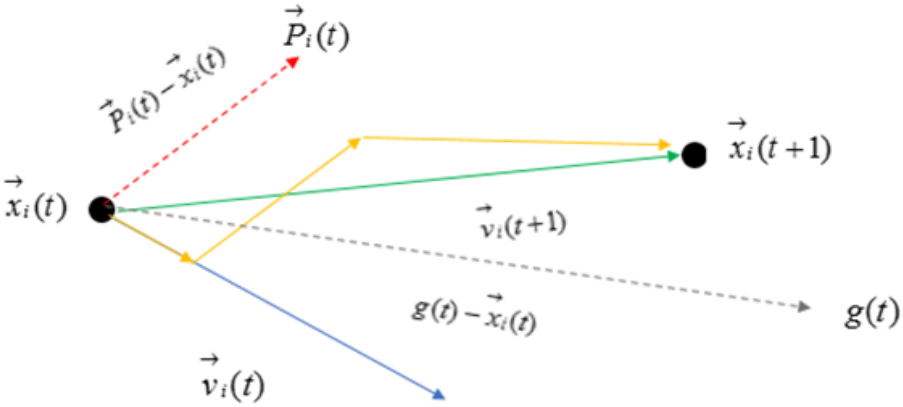

FIGURE 5. Vector of PSO calculation

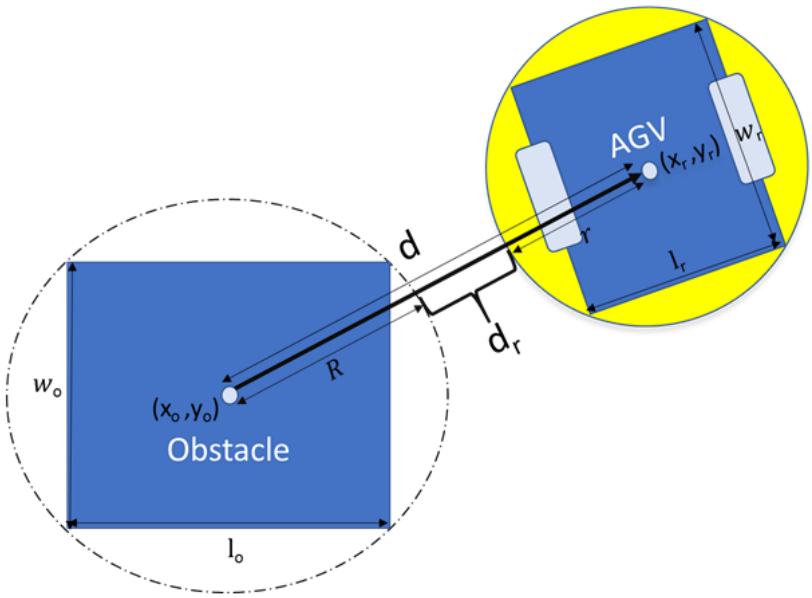

FIGURE 6. Safety region model

TABLE 1. Condition of obstacle avoidance function

Condition	OA value	AGV and Obstacle
$d < R + r$	➔1 ➔0	High risk for crashing Low risk for crashing
$d = R + r$	0	Restriction zone
$d > R + r$	0	Safety zone

4. **Interpolation.** Interpolation is the new data points construction from the range of known data points. The data missing between points will be filled from interpolation by estimation.

4.1. **Linear interpolation.** The simplest form of interpolation is linear interpolation. The concept is to connect straight line with data points. The linear equation is shown in Equation (6).

$$y = f(x) = Ax + B \tag{6}$$

where A is slope, and B is y-intercept. The data in $[a, c]$ are estimated for straight line creation. From Equation (6), it can be substituted by a and c as Equations (7) and (8)

respectively.

$$f(a) = Aa + B \tag{7}$$

$$f(c) = Ac + B \tag{8}$$

After solving the problem, A and B are shown in Equations (9) and (10).

$$A = \frac{f(c) - f(a)}{c - a} \tag{9}$$

$$B = f(c) - \frac{f(c) - f(a)}{c - a}c \tag{10}$$

Substitute A and B into Equation (6) to find $f(b)$ in Equation (11) where $a \leq b \leq c$.

$$f(b) = \frac{f(c) - f(a)}{c - a}b + \left[f(c) - \frac{f(c) - f(a)}{c - a}c\right] \tag{11}$$

Linear interpolation needs at least 2 data points for calculation to find the coefficient of Equation (11).

4.2. **Cubic-spline interpolation.** For cubic-spline interpolation, it is a piecewise polynomial using not-a-knot end conditions. About the third order polynomial, the equation will be shown as Equation (12).

$$y = f(x) = \alpha_3 x^3 + \alpha_2 x^2 + \alpha_1 x + \beta_1 \tag{12}$$

The coefficients for Equation (12) are computed on each interval by using the adjacent data points to make smooth line from point to point. However, the cubic-spline needs adjacent data points at least 4 points for calculation of 4 unknown coefficients $(\alpha_3, \alpha_2, \alpha_1, \beta_1)$.

The graph of data points with interpolation between linear and cubic-spline is shown in Figure 7. The graph from cubic-spline will be smoother than linear due to polynomial term.

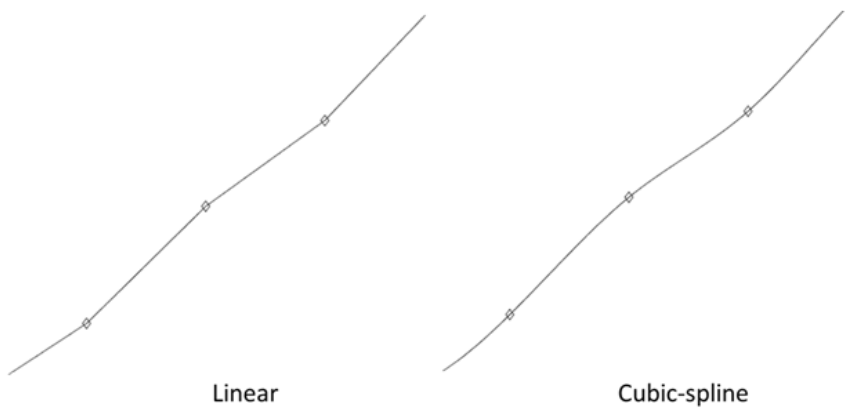

FIGURE 7. Data points with linear interpolation and cubic-spline interpolation

5. **Proposed Method.** In this research, the proposed method is the Particle Swarm Optimization for path planning with obstacle avoidance based on the layout from Seagate Technology (Thailand) Ltd (Hard Disk Drive manufacturing). The fitness function and obstacle avoidance are the new ones which are developed in this research. The fitness function inside PSO for path planning calculation is shown in Equation (13)

$$L = \sum_{i=1}^{n-1} \left[\sqrt{(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2}\right] \tag{13}$$

The fitness function on this research is the distance between start point to target point (goal) for path planning. Equation (13) represents the distance which is calculated sum of distance between point to point on the path from start point to target point. (x_i, y_i) is the position in 2D space. However, the results from Equation (13) can be used for path planning only. This research designed the fitness function for this system. New fitness function is shown in Equation (14) where OA is Equation (5), L is Equation (13), γ is coefficient for distance and β is coefficient for OA value (safety factor).

$$Z = \gamma * L * + \beta * OA \tag{14}$$

The inertia weight for PSO calculation will use value from the multiplication between weight and weight damping ratio as shown in Equation (15).

$$w_{i+1} = wdamp * w_i \tag{15}$$

The searching process will be started until it found minimum value of fitness function and OA is in minimum value in range $(0, 1)$. It means that the algorithm needs to find minimum value on both fitness function and OA function to conclude the best solution.

The process flow of proposed algorithm is shown in Figure 8. The algorithm will be stopped when it met stopping criteria. The minimum value of OA and fitness are concerned for each iteration loop to find the best solution.

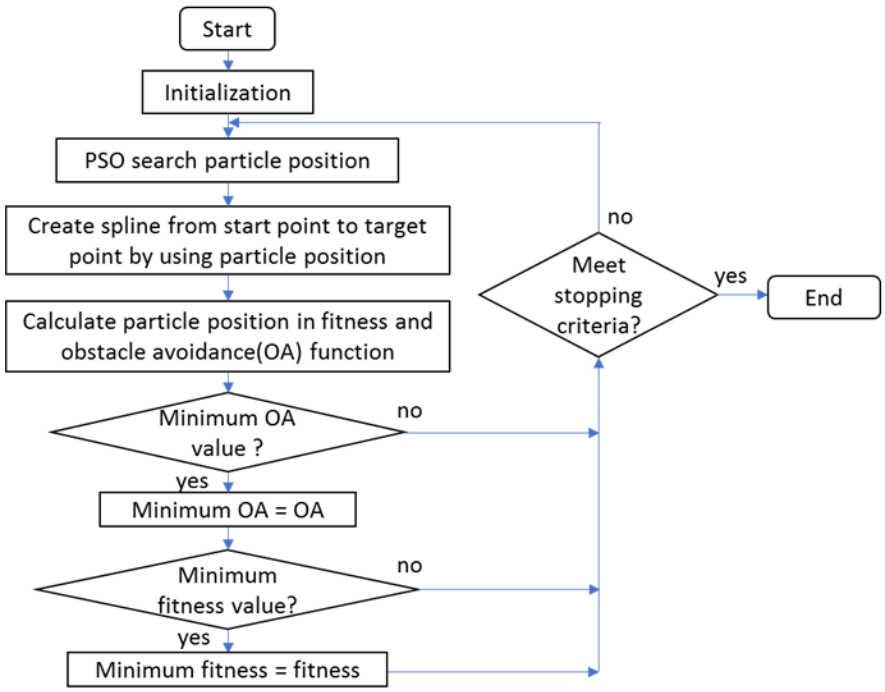

FIGURE 8. Process flow of proposed algorithm

6. **Simulation Results.** The simulation is done by MATLAB with 200 iterations because the value will be saturated after 100 iterations. More than 100 iterations are required to find the accurate value. The number of handling points is set to 30 with 200 population sizes (swarm size) to support 20×22 unit^2 on model environments. The inertia weight is set to 1 with 0.99 inertia weight damping ratio as literature review. The acceleration coefficient is set to 1.4 because it represents the repeatability of fitness value after testing with model. In simulation, the start point and target point will be shown as Figure 9 which shows the path planning results on the model. This research simulates the results of path planning from PSO and obstacle avoidance function. However, the connecting path

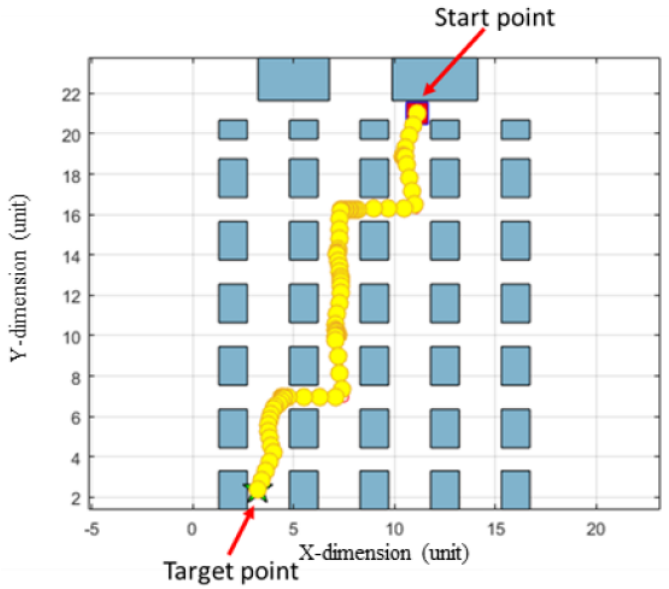

FIGURE 9. Path planning results with start and target point

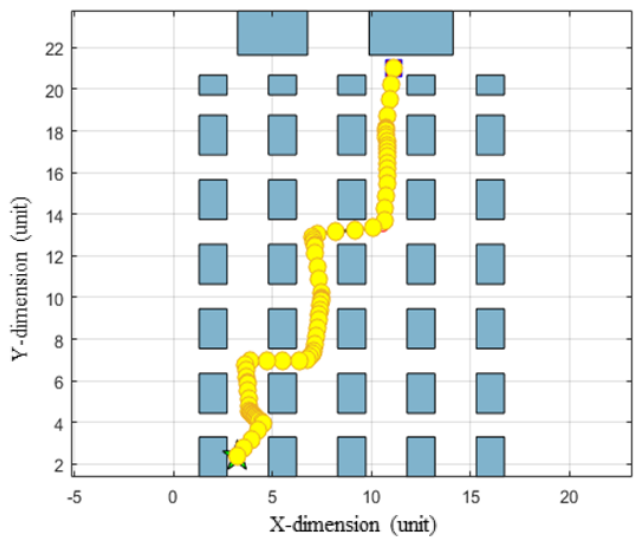

FIGURE 10. Path results on model with linear interpolation

is one of important sections to create path from point to point. The linear interpolation and cubic spline interpolation are simulated on the model of this research.

Figures 10 and 11 show the path results from proposed method on the simulation model by using linear interpolation and cubic-spline interpolation. Figure 12 shows the value of fitness function on each iteration. Fitness function values of spline (orange line) in Figure 12 are under the value of linear (blue line) after 43th iteration until 200th iteration. In Figure 13, the spline shows the obstacle avoidance function less than linear interpolation also.

The results from cubic-spline interpolation with proposed method are better than the results from linear interpolation in terms of minimum fitness value and minimum OA value. However, the total distance (L) from linear interpolation is 25.2801 units but the total distance from cubic-spline interpolation is 25.8663. It means that the total distance from linear interpolation is less than the total distance from cubic-spline interpolation.

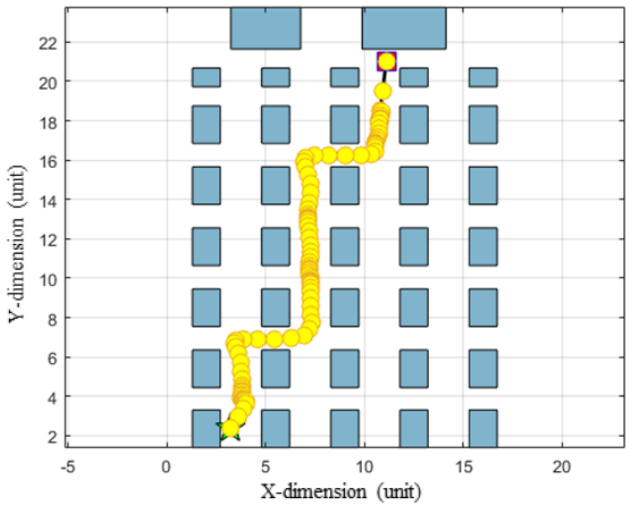

FIGURE 11. Path results on model with cubic-spline interpolation

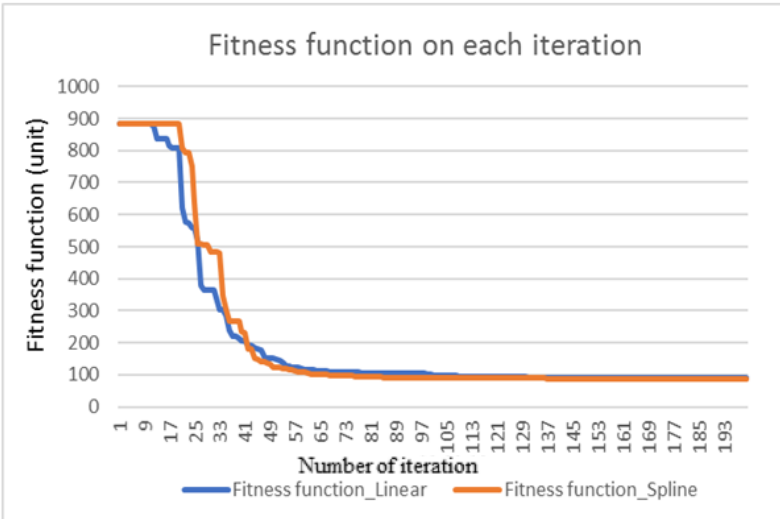

FIGURE 12. Fitness function on each iteration of linear interpolation and cubic-spline interpolation

The reason why the fitness value from cubic-spline is smaller than linear is the OA value from Equation (5). Cubic-spline can make curve path due to the third order polynomial calculation and curve path effect the high ratio of $\frac{d}{R+r}$. From Table 1, the OA value will converge to 0 on this case. Moreover, OA is in Equation (14) for fitness function calculation. Minimum OA value will affect minimum fitness function also.

In addition, the first path of cubic-spline in Figure 11 is still one problem because cubic-spline cannot generate the point along the first path (start point to first point). However, this result can affect the path results for AGV. The AGV has a risk to crash to the obstacle on this case because no data point is taken into fitness function calculation. The reason is that the cubic-spline concept needs to know data points at least 4 points to solve the coefficient of Equation (12). From this reason, the samples of data point need to increase to solve first phase problem from cubic-spline interpolation results. Total data points on interpolation process are changed from 100 to 200 for simulation. The new path results on model with cubic-spline interpolation at 200 total data points for interpolation process are shown in Figure 14 and it shows that the start point to first path can be

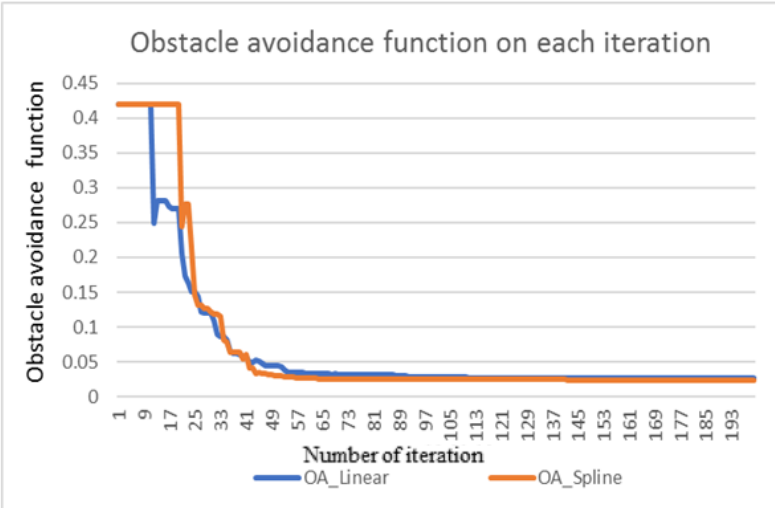

FIGURE 13. Obstacle avoidance function on each iteration of linear interpolation and cubic-spline interpolation

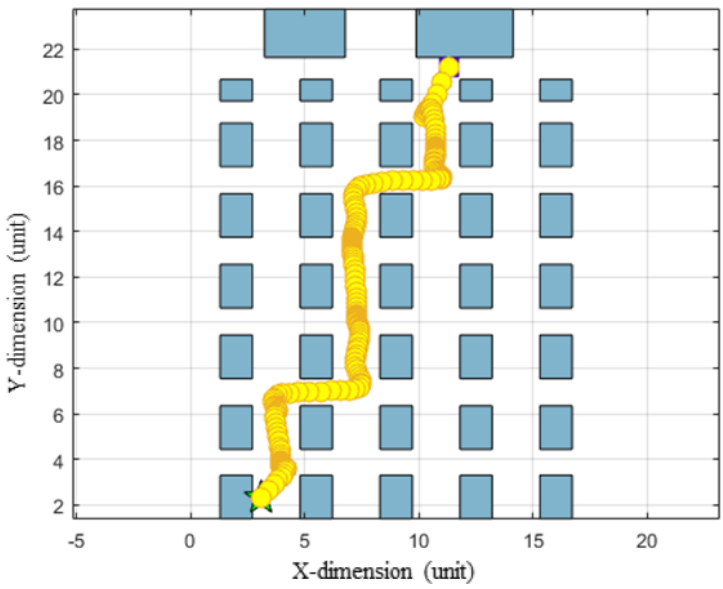

FIGURE 14. Path results on model with cubic-spline interpolation with 200 data points for interpolation

connected together after data points increasing. Then, the new data point results are compared in terms of fitness function, obstacle avoidance function and total distance as shown in Figures 15-17.

In Figure 15, the results of fitness function between linear and cubic-spline interpolation with 100 and 200 data points show the minimum fitness function on cubic-spline at 200 data points. In Figure 16, the results of obstacle avoidance show the same trend as fitness function due to the relationship on Equation (14).

In Figure 17, the total distance results show the opposite trend. The total distance results from linear interpolation are less than the cubic-spline interpolation and the increasing of data point can affect the high value of total distance on both interpolation method but the OA value is reduced after data point increasing. 200 data points are better than the previous in term of risk for crashing. This research selects cubic-spline interpolation with proposed method for next simulation.

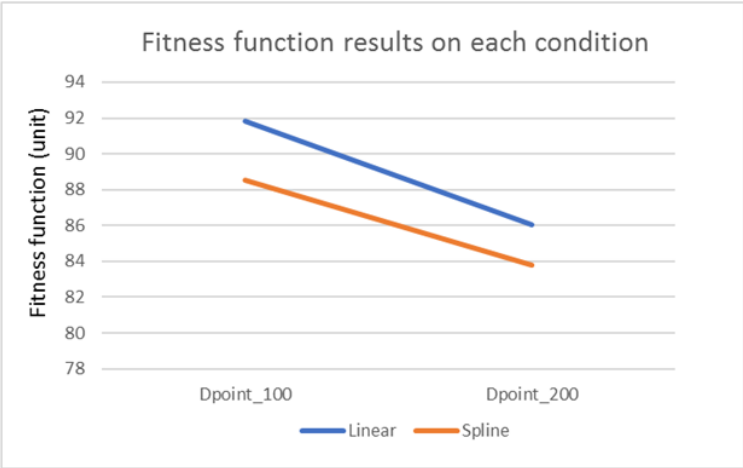

FIGURE 15. Fitness function results between linear and cubic-spline interpolation with 100 and 200 data points

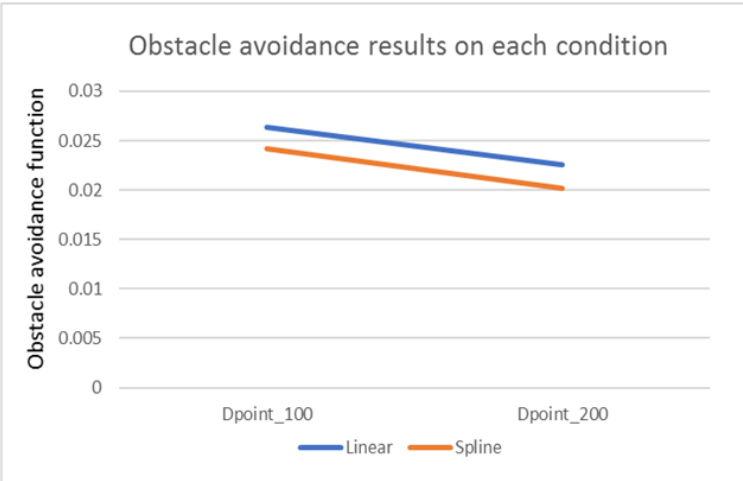

FIGURE 16. Obstacle avoidance function results between linear and cubic-spline interpolation with 100 and 200 data points

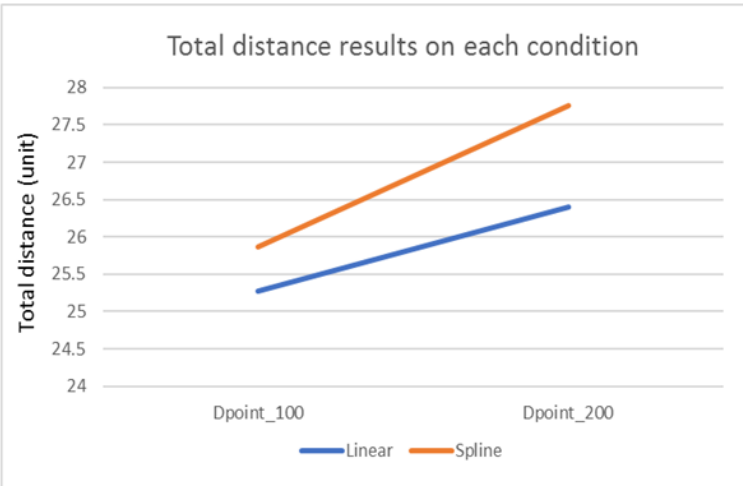

FIGURE 17. Total distance results between linear and cubic-spline interpolation with 100 and 200 data points

In practical situation of manufacturing, the layout on manufacturing can be changed due to factory requirements. This research simulated the layout which is not straight line as previous layout. The layout changed condition is referred to layout plan of Seagate Technology (Thailand) Ltd. Figure 18 shows the path results between the shortest path and safety path on layout changed condition. The total distance on shortest path is 18.81 and safety path is 22.29. However, the OA value that it can represent the risk of collision shows 0.165 on shortest path and 0.007 on safety path. The result shows that the shortest path is better in term of minimum total distance but it shows high risk for collision. In case of safety path, it shows higher total distance but the risk of collision is very low and it is a good choice for factory because the safety is first priority.

On layout changed condition, this research creates new layout by adjusting the gap to verify the model performance. Then, the results have been compared between shortest path and safety path in Figure 19.

Figure 19 shows the right to left path results between shortest path and safety path on new layout. The shortest path shows high risk of collision and the safety path shows low risk for collision as same as the results from Figure 18. For numeric data, the total distance from shortest path is 21.87 and safety path is 25.51 but the OA value from shortest path is 0.2244 and safety path is only 0.0081.

The left to right path results between shortest path and safety path are shown in Figure 20. In Figure 20, the shortest path still shows high risk of collision on this path and the safety path shows low risk for collision as Figure 18 and Figure 19. The total distance of shortest path is 21.75 and safety path is 28.97. The OA value of shortest path is 0.2062 and safety path is only 0.0083. The results in Figures 18-20 illustrate the better performance for obstacle avoidance on safety path from proposed method of this research than the conventional shortest path searching.

7. **Conclusions.** This research considered path planning on particle swarm optimization with obstacle avoidance for AGV in Hard Disk Drive manufacturing. The main purpose is to develop the new algorithm for safety constraint to avoid the accident in manufacturing by using particle swarm optimization for low risk of collision path searching. The process step for model calculation starts at PSO and stops when it meets the stopping criteria. However, the goal for searching is combined between the obstacle avoidance function and total distance to find the minimum results. The minimum of fitness function can represent

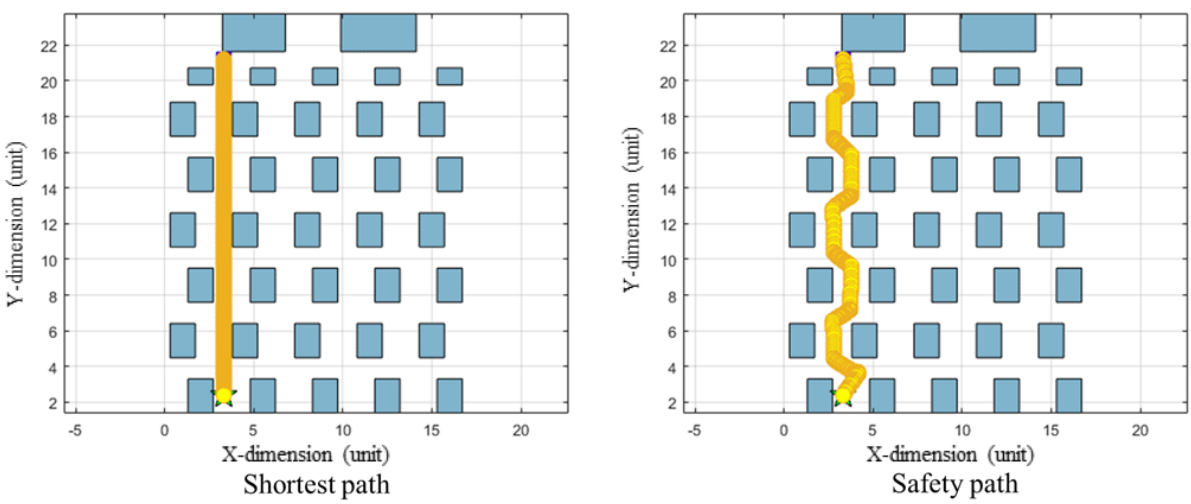

FIGURE 18. Path results between shortest path and safety path

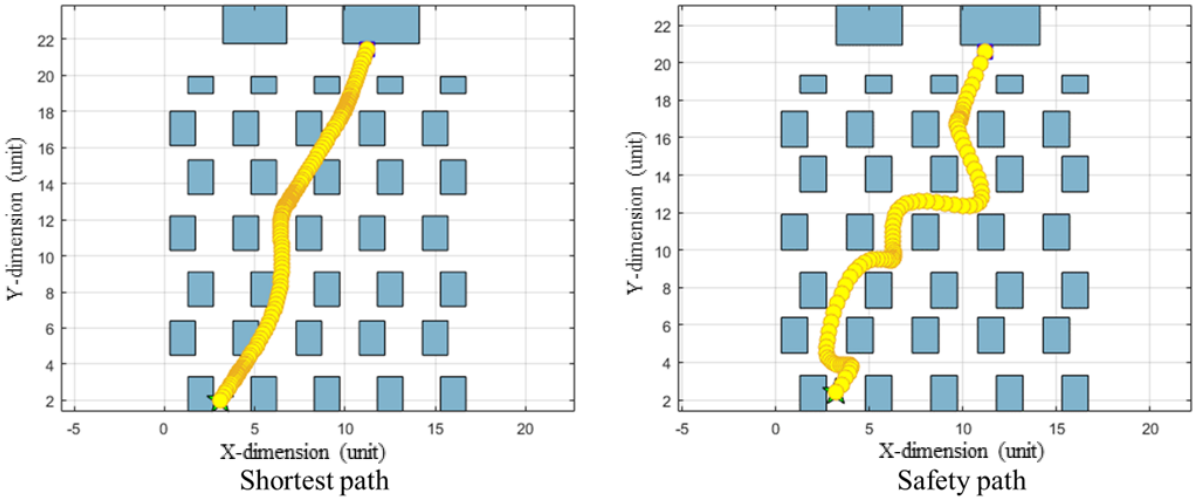

FIGURE 19. Right to left path results between shortest path and safety path on new layout

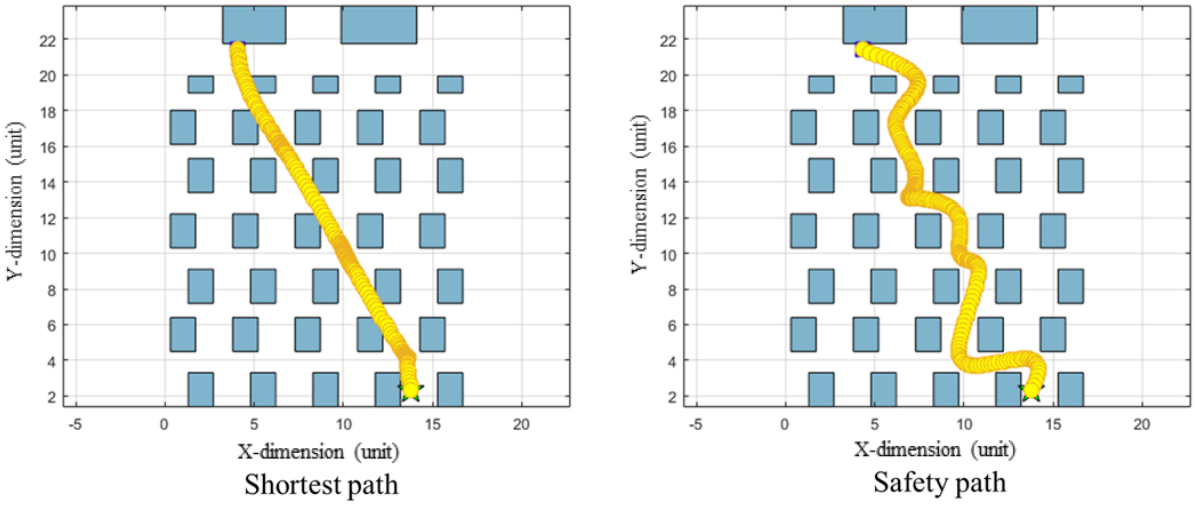

FIGURE 20. Left to right path results between shortest path and safety path on new layout

the low risk for collision and shortest path but the priority is set to non-collision. The minimum value of obstacle avoidance function shows the low risk for collision between AGV and obstacle. Inside the model, the PSO results will report the particle position on each point. The model is required interpolation on the system to connect path between point to point for robot path from start point to target point. 2 interpolations which are linear and cubic-spline are tested. The performance from cubic-spline interpolation is better than linear interpolation for obstacle avoidance on layout from Seagate Technology (Thailand) Ltd, and changeable layout plan. In addition, the results from proposed method of this research illustrate good performance on safety path when it is compared between the conventional shortest path searching and safety path searching on this research. This model can be applied for Hard Disk Drive manufacturing of Seagate Technology (Thailand) Ltd with safety constraint.

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REFERENCES

[1] P. Alexandros, L. Rudolf, P. Jan and N. Gerhard, Probabilistic prioritization of movement primitives, *IEEE Robotics and Automation Letters*, vol.2, no.4, pp.2294-2301, 2017.

[2] G. Han, H. Wang, S. Li, J. Jiang and W. Zhang, Probabilistic neighborhood location-point covering set-based data collection algorithm with obstacle avoidance for three-dimensional underwater acoustic sensor networks, *IEEE Access*, vol.5, pp.24785-24796, 2017.

[3] C. Evers and P. A. Naylor, Optimized self-localization for SLAM in dynamic scenes using probability hypothesis density filters, *IEEE Trans. Signal Processing*, vol.66, no.4, pp.863-878, 2018.

[4] M. A. Abbas, R. Milman and J. M. Eklund, Obstacle avoidance in real time with nonlinear model predictive control of autonomous vehicles, *Canadian Journal of Electrical and Computer Engineering*, vol.40, no.1, pp.12-22, 2017.

[5] A. K. Kar, N. K. Dhar, S. S. F. Nawaz, R. Chandola and N. K. Verma, Automated guided vehicle navigation with obstacle avoidance in normal and guided environments, *The 11th International Conference on Industrial and Information Systems (ICIIS)*, India, 2016.

[6] T. Nageli, J. Alonso-Mora, A. Domahidi, D. Rus and O. Hilliges, Real-time motion planning for aerial videography with dynamic obstacle avoidance and viewpoint optimization, *IEEE Robotics and Automation Letters*, vol.2, no.3, pp.1696-1703, 2017.

[7] 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.

[8] 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.

[9] S. Koziol, R. Wunderlich, J. Hasler and M. Stilman, Single-objective path planning for autonomous robots using reconfigurable analog VLSI, *IEEE Trans. Systems, Man, and Cybernetics: Systems*, vol.47, no.7, pp.1301-1314, 2017.

[10] P. Grosch and F. Thomas, Geometric path planning without maneuvers for nonholonomic parallel orienting robots, *IEEE Robotics and Automation Letters*, vol.1, no.2, pp.1066-1072, 2016.

[11] S. Yeasmin, P. C. Shill and A. K. Paul, A new method for smooth trajectory planning for 3R robot arm using enhanced particle swarm optimization algorithm, *The 3rd International Conference on Electrical Information and Communication Technology (EICT)*, Bangladesh, 2017.

[12] N. Setyawan, R. E. A. Kadir and A. Jazidie, Adaptive gaussian parameter particle swarm optimization and its implementation in mobile robot path planning, *International Seminar on Intelligent Technology and Its Application*, Indonesia, 2017.

[13] M. R. Panda, R. Priyadarshini and S. K. Pradhan, Autonomous mobile robot path planning using hybridization of particle swarm optimization and tabu search, *IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)*, India, 2016.

[14] A. D. Falehi and M. Rafiee, Novel optimal harmonic mitigation based on MOPSO to control switching of ODD-nary multilevel inverter, *International Journal of Innovative Computing, Information and Control*, vol.14, no.1, pp.243-260, 2018.

[15] A. Ayari and S. Bouamama, Collision-free optimal paths for multiple robot systems using a new dynamic distributed particle swarm optimization algorithm, *Proc. of the 18th International Conference on Advanced Robotics (ICAR)*, China, 2017.

[16] L. Liao, X. Cai, H. Huang and Y. Liu, Improved dynamic double mutation particle swarm optimization for mobile robot path planning, *Chinese Control and Decision Conference (CCDC)*, China, 2016.

[17] N. Mizuno and C. H. Nguyen, Parameters identification of robot manipulator based on particle swarm optimization, *The 13th IEEE International Conference on Control & Automation (ICCA)*, Macedonia, 2017.

[18] M. K. Rath and B. B. V. L. Deepak, PSO based system architecture for path planning of mobile robot in dynamic environment, *Proc. of Global Conference on Communication Technologies (GCCT 2015)*, India, 2015.

[19] Z. Nie, X. Yang, S. Gao, Y. Zheng, J. Wang and Z. Wang, Research on autonomous moving robot path planning based on improved particle swarm optimization, *IEEE Congress on Evolutionary Computation (CEC)*, Canada, 2016.

[20] Y. Guo, W. Wang and S. Wu, Research on robot path planning based on fuzzy neural network and particle swarm optimization, *The 29th Chinese Control and Decision Conference (CCDC)*, China, 2017.

[21] Z. Wang, X. Xiang, J. Yang and S. Yang, Composite Astar and B-spline algorithm for path planning of autonomous underwater vehicle, *IEEE the 7th International Conference on Underwater System Technology: Theory and Applications (USYS)*, Malaysia, 2017.

[22] A. Khan, I. Noreen and Z. Habib, Coverage path planning of mobile robots using rational quadratic B'ezier spline, *International Conference on Frontiers of Information Technology*, Pakistan, 2016.

[23] Y. Wang, W. Cai and Y. R. Zheng, Dubins curves for 3D multi-vehicle path planning using spline interpolation, *OCEANS*, Anchorage, USA, 2017.

[24] D. Lee, H. Song and D. H. Shim, Optimal path planning based on spline-RRT* for fixed-wing UAVs operating in three-dimensional environments, *The 14th International Conference on Control, Automation and Systems (ICCAS 2014)*, South Korea, 2014.

[25] K. Yang, S. K. Gan, J. Huh and S. Joo, Optimal spline-based RRT path planning using probabilistic map, *The 14th International Conference on Control, Automation and Systems (ICCAS 2014)*, South Korea, 2014.

[26] N. Arana-Daniel, A. A. Gallegos, C. L'opez-Franco and A. Y. Alanis, Smooth global and local path planning for mobile robot using particle swarm optimization, radial basis functions splines and B'ezier curves, *IEEE Congress on Evolutionary Computation (CEC)*, China, 2014.

[27] M. Neubauer and A. Müller, Smooth orientation path planning with quaternions using B-splines, *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Germany, 2015.

[28] S. Zhang, L. Sun, Z. Chen, X. Lu and J. Liu, Smooth path planning for a home service robot using η^3-Splines, *IEEE International Conference on Robotics and Biomimetics*, Indonesia, 2014.

[29] D. Lee and D. H. Shim, Spline-RRT* based optimal path planning of terrain following flights for fixed-wing UAVs, *The 11th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI 2014)*, Malaysia, 2014.

[30] W. Ojenge, W. Okelo-Odongo and P. Ogao, Comparing PSO and GA optimizers in MLP to predict mobile traffic jam times, *International Journal of Computer Science and Information Security (IJCSIS)*, vol.13, no.10, pp.19-30, 2015.

[31] C.-C. Chiu, Y.-T. Cheng and C.-W. Chang, Comparison of particle swarm optimization and genetic algorithm for the path loss reduction in an urban area, *Journal of Applied Science and Engineering*, vol.15, no.4, pp.371-380, 2012.

[32] V. Kachitvichyanukul, Comparison of three evolutionary algorithms: GA, PSO, and DE, *Industrial Engineering & Management Systems*, vol.11, no.3, pp.215-223, 2012.