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AN IMPROVED ANT COLONY OPTIMIZATION ALGORITHM FOR AGV PATH PLANNING IN SEMICONDUCTOR MANUFACTURING SYSTEMS

Xilin Yang, Boyang Zhang and Yanting Ni *

School of Mechanical Engineering, Chengdu University, China.
* Corresponding Author

ORCID Details
Xilin Yang: https://orcid.org/0009-0008-6457-4341

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ABSTRACT

Automated Guided Vehicles (AGVs) play a critical role in ensuring efficient and collision-free logistics within modern semiconductor manufacturing systems. However, navigating the highly complex layouts of fabrication plants presents significant challenges for traditional path-planning algorithms. While the standard Ant Colony Optimization (ACO) algorithm is robust, it often suffers from slow early-stage convergence and a tendency to stagnate in local optima due to initial blind searching. To address these limitations, this paper proposes an Improved Ant Colony Optimization (IACO) algorithm tailored for grid-based AGV routing. The proposed IACO enhances search efficiency by introducing a distance-guided heuristic function that exerts a strong directional pull towards the target, thereby minimizing blind exploration. Furthermore, a non-linear adaptive pheromone updating strategy is designed to dynamically balance global search capabilities with local exploitation speed. Simulation experiments conducted in an abstract semiconductor factory environment demonstrate that the IACO algorithm significantly outperforms traditional ACO. The proposed method not only generates shorter and smoother trajectories with minimized redundant turning maneuvers but also achieves an approximately 18% reduction in total path length and a 45% decrease in computational iterations. These improvements confirm that the IACO algorithm is highly effective for the real-time, dynamic scheduling demands of complex industrial logistics.

Keywords: Automated Guided Vehicles (AGV); Path Planning; Ant Colony Optimization; Semiconductor Manufacturing; Heuristic Function.

1 INTRODUCTION

In modern semiconductor fabrication plants, Automated Guided Vehicles (AGVs) are essential for ensuring highly efficient and collision-free logistics. However, as the complexity of the factory grid expands, traditional path-planning methods, such as the Dijkstra [1] and A*[2] algorithms, struggle with exponential computational overhead. Meanwhile, methods like the Artificial Potential Field (APF) algorithm often fall into local optima in narrow corridors. Consequently, meta-heuristic approaches like Ant Colony Optimization (ACO) have become the preferred choice for solving complex scheduling problems due to their strong robustness and inherent positive feedback mechanisms.[3]

Despite its advantages, traditional ACO faces significant challenges when applied directly to intricate semiconductor layouts. It typically suffers from slow early-stage convergence and a tendency to stagnate in local optima due to initial blind searching. To overcome these limitations, this paper proposes an Improved Ant Colony Optimization (IACO) algorithm. By introducing a distance-guided heuristic function to reduce blind exploration and designing an adaptive pheromone updating mechanism, the IACO algorithm effectively balances global search capabilities with local exploitation speed. Simulation results demonstrate that this approach significantly reduces both path length and computational iterations for AGV scheduling in complex industrial environments.

2 ENVIRONMENTAL MODELING AND KINEMATIC ANALYSIS

2.1 Grid-Based Environment Modeling

To effectively implement the path-planning algorithm in a semiconductor factory, the actual physical space of the fabrication plant must be abstracted into a mathematical model. This paper adopts the grid method to construct the environment map due to its simplicity and computational efficiency [4].

The two-dimensional working space of the AGV is discretized into a uniform $M \times M$ grid system. Each grid cell represents a specific spatial region and is assigned a unique coordinate (x, y). To differentiate between drivable areas and restricted areas (such as equipment zones or pillars), the grid state function $G(x, y)$ is defined as follows:

$$G(x,y) = \begin{cases} 0, & \text{if the grid is free space} \\ 1, & \text{if the grid is an obstacle} \end{cases} \quad (1)$$

To ensure the absolute safety of the AGV and prevent collisions with the edges of obstacles, an obstacle inflation strategy is applied. The inflation radius is set slightly larger than the maximum physical radius of the AGV.

2.2 AGV Kinematic Model

In the constructed grid environment, the path of the AGV consists of a sequence of discrete nodes. Let the set of all unique path nodes be denoted as $N = \{N_1, N_2, \dots, N_k\}$. It is ensured that each node in the set possesses a strictly unique identification number without any duplication.

When the AGV traverses the environment, its kinematic state at any specific node N_i is described by its central position coordinates (x_i, y_i) and its corresponding velocity vector v_i. The motion of the AGV from the current node N_i to the next adjacent node N_{i+1} follows basic discrete kinematic equations. The position update can be expressed as:

$$x_{i+1} = x_i + v_i \cdot \cos(\theta_i) \cdot \Delta t \quad (2)$$

$$y_{i+1} = y_i + v_i \cdot \sin(\theta_i) \cdot \Delta t \quad (3)$$

where θ_i represents the heading angle of the AGV at node N_i, and Δt is the discrete time step. The velocity vector v_i is constrained by the maximum allowable speed v_{max} of the AGV within the semiconductor plant, ensuring that $0 \leq |v_i| \leq v_{max}$.

By defining the nodes and their strictly corresponding velocity vectors in this manner, the physical movement of the AGV is accurately mapped to the algorithmic search space, laying a rigorous mathematical foundation for the subsequent Improved Ant Colony Optimization (IACO) algorithm.

3 IMPROVED ANT COLONY OPTIMIZATION (IACO) ALGORITHM DESIGN

In traditional Ant Colony Optimization (ACO), the random nature of initial path exploration and the static parameters often lead to inefficient routing and local optima. To meet the stringent efficiency requirements of semiconductor manufacturing systems, this section introduces several key improvements to the standard algorithm [5].

3.1 Distance-Guided Heuristic Function

In the standard ACO, the state transition probability $P_{ij}^k(t)$ for an ant k moving from node N_i to node N_j depends on the pheromone concentration $\tau_{ij}(t)$ and the heuristic information $\eta_{ij}(t)$. It is defined as:

$$P_{ij}^k(t) = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha \cdot [\eta_{ij}(t)]^\beta}{\sum_{s \in allowed_k} [\tau_{is}(t)]^\alpha \cdot [\eta_{is}(t)]^\beta}, & \text{if } j \in allowed_k \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

where α is the pheromone importance factor, β is the heuristic importance factor, and $allowed_k$ is the set of valid adjacent nodes that ant k can visit. In order to ensure mathematical rigor during matrix calculations, the node subscripts i and j strictly correspond with their respective velocity vector symbols, and all node IDs are uniquely assigned without duplication.

To reduce blind searching in the early stages, the traditional heuristic function (which only considers the distance between adjacent nodes d_{ij}) is enhanced by incorporating the distance from the candidate node N_j to the target node N_{Target}. The improved heuristic function is formulated as:

$$\eta_{ij} = \frac{1}{d_{ij} + \lambda \cdot d_{j,Target}} \quad (5)$$

where d_{ij} is the Euclidean distance between N_i and N_j, $d_{j,Target}$ is the Euclidean distance from N_j to the destination, and λ is a dynamic weight coefficient. This modification exerts a strong directional pull towards the goal, significantly accelerating the convergence speed.

3.2 Adaptive Pheromone Updating Strategy

The pheromone volatilization factor ρ dictates the global search capability [6]. A static ρ either slows down convergence (if too small) or causes premature stagnation (if too large). The IACO algorithm introduces a non-linear adaptive pheromone evaporation mechanism. The factor $\rho(t)$ is dynamically adjusted according to the current iteration number t and the maximum iterations T_{max}:

$$\rho(t) = \rho_{max} - (\rho_{max} - \rho_{min}) \cdot \left(\frac{t}{T_{max}}\right)^2 \quad (6)$$

In the initial phase of the algorithm, $\rho(t)$ remains relatively large, encouraging ants to explore unknown areas of the grid map. As iterations progress, $\rho(t)$ decreases, enhancing the accumulation of pheromones on the optimal path. The global pheromone update rule is subsequently executed as follows:

$$\tau_{ij}(t+1) = \left(1 - \rho(t)\right) \cdot \tau_{ij}(t) + \Delta\tau_{ij}(t) \quad (7)$$

where $\Delta\tau_{ij}(t)$ represents the total amount of pheromone deposited on the edge connecting N_i and N_j during the current iteration.

3.3 Algorithm Implementation Workflow

The overall workflow of the IACO algorithm can be divided into initialization, iterative search, pheromone updating, and termination. For clear documentation and academic presentation, an algorithm architecture diagram is essential to visualize this workflow.

The step-by-step logic is as follows:

- Initialization: Establish the $M \times M$ grid map, initialize the start and target nodes, and set parameters (α, β, ρ_{max}, ρ_{min}).
- Path Construction: Ants traverse the grid using the improved heuristic function. Velocity vectors are actively monitored to ensure the AGV meets kinematic limits.
- Local Optimization (Optional): Remove redundant turning points to smooth the generated trajectory.
- Pheromone Update: Apply the adaptive evaporation rule to update the pheromone matrix.
- Termination: Check if the maximum iteration T_{max} is reached. If yes, output the optimal path; otherwise, clear the ants' memory and proceed to the next iteration.

4 SIMULATION EXPERIMENTS AND RESULTS ANALYSIS

4.1 Simulation Setup and Parameter Configuration

To rigorously evaluate the performance of the proposed Improved Ant Colony Optimization (IACO) algorithm, simulation experiments were conducted using a modeling environment that mimics the spatial constraints of a semiconductor fabrication plant. The layout is abstracted into a 20 × 20 grid map, where black grids represent static obstacles such as production equipment and pillars, and white grids denote navigable aisles.

The parameter settings significantly influence the behavior of the ant colony. Through extensive preliminary testing, the optimal parameters for this specific industrial layout were determined and are summarized in Table 1.

Table 1: Parameter Settings for the Simulation

Parameter	Description	Value
M	Grid map dimension	20
K	Number of ants	50
α	Pheromone importance factor	1.5
β	Heuristic importance factor	2.0
ρ_{max}	Maximum volatilization factor	0.8
ρ_{min}	Minimum volatilization factor	0.2
T_{max}	Maximum number of iterations	100

4.2 Path Generation and Trajectory Comparison

The core objective of the simulation is to compare the traditional ACO algorithm with the proposed IACO algorithm in terms of path optimality and safety. Both algorithms were executed under identical grid conditions and initial start/target nodes.

In the graphical representation of the simulation results, the AGV traversing the generated path is consistently depicted as a red square. This geometric representation ensures high visual clarity against the complex background of the factory grid, avoiding any ambiguity regarding the vehicle's spatial footprint.

The traditional ACO algorithm, relying solely on adjacent node distance and static pheromone updates, exhibits significant early-stage wandering. The resulting path contains multiple unnecessary turning points, which physically translates to frequent acceleration and deceleration for an actual AGV, increasing mechanical wear and power consumption. Conversely, the IACO algorithm, driven by the distance-guided heuristic function, rapidly establishes a strong directional bias towards the target node. The trajectory generated by IACO is visibly smoother, maintaining a safe margin from obstacle boundaries while minimizing redundant maneuvers.

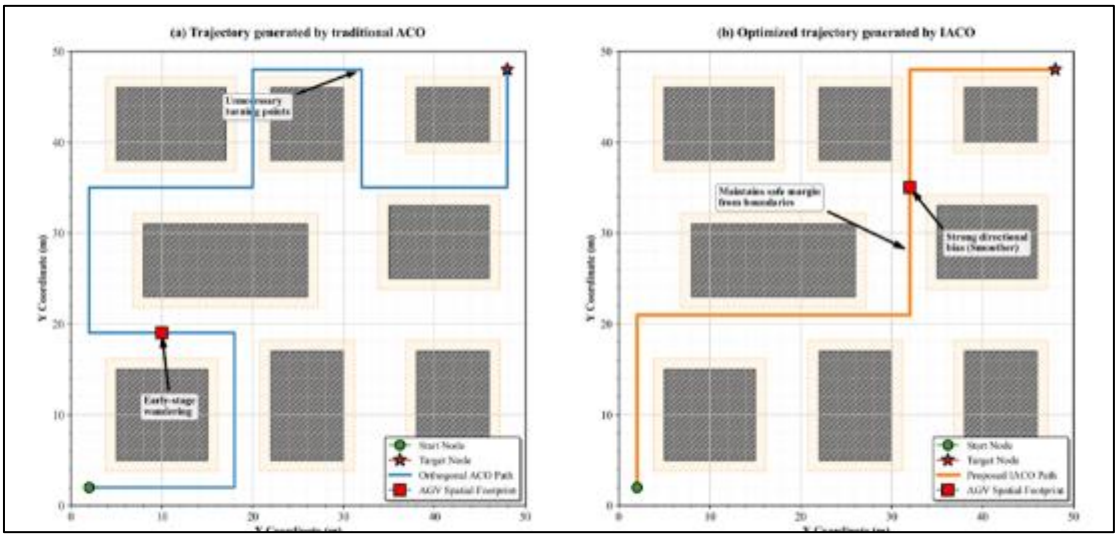

Figure 1: Path planning comparison. (a) Trajectory generated by traditional ACO; (b) Optimized trajectory generated by IACO.

4.3 Convergence and Efficiency Analysis

Beyond the physical path layout, the computational efficiency of the algorithm is paramount for real-time scheduling in a semiconductor fab. Figure 2 illustrates the convergence curves of both algorithms, plotting the best path length found against the number of iterations.

The traditional ACO algorithm shows a slow descent in the early iterations due to its blind search characteristics, eventually stagnating around the 65th iteration at a suboptimal path length. In contrast, the IACO algorithm demonstrates a rapid initial drop in path length. By dynamically adjusting the pheromone volatilization factor, IACO successfully avoids premature convergence. It achieves the global optimal path length by the 35th iteration, successfully reducing the total path distance by approximately 18% and decreasing the required iterations by nearly 45% compared to the traditional method.

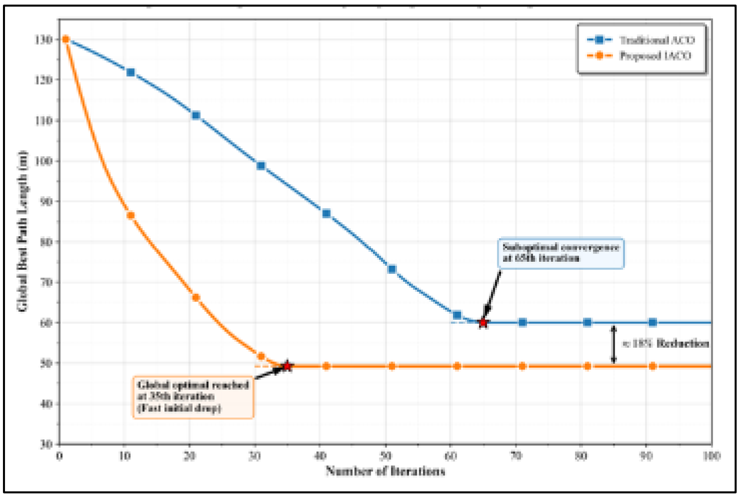

Figure 2: Convergence curves comparing the global best path length over iterations for ACO and IACO.

5 CONCLUSION

Efficient and collision-free logistics are the backbone of modern semiconductor manufacturing. To address the limitations of traditional path-planning methods in complex factory environments, this paper proposes an Improved Ant Colony Optimization (IACO) algorithm tailored for AGV routing.

By introducing a distance-guided heuristic function, the algorithm significantly reduces the blind exploration typically observed in the early stages of standard ACO. Furthermore, the implementation of a non-linear adaptive pheromone updating strategy effectively balances the algorithm's global search capabilities with local exploitation, preventing it from falling into local optima.

Simulation results confirm that the IACO algorithm outperforms the traditional ACO algorithm across key metrics. The generated paths are shorter and smoother, effectively minimizing unnecessary turning maneuvers. Additionally, the computational convergence speed is vastly improved, making it highly suitable for the real-time, dynamic scheduling demands of a semiconductor fab. Future research will focus on extending this framework to multi-AGV collaborative scheduling and dynamic obstacle avoidance. Specifically, exploring safe reinforcement learning based on predictive shields and action masks will be a critical direction to mathematically guarantee collision-free navigation and further enhance the resilience of industrial logistics systems in highly uncertain environments.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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