

SIMULATION APPROACH OF CUTTING TOOL MOVEMENT USING ARTIFICIAL INTELLIGENCE METHOD

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Abstract

In recent years, the productivity of machine tools has been significantly improved by using computer-based CAD/CAM systems for Computer Numerical Control (CNC). Various types of CAM software in the market that provide tool path programming and can be applied for different types of the machining process such as drilling, milling, and turning. However, sometimes the default tool path generated in the CAD/CAM system is not the optimal tool path which produces longer distance and increase the machining time. In this paper, we present cutting tools movement by Genetic Algorithm (GA) and Ant Colony Optimization (ACO) method in generation of shortest tool path. For observation of the performance of both methods, comparisons with conventional method have been carried out. The shortest path of drilling tool path adapts Travelling Salesman Problem (TSP) in determining the distance during machining. The simulation result shows that ACO and GA based tool path optimization is useful to find a lower distance of tool path generation for holes drilling process.

Keywords: Genetic Algorithm, Ant Colony Optimization, Tool path, Simulation.

1. Introduction

Today, the productivity and efficiency of Computer Numerical Control (CNC) machine has been significantly improved by using Computer Aided Design and Computer Aided Manufacturing (CAD/CAM) programming systems. With computer-based CAD/CAM systems, the generation of the G-code file for each cutting and machining process has become easier compared to manual

programming. However, the tool path generated from the CAD/CAM systems is not the guaranteed as optimal tool path and there is possibilities that the tool path distance is longer in order to complete each drilling process. Therefore, optimization of the CNC machine tool path should be done before starting a machining process to ensure the tool path taken will produce the shortest path of cutting tool travel. Realizing on the disadvantage, many researchers are tempted to do research on tool path optimization in order to obtain the optimal cutting tool path.

For instance, in printed circuit board (PCB), Ancau optimized the tool path by focusing on tool path length and processing time [1]. The original hybrid heuristic algorithm was presented to solve the Travelling Salesman Problem (TSP). The algorithm adopted the structure of a general optimization procedure and applied for tool path length. Numerical tests were performed to establish the performance of the heuristic hybrid algorithm. Furthermore, due to tool path planning from commercial CAD software was not fully optimized in terms of tool travel distance, Abbas investigated optimal path planning for CNC drilling machine by Ant Colony Optimization (ACO) [2]. The ACO algorithm was applied to solve the TSP for searching shortest distance of the tool path. However, they focused only for products that involved a large number of holes arranged in a rectangular matrix, such as boiler plates, drum, etc. By using Genetic Algorithm (GA) method, Kumar and Pacahauri [3] and Nabeel et al. [4] also used the Traveling Salesman Problem (TSP) to reduced total time and distance of tool travel for drilling sequence.

Furthermore, due to the G-code generated through CAD/CAM software cannot be considered as route optimization, similar study by Othman et al. [5] has been carried out on tool path optimization by modelling a binary particle swarm optimization (BPSO) algorithm to search an optimized route in PCB holes drilling. In BPSO, each particle represented as possible route of tool path drilling process. The result of BPSO was compared with others previous study done by Zhu [6] and Zhu [7] which focused on Global Convergence Particle Swarm Optimization (GCPSO) and Particle Swarm Optimization.

In this paper, artificial intelligence (AI) methods namely GA and ACO are adapted to determine the optimal tool path and shortest length for drilling process. In addition, comparisons have been done to investigate the method for shorter tool path. Finally, the result of GA and ACO is compared with simulation of conventional CAD/CAM method.

2. Geometrical Model

In this study, we used model of PCB which consist of 76 holes as shown in Fig. 1. The model has a dimension of work piece 8 cm × 10 cm × 2 cm. Each holes with diameter of 0.5 cm and 1.0 cm depth to be drilled. The clearance height is 0.5cm from the work piece. After the drilling of each hole, the tool will rise up from the work piece in z-axis to avoid any contact with the work piece when the tool is moved to the next hole drilling process.

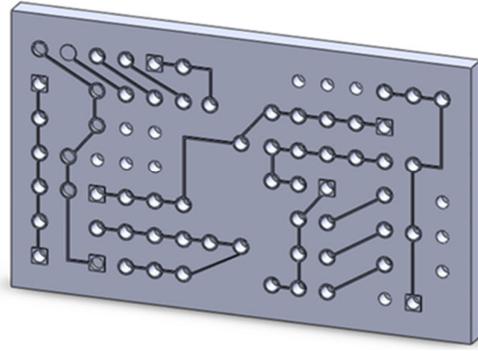


Fig. 1. Models of a printed circuit board.

2.1. Genetic algorithm

In the GA method, four steps are taken which are initialization, selection, reproduction and termination. The GA starts with initialization whereby initial populations are generated by randomly creating a path from the points to be drilled. The populations with the lowest cost will be selected as the parent population in selection step.

The objective function in our tool path optimization is to minimize the travel distance as shown in Eq. (1):

$$f(x, y, z) = d_o + \sum_{i=1}^{n-1} \sum_{j=2}^n \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2} + \sum_{k=1}^n z_k + d_n \quad (1)$$

where d_o is distance from origin to first point, z_k is the value of height from the work piece, d_n is distance from last point to origin, formulated as:

$$d_n = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2} + 2z_k \quad (2)$$

where, x and y are absolute coordinates, and z is the z -axis tool drilling movement at each point.

The reproduction is carried out to create new child populations by using crossover and mutation on the parent populations. Figure 2 shows a single-point crossover for six drilling holes. Each hole represents the number of chromosome. Single-point crossover is performed by randomly selecting a crossover point within a chromosome, and then interchanges the two parent chromosomes at the point to produce child population. TSP is applied in order to prevent same chromosome in child population. Hence, the repeated chromosome is swapped among the two populations. Then, mutation is performed to avoid fast convergence of the solution and create the new path to be explored by randomly selecting a few points in the child population. After the reproduction, the convergence of the objective function is checked for stopping criteria and if the criteria are met, GA will undergo termination. However, if the criteria are not met, GA will repeat the selection and reproduction steps until the stopping criteria are to be met. Flow chart of genetic algorithm is illustrated in Fig. 3.

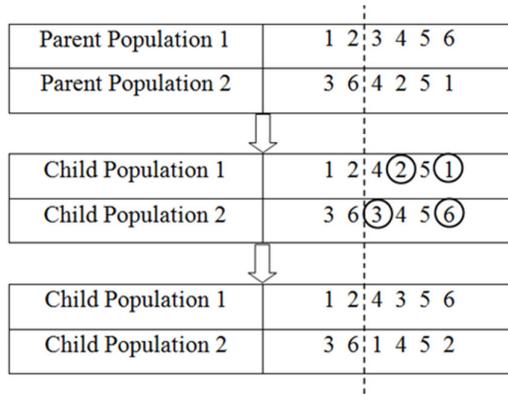


Fig. 2. Single crossover of genetic algorithm.

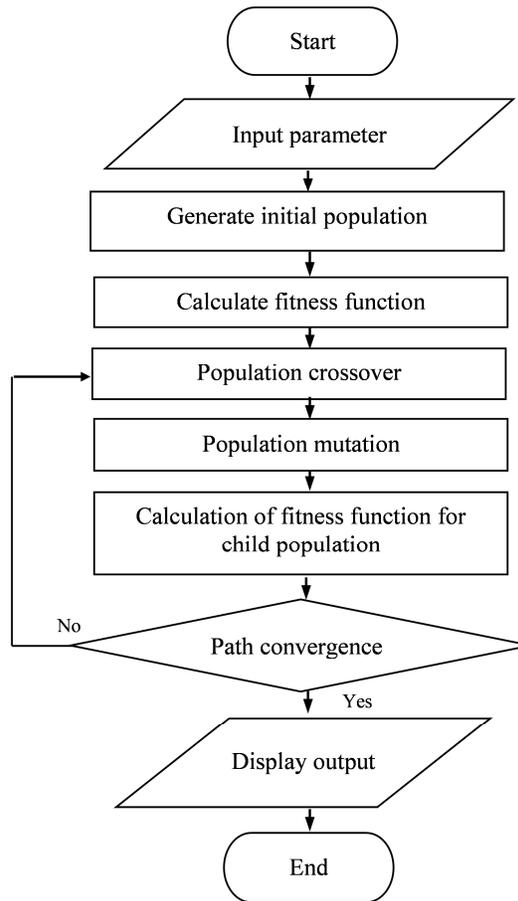


Fig. 3. Flowchart of genetic algorithm.

2.2. Ant colony optimization

In the ACO method, we applied the ant system in the TSP for searching the shortest tool path. Initially, ants are placed on n cities, and it moves from city i to city j using a formula called the rule arbitrary probability as follows:

$$P_{i,j}^k(t) = \frac{[\tau_{i,j}(t)]^\alpha [\eta_{i,j}(t)]^\beta}{\sum_{j \in N_i^k} [\tau_{i,j}(t)]^\alpha [\eta_{i,j}(t)]^\beta} \quad j \in N_i^k \quad (3)$$

where

- N_i^k = list of nodes, which were not visited by the ant
- $\tau_{i,j}(t)$ = intensity of trail on edge (i,j) at time t
- α = weight of the trail
- $\eta_{i,j}(t)$ = $1/d_{ij}$ is called the visibility
- β = weight of the visibility

In this study, the adapted ACO is used to determine the shortest distance of cutting tool movement for holes drilling. Each hole is represented by the cities visited by the salesman in TSP. The fitness function used in ACO method is equivalent with the fitness function of GA as shown in Eq. (1). The flowchart of the process in ACO is shown in Fig. 4. Once all ants completed their own loop, the pheromone will be updated on all the vertices according to the global updating rule as shown in Eq. (4). The major of this rule is to reward the vertices belongs to the shortest loop.

$$\tau(i,j) = (1-\rho)\tau(i,j) + \sum_{k=1}^m \Delta\tau_k(i,j) \quad (4)$$

$$\Delta\tau_k(r,s) = \begin{cases} 1/L_k & \text{if } (r,s) \in \text{journey by ant } k \\ 0 & \text{others} \end{cases} \quad (5)$$

where

- ρ = evaporation rate
- m = number of ant
- $\Delta\tau_k$ = quantity of pheromone laid on the edge
- L_k = length of the tour constructed by ant k

3. Results and Discussions

The simulations of tool path generation were performed in MATLAB. The location of holes of PCB is shown in Fig. 5(a). In GA simulation, 250 populations were chosen. The crossover rate and mutation rate was 0.8 and 0.08, respectively. Meanwhile for ACO simulation, the number of ants was 100, and the value of α and β is 3. Figure 5(b) shows the best route obtains by the GA method. The shortest distance obtain is 2580 mm. On the other hand, the best routes obtained by the ACO method are 1019 mm as shown in Fig. 5(c). From the results, the ACO method is produce better result compared to GA in finding the shortest distance of tool path.

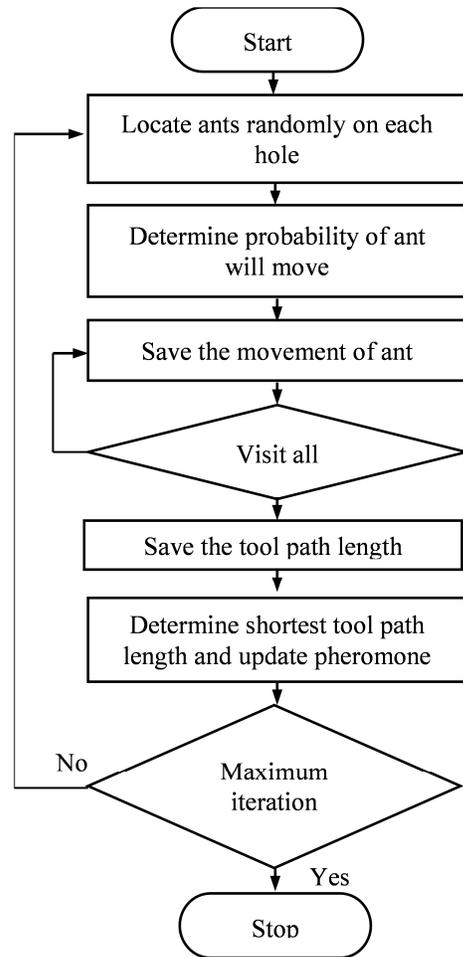
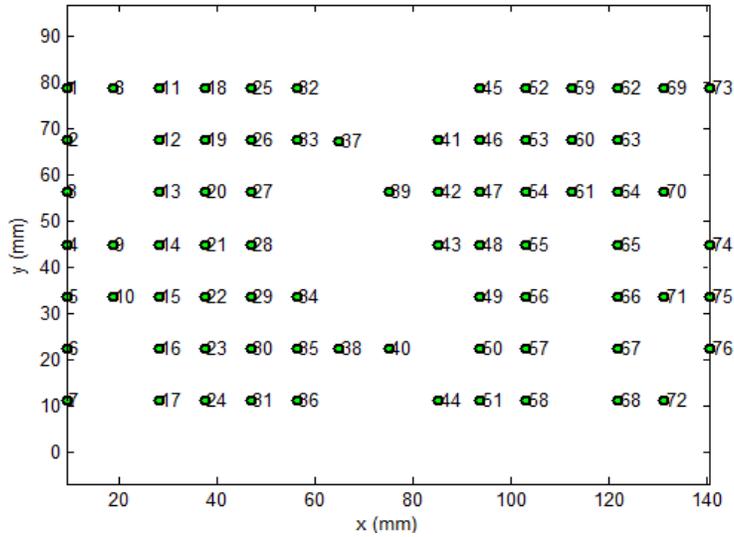


Fig. 4. Single crossover of genetic algorithm.

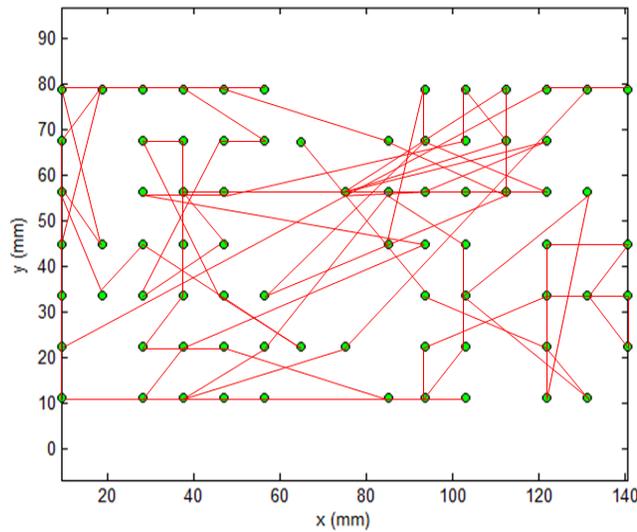
In our drilling case, the tool path is classified as TSP in which the hole can only be drilled once by the cutting tool. In ACO method, the shortest path is determined based on the pheromone left by ants. The first ants leave a pheromone trail and the next ants will follow the trail which has stronger pheromones. If the number of ants through the shorter path increases, the effect of the pheromone trail left behind will stronger. Thus, the number of ants must also consider in producing a shorter travel distance. The more ants, the more the solution is formed. In the case of drilling, each ant will be required to form a sequence in drill holes that need to generate the shortest path. Besides that, the value of α and β also give significant role in influencing the decision.

While, in GA the parameters involved are number of population, crossover rate and mutation rate. The selection of these parameters should be suitable with the problem. According to Randy and Haupt [8], if a problem which required a large space of solution, it is suggested to choose a set of parameters i.e., number of

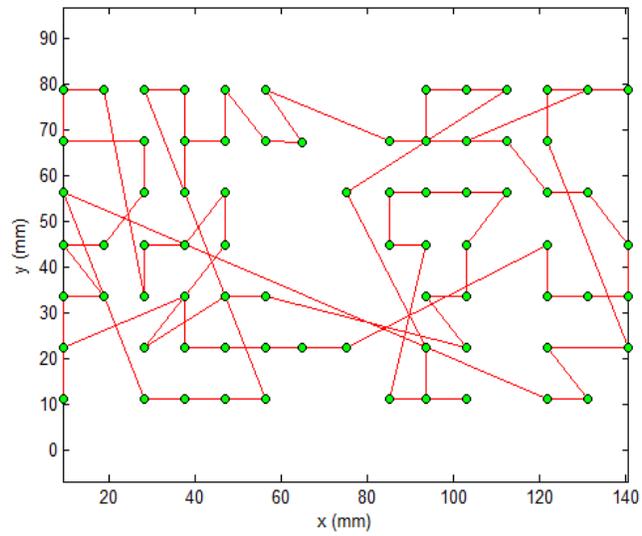
population, crossover rate and mutation rate as 50, 0.6, and 0.001, respectively. However, the number of population should not be less than 30, for arbitrary types of problems. If the population size is small, genetic algorithms will have a slight variation of the possibility to do a crossover and mutation. Meanwhile, if population size is too higher, the genetic algorithms require more time to finding a solution.



(a)



(b)



(c)

Fig. 5. Simulation of tool path in PCB
(a) The holes, (b) Tool path by GA, (c) Tool path by ACO

Based on our comparison of both GA and ACO simulation, ACO gave better solution compared to GA. We also compared our simulation with commercialize CAD/CAM software. Figure 6 shows an example of tool path generation by commercial CAD/CAM software.

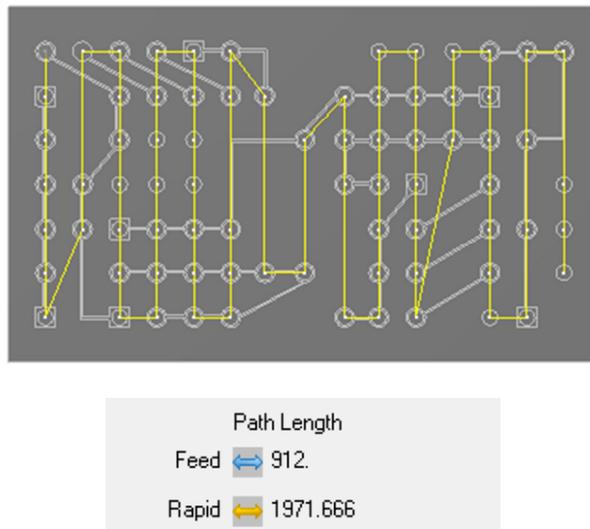


Fig. 6. The simulation of tool path using MasterCAM.

The result of this comparison is shown in Table 1.

Table 1. Comparison of tool path length.

Method	Tool path length(mm)
GA	2580
ACO	1019
MasterCAM	2883.66

4. Conclusions

This paper presented a comparison of artificial intelligence (AI) optimization algorithm methods which is ACO and GA. The ACO utilised the process used by ants to search for food source which used pheromone trail deposition/evaporation technique to map their way. On the other hand, the GA is an optimization technique, inspired by the law of biological reproduction and survival of fittest theory.

Based on simulation results, it can be ascertained that our optimization method performed better performance compared to the conventional CAD/CAM simulation software in generating tool path. However, these techniques need to be further explored to find their suitability to certain applications. Also, there is a need to combine two or more techniques so that they complement each other and accomplish their respective limitations. As conclusion, our heuristic tool path optimization method provides shorter path compared to commercial tool path simulated by MasterCAM.

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