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Tool Routing Path Optimization for Multi-Hole Drilling Based on Ant Colony Optimization

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Abstract: Currently, most companies that conduct business in both domestic and global markets are facing growing international competition and recognize the importance of reducing manufacturing lead time, for example, companies in the machining industry. In general, machining can be performed manually, automatically or by Computer Numerical Control (CNC). The optimization of tool routing path operation in machining can lead to significant reduction in non-productive machining time. This paper focuses on the development of the Ant Colony Optimization (ACO) algorithm for use in searching for the optimal tool routing path and the relationship with its control parameter values. The simulation of a machining operation is conducted in MATLAB with incremental positioning axis movement based on the Travelling Salesman Problem (TSP). The results indicate that the relationship between the travelled distance of the ant and the ant's control parameters are significant in increasing the hole drilling operation efficiencies. This result indicates that ACO algorithm programming can be used to optimize the tool routing path.

Key words: Tool routing path · Ant Colony Optimization · Travelling Salesman Problem · CNC machine

INTRODUCTION

Ant Colony Optimization (ACO) is a technique with high capacity that has been used to solve complex problems, such as the travelling salesman problem (TSP), quadratic assignment problems (QAP), vehicle routing and many others [1]. In a machining process by Computer Numerical Control (CNC) such as milling machines, the tool routing path for the machining operation plays a very important role. The tool routing path has consistently been the weak link in the chain. A high-quality cutting tool that is driven by innovative tool routing path programs can increase the manufacturing efficiency of the tool. Therefore, the searching for the tool routing path is vital for reducing the processing time and achieving the parts manufacturing lead time [2, 3]. Hole-making operation processes, such as drilling, reaming and tapping, require most of the machining process time for manufactured parts. The point-to-point (PTP) movement in the multi-hole drilling process and the requirement for each operation is different, depending on the tool switching process and the XY table movement from one location to another. The optimization of the hole drilling operation will lead to the reduction of the machining time and the improved the productivity of the manufacturing systems [4].

Based on previous research, there are several types of optimization models that have been successfully implemented to determine the optimal tool routing paths. The study of Ghaiebi and Solimanpur [4] focused on determining the optimal tool path of multi-hole drilling operations in conditions where a hole may require several tools with different diameters to complete the drilling operations. They investigated the optimization of hole-

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making operations in conditions where the hole-making process may require several tools to complete, with the objective of minimizing the summation of the tool airtime and the tool switch time.

Kenneth *et al.* studied the algorithm for minimizing the non-productive time or airtime for milling by optimally connecting different tool path segments by formulating the traveling salesman problem (TSP) with precedence constraints and solving the problem using a heuristic method. Their developed algorithm was implemented in an automated process planning system; the algorithm can be applied to other areas of path planning optimization such as fused deposition modeling and laser cutting [5].

In contrast, to minimize the overall cost of processing hole-drilling operations, Kolahan and Liang used a Tabu search approach. In their study on tool travel time, tool switching time, selection of tool and tool speed specification, they proved that the tabu search approach can reduce the total production cost significantly in a reasonable search [6]. Other researchers, such as Onwubolu and Clerc used a particle swarm optimization (PSO) to solve the problem of the optimal route for drilling via the TSP model. Their research indicated that the new optimization approach involving the particle swarm optimization and the traveling salesman can reduce the cost of production of drilling [7]. Tewolde and Weihua implemented an appropriate genetic algorithm (GA) and ACO to address the problems of integration in the context of the tool routing path creation in a spray process. Their problem is modeled as variations of the rural postman problem RPP. The result indicated that the ACO method can produce better solutions than the GA when the complexity of the problem is increasing [8].

In this paper, we present an ACO simulation approach for determining the optimum distance for a multi-hole drilling process involving a simple workpiece. This simulation is important to improve the efficiency of CNC machining in a manufacturing system.

MATERIALS AND METHODS

In this paper, the simple workpiece model considered for the optimization of the drilling at certain coordinates is shown in Figure 1.

Because ACO is a population-based optimization approach, it has been used effectively in solving the combinatorial optimization problems. Our approach is a simulation based on the behavior of real ants that involves searching for the shortest routing path from the nest to a food source [4, 9]. The ACO approach used to find the optimal tool routing path is based on a cost function as shown in Equation 1:

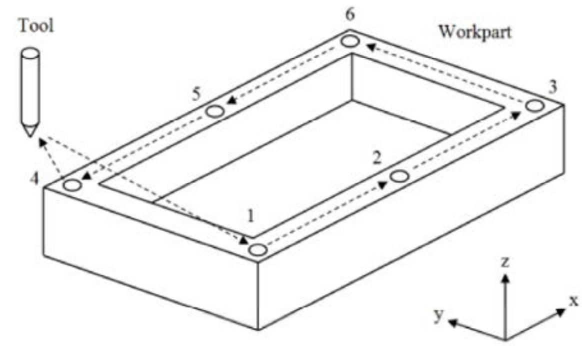

Fig. 1: Simple workpiece model used for simulation.

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

where the tool routing path is calculated by the incremental positioning related to the coordinates point (*x,y*) of the previous point during the drilling process and the z-axis is a 0.5-cm distance between the tool tip and the workpiece surface. The depth of the drilling is 1 cm, as shown in Equation 1. The ACO algorithm started when the ant colony, which consists of *N* ants starting at the designated first point, travels through the layers of the node destination. The node destination in this study is the set of coordinates of the drilling point for all of the iterations. Each ant can only choose one node destination for each routing path based on the state transition rule, as shown in Equation 2. According to Sumathi and Surekha, the ACO algorithm begins at the starting node and iteratively moves from one node to another node [10]. When an ant arrives at a node, the ants will choose to move to the node that has yet to be passed in time, t, with probability as,

$$p_{i,j}^{k}(t) = \frac{[\tau_{i,j}(t)]^{\alpha}[\eta_{i,j}(t)]^{\beta}}{\sum_{t \in N_i^k} [\tau_{i,j}(t)]^{\alpha}[\eta_{i,j}(t)]^{\beta}}\, j \in N_i^k \tag{2}$$

where,

N_i^k = Feasible neighborhood of the ant$_k$, that is, the set of nodes which ant$_k$ has not yet visited.

$\tau_{i,j}(t)$ = Pheromone value on the edge (i,j) at the time t.

α = Weight of the pheromone.

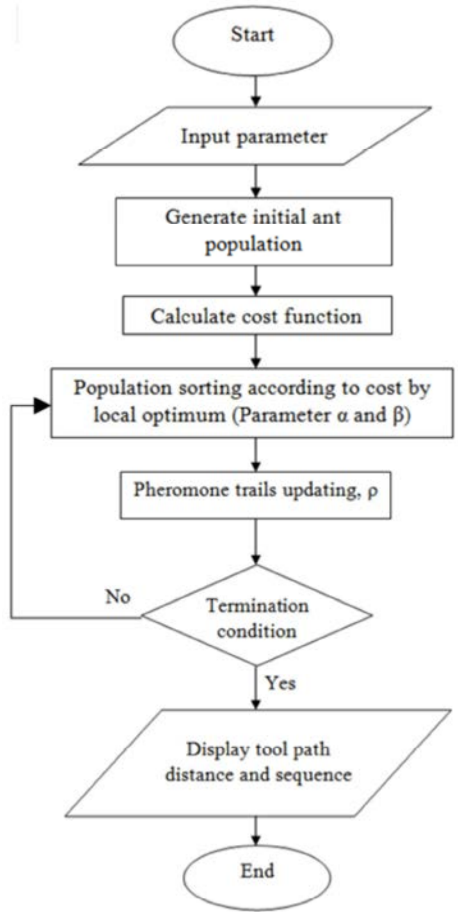

Fig. 2: Flow chart of the ACO algorithm

$\eta_{i,j}(t)$ = Priori available heuristic information on the edge (i,j) at the time t.
β = Weight of heuristic information.

The parameters α and β determine the relative influence of the pheromone trail and the heuristic information, respectively. Once the routing path is completed, the ants deposit some pheromone onto the routing path based on the local updating rule, which is the pheromone value $\tau_{i,j}(t)$ traversed on the arc (*i,j*) as follows,

$$\tau_{i,j} \leftarrow \tau_{i,j} + \Delta\tau^{k} \quad (3)$$

Next, after all of the ants return to the home node, the pheromone information is updated according to the relation of the following equation.

$$tau_{i.j}(t) = \rho\tau_{i,j}(t-1) + \sum_{k=1}^{n} \Delta\tau_{i,j}{}^{k} \forall(i,j) \quad (4)$$

where:

ρ =Pheromone trail evaporation rate ($0 < \rho < 1$)
$\Delta\tau_{i,j}(t)$ =Pheromone deposited on arc (i,j) at time t by the best ant *k*.

The objective of the pheromone updating is to increase the pheromone value associated with good or promising routing paths. The pheromone deposited on arc (*i,j*) by the best ant is taken as the following equation,

$$\Delta\tau_{i,j}{}^{k}(t) = \begin{cases} \frac{Q}{L_k(t)} & \text{if the edge (i,j) choosen by ant}_k \\ 0 & \text{Otherwise} \end{cases} \quad (5)$$

Q = Constant for pheromone updating.
L_k = Length of the routing path traveled by the *k*th ant.

The variables and parameters studied in this paper are the difference in the node value and the parameters ρ, α and β. The value of the initial population of the ants is constant at a value of 100 and the iteration termination condition is when a maximum of 300 iterations occurs. For simplification, Figure 2 shows the overall flow of the discussed ACO algorithm.

RESULTS AND DISCUSSIONS

In this study, a new algorithm was developed to determine the shortest or optimal routing path for a three-axis CNC drilling machine. We performed a series of simulations to examine the comparison of the results obtained to monitor the influence of different parameters used in each of the simulations.

Table 1 shows the simulation results of the multi-hole drilling optimization. Three simulations were conducted with the following parameters: the maximum number of generations is 300, the number of ant population 100, ρ is 0.1, α is 2 and β is 3. From the simulation result, the average of optimum distance for six drilling points was closer to the optimum distance for the drilling points. This result is because the probability to generate a tool routing path is lower.

In Figure 3, the smaller number of drilling points indicated a more stable average distance curve.

Table 2 presents the results obtained with different ρ. In all of the three simulations, the following parameters were used: 10 holes to be drilled, the maximum number of generations is 300, the ant population number is 100, α=2 and β=3. The simulation results indicate that the average of optimum distance for ρ=0.1 is approaching the optimum

Table 1: Simulation results for multi-hole drilling

Parameter	Simulation 1	2	3
No. of points to be drilled	6	10	12
No. of possible routing paths	60	181,440	19,958,400
Optimum distance (cm)	50	62.04	68.63
Average of the optimum distance (cm)	50.25	63.37	71.29
Shortest distance (cm)	50	62.04	68.63
Iteration time taken (s)	2.12001	3.71480	5.50881

Table 2: Results for different evaporation rates of the pheromone trail, ρ

Parameter	Simulation 1	2	3
Evaporation rate coefficient, ?	0.1	0.35	0.99
Optimum distance (cm)	62	62	62
Average of optimum distance (cm)	63.38	64.17	81.45
Shortest distance (cm)	62.04	62.25	62.65
Iteration time taken (s)	3.84452	3.83968	3.90786

Table 3: Results for different pheromone weight, α

Parameter	Simulation 1	2	3
Pheromone weight, α	0.5	2.5	4
Optimum distance (cm)	62	62	62
Average of the optimum distance (cm)	68.64	63.07	62.54
Shortest distance (cm)	62.53	62	62
Iteration time taken (s)	3.80095	4.15583	4.18314

Table 4: Results for the different heuristic information weight, β

Parameter	Simulation 1	2	3
Heuristic information weight, β	0	2	4
Optimum distance (cm)	62	62	62
Average of the optimum distance (cm)	87.72	71.38	62.36
Shortest distance (cm)	85.70	65.01	62
Iteration time taken (s)	3.17458	2.96543	4.00446

distance for the drilling points. This optimum distance is a result of the ACO algorithm: the higher the pheromone trail, the lower probability for the recurrence of the ant trail path.

Table 3 shows the results with different values of the weight of the pheromone α. In the simulations, the number of holes to be drilled is 10 holes, the maximum number of generations is 300, the number of ant population is 100, ρ= 0.1 and β=3.

In Figure 4, the tool routing path revealed the relationship between the distances travelled with the number of generations for different pheromone weights, α. The results indicate that when higher value of the pheromone weight, α, is adopted, a shorter distance can be achieved when the weight of heuristic information, β, is set to a constant value.

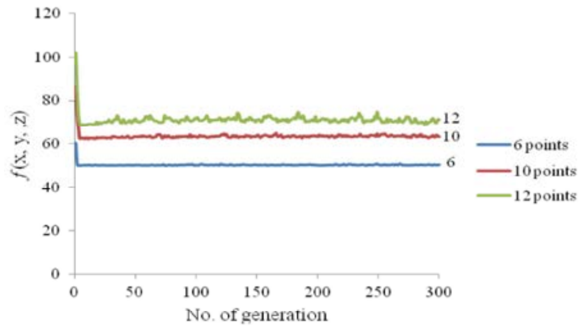

Fig. 3: Relationship between the tool routing path distance and the number of generations

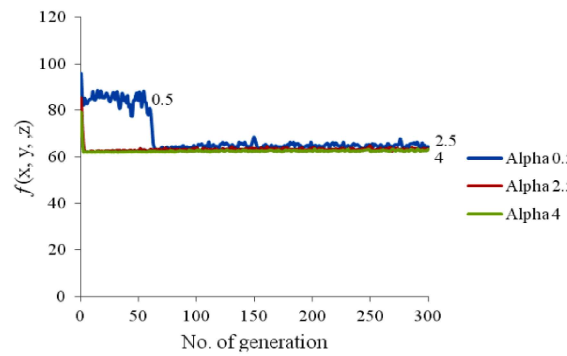

Fig. 4: Relationship of the tool routing path and the pheromone weight, α

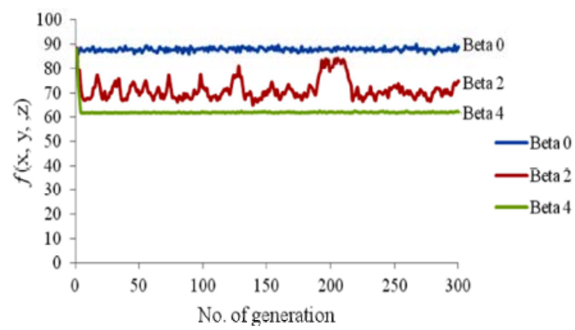

Fig. 5: Relationship between the tool routing path and the heuristic information weight, β.

Table 4 shows the results obtained when the value of weight of the heuristic information, β, is different.

In Figure 5, a higher value of the weight of the heuristic information, β, can produce a more stable average distance when the pheromone weight, α, is constant. From Table 4, the results show that the average optimum distance for β is 4, which is approaching the optimum distance of the drilling point. A smaller value of β will produce a longer distance, as shown in the graph curve.

CONCLUSIONS

This paper used an ACO algorithm to determine the shortest tool routing path for 6-, 10- and 12-hole drilling operations using a CNC machine. We observed the relationship between the different control parameter values of α, β and ρ with an average travelled distance for multi-hole drilling. The results indicated that the selection of a suitable set of control parameters values can be used to obtain the global best solution.

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