CHAPTER 5

OPTIMIZATION OF EDM PARAMETERS

Manufactures and users of Electro Discharge machine have interest in acquiring better stability and higher productivity in the machining process. The higher rate of metal removal with desired accuracy and minimal surface damage make the EDM operation cost effective and the process more economical and affordable. However, as number of variables is more optimal, machining performance is rarely achieved. It is necessary to investigate how the erosion parameters have affect on the machining process. The final results will provide significant information to achieve optimal performance in the process. Often optimization problems have multiple objectives. Most of the time these objectives have conflicts (i.e., optimizing one objective causes the other objectives to be poor).

In the present scenario ACO technique is used to optimize any problem in engineering and for aging behavior of real ants to select the shortest path from nest to the food. The objective is to maximize MRR and minimize TWR.

Ant colony optimization (Heidar Ghaiebi & Maghsud Solimanpur 2007) is a population-based optimization approach that has been effectively used to provide solution to different combinatorial optimization problems. This approach is based on the simulation of foraging behavior of real ants. Pheromone is a chemical substance of the ants on the path they travel. The chemical substance pheromone is laid in various paths and the ants choose the moving direction from the smell produced. In a nutshell, when the pheromone
in the path is more, ants travel often or probability of the travel is high. Immediately after an ant selects path, its own pheromone is deposited which makes other ants to follow. This is the result of saturation of pheromone along the path. Also, the route seems to be the shortest way to the food source from the nest. It is due to the fact that ants select all possible paths with equal probability. This indicates that the frequency of selecting the shortest paths from the nest to the food source is higher than other path and this mechanism enables them to find the shortest path. It is the same scenario in ACO to optimize the objective function like minimum distance, minimum time, minimum cost etc.

5.1 SCHEMES OF THE ANT COLONY ALGORITHM

The objective function as mentioned previously is minimized subject to practical constraints. In the first step, 200 solutions are generated randomly within parameter bounds satisfying the constraints and the global and the local search are performed. In this paper, the continuous ants colony algorithm (CACO) Jayaram (2000) is implemented. The CACO scheme is explained in Figure 5.1.

5.1.1 Global Search

The initial solution has two classifications namely superior and inferior solutions based on the fitness values. Global updates have applications only on inferior regions whereas the global search for CACO is entirely different from other non-traditional optimization technique. The following three operators are randomly generated initial solution.

a. Random walk
b. Mutation
c. Trail diffusion
Figure 5.1 Flow chart for the ant’s colony algorithm scheme
5.1.2 Random Walk (or) Crossover

90% of the solutions (randomly chosen) which are inferior are replaced with randomly selected superior solutions.

The distribution of ants and the selection of solutions are illustrated in Figure 5.2.

![Figure 5.2 Distribution of Ants for local and global search](image)

5.1.3 Mutation

After random walk step, when a value is added or subtracted to each and every variable, new solutions in the inferior region are created that lead to probability which is equal to a defined mutation probability. The mutation size is reduced as per the relation (Han-ming chow et al 2000).
\[ \Delta (S, H) = R \left( 1 - r^{(1-T)d} \right) \]

where \( r \) is a random number from [0,1], \( H \) is the maximum step size, \( S \) is the ratio of the current iteration number to that of the total number of iterations, and \( d \) is a positive parameter controlling the degree of nonlinearity. The value of \( b \) considered in this work is 10 which was arrived at on a trial basis.

### 5.1.4 Trail Diffusion

Trail diffusion, which is another element in the global search is applied on the inferior solutions, which were not selected during the random walk and mutation stages. Here, two parents are selected at random from the present parent superior solutions. The variables of the child’s position vector can have either

1. The value of the corresponding variable from the first parent;
2. The corresponding value of the variable from second parent;
3. The result arrived from the weighted average of the above:

\[ x \text{ (child) } = (\alpha). x_i \text{ (parent1)} + (1-\alpha). x_i \text{ (parent2)} \]

where \( \alpha \) indicates a uniform random number in the range [0,1]. The probability of selecting the third option is set equal to the mutation probability while allotting equal probability in the first two steps. The trail value of the newly created child solutions is lying between the values of the original parent solutions (Vijayakumar et al 2003).

### 5.1.5 Local Search

In the ACO algorithm, local (artificial) ants select a region \( i \) with a probability.
\[ P_i(t) = \frac{\tau_i(t)}{\sum_j \tau_j(t)} \]

where \( i \) is the region index and \( \tau_i(k) \) represents pheromone trail on region \( i \) at time \( t \). After selecting the region, the ant moves through the shortest distance (finite random increment) and the direction of movement is retained if the fitness value improvement is observed. Otherwise it is reversed. Correspondingly, the solutions position vector is updated and pheromone trail value is improved based on the fitness value.

In the continuous algorithm, the pheromone values decreased after each iteration by:

\[ \tau_i(t+1) = \delta \tau_i(t) \]

where \( \delta \) denotes the evaporation rate which is assumed to be 0.2 on a trial basis and \( \tau_i(t) \) is the trail associated with solution at time \( t \).