Parametric Optimization of Electrochemical Machining Process by Particle Swarm Optimization Technique

Mr. Sumit Bhandari[1], Mr. Nitin Shukla[2]

[1](M.Tech. Scholar(Production Engineering), Dr. C. V. Raman University,Kota, Bilaspur,C.G., India

[2](Assistant Professor(Mechanical Engineering Dr. C. V. Raman University,Kota, Bilaspur, C.G.,India

Abstract

This paper presents the Optimization of Non-Traditional Machining (NTM) process for the Electrochemical Machining Process by Particle Swarm Optimization Technique. The main aim of the work is to find the optimum values of machining parameters. The Non-Traditional or Unconventional Machining Process has proved to be better than conventional machining process to a large extent.

Keywords—*Conventional Machining; Electrochemical Machining Process; Non-Traditional Machining; Partical Swarm Otimization; Parametric Optimization*

I. INTRODUCTION

During the last few decades, technologically advanced industries, such as aeronautics, nuclear reactors, automobiles have been demanding materials, like high strength temperature resistant (HSTR) alloys having high strength-to-weight ratio to be used by them. Due to this reason, the researchers in the area of material science have been developing materials having higher strength, hardness, toughness and other diverse properties [1].

In conventional machining processes, the increase in hardness of the work material causes a significant decrease in economic cutting speed. Increase in hardness and strength of the cutting tool in order to machine hard and difficult-to-machine materials, like titanium, stainless steel, nimonics and similar other high strength materials also cause increase in the cost of machining. The advancing strength level would have a dangerous effect on the total cost of machining if there would not be any corresponding improvement in the machining process. Figure 1.1 shows the effect of work material hardness on national machining cost of the USA.

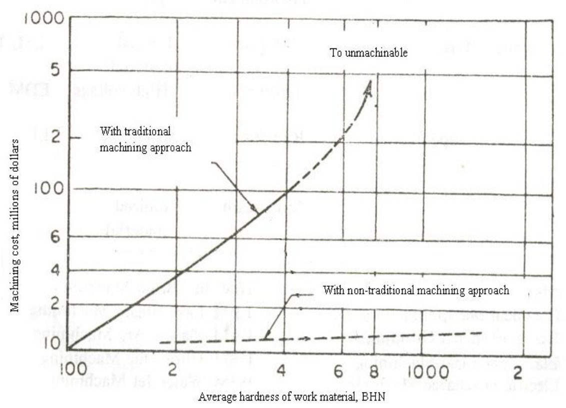

Figure 1 Effect of Work Material Hardness on National Machining Cost In The USA

Production of complex and difficult shapes in hard and high strength materials is difficult by using the traditional machining processes. The requirement of better surface finish, low value of tolerance, higher production rate and complex shape have also forced the researchers to come up with better and improved machining techniques.

In order to meet the above-mentioned requirements, a set of machining processes were developed which were

Electrochemical Machining Process

Electrochemical machining (ECM) is one of the most important NTM processes. It is considered as the reverse of electroplating process with some modifications. It is based on the principle of electrolysis. In a metal, the movement of current is carried out with the help of free electrons. However, in an electrolyte, the flow of current is achieved through the movement of ions. Thus, the flow of current in an electrolyte is accompanied by the movement of matter. In ECM, the tool is connected to the negative terminal, whereas, the workpiece is connected to the positive terminal. Figure 2 shows the schematic representation of an ECM setup. The gap between the tool and the workpiece is filled up with a suitable electrolyte. When the current passes through the electrolyte, the dissolution of the anode occurs. Although the rate of dissolution is not constant throughout the region, it is more where the gap between the tool and the workpiece is less, as the current density is inversely proportional to the gap. In ECM process, the tool is provided with a constant feed motion. The electrolyte is supplied through the tool, and the small gap between the tool and the workpiece. The electrolyte is chosen in such a way that there is dissolution of the anode (workpiece), however, no deposition takes place in cathode (tool). The current that is used is in the order of few thousand amperes and the voltage used is in of the order of 8-12 volts. The gap between the tool and the workpiece is maintained at 0.1-0.2 mm. In ECM, the rate of metal removal is independent of the workpiece material. Hence, it is advantageous for the application when the workpiece possesses very low machinability or the shape to be machined is complicated.

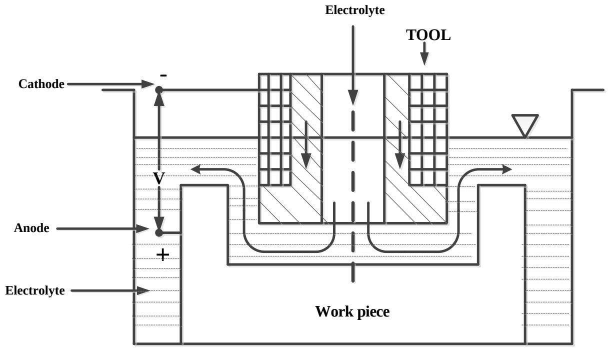

Figure 2 Schematic Diagram of an ECM Setup

II. NEED FOR PARAMETRIC OPTIMIZATION FOR NON-TRADITIONAL MACHINING PROCESSES

In order to make proper use of the machining process, it is very important to understand that

i) the NTM processes can never replace the conventional machining processes, they can only compliment them, and
ii) a particular NTM process which is suitable under a certain machining condition might not be suitable under other conditions.

So, it is important to find out the optimal parametric conditions under which the NTM machining processes will be able to perform their best.

It has been found out that selection of the optimal parametric conditions for an NTM process is vital because it affects the economics of that machining process.

It is very important to find out the optimal process parameters of these machining processes to use them efficiently and achieve a high degree of dimensional accuracy.

Due to unavailability of a suitable technological performance equation, it is very difficult to implement the optimized parametric conditions. In such circumstances, a large number of experiments has to be conducted in order to establish an empirical performance equation for each operating environment and work material combination for a given machining operation.

The needs for parametric optimization of NTM processes have been discussed in the previous section. The parametric optimization of an NTM process is undertaken in mainly two stages, i.e.

a) mathematical modelling of the optimization problem taking into consideration the relationship between the process parameters and performance measures (responses), and
b) optimization of the mathematical model in order to determine the optimal or near optimal value of the performance measures and corresponding combination of the process parameters.

III. PARTICLE SWARM OPTIMIZATION TECHNIQUE

Kennedy and Eberhart [13] defined swarm as a population of interactive elements or agents who are able to optimize some global objective through collaborative search in space. Figure 1 shows a pictorial representation of the simple scheme of a swarm. There are various optimization techniques that have been developed using this concept of swarm intelligence, e.g. ACO, ABC and PSO. The concept of PSO algorithm is discussed below.

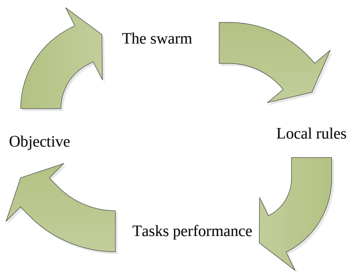

Figure 3 Scheme of a Swarm

The PSO algorithm was first introduced by Kennedy and Eberhart [13, 16-21]. PSO is based on the social behavior of animals and birds. It is influenced by the social behavior in a flock of birds, school of fishes and a group of people. In PSO, the group is also known as swarm. It is a population-based stochastic optimization process. The swarm consists of number of individuals called the particles. These particles fly in a n-dimensional space.

In PSO algorithm, the flight trajectory of a particle is influenced by the trajectory of neighborhood particles as well as the flight experience of the particle itself. Each particle is treated as a point in the n-dimensional space. Each particle keeps information of its best coordinates in the problem space.

This optimization method has its own advantages, i.e.

a) It is insensitive to scaling of the design variables.
b) Its implementation is simple.

PSO has been used in several fields, such as electrical generation and power systems, design and control of neural networks, designing and optimizing communication networks, design and restructure of economic load dispatch and electricity network, optimization of supply chain model, optimal scheduling etc. Over the years, the application of PSO has kept on increasing. Figure 2 shows the aggregation of applications of PSO technique over the past few years [21].

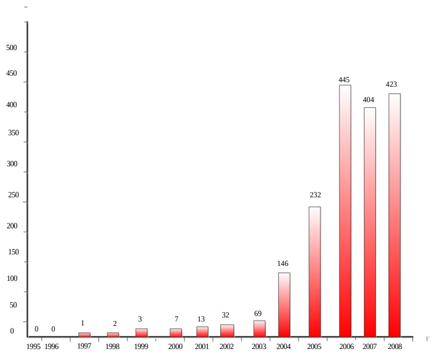

Figure 4 Aggregation Chart for Applications of The PSO Over Different Years

IV. OBJECT AND SCOPE OF PRESENT WORK

The objectives of the present research work are set as follows:

a) to develop the related computer codes for PSO algorithm in MATLAB 7.1 for parametric optimization of NTM processes,
b) to solve the single response and multi-response optimization problems for electrochemical machining process using PSO algorithm, and compare the derived results with those obtained by the previous researchers,
c) to solve the single and multi-response optimization problem for electrochemical grinding process using PSO algorithm,
d) to use the computer codes for PSO algorithm developed for parametric optimization of electrochemical discharge machining process,
e) to solve the single and multi-response optimization problem of Nd:YAG laser machining process using PSO algorithm,
f) to use PSO algorithm for parametric optimization of electrical discharge machining process, and
g) to optimize the process performances of wire electric discharge machining process using PSO algorithm.

V. METHODOLOGY

The whole process in the project takes place according to the flow chart shown below. This gives the overall method used in the project.

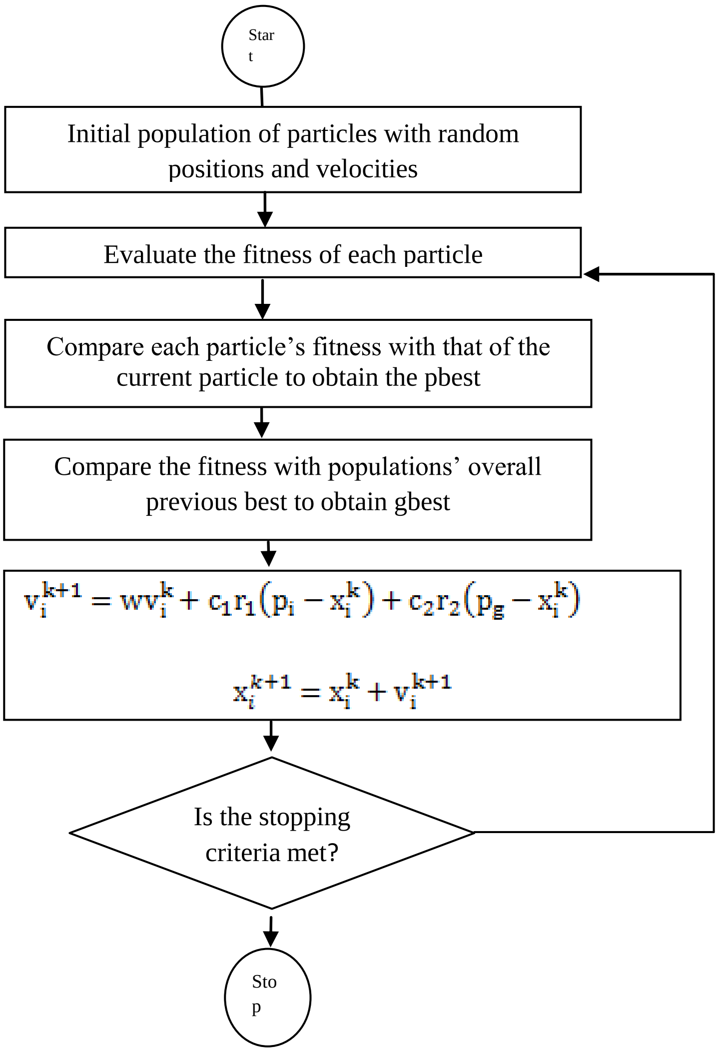

Figure 5 Flowchart for PSO Algorithm

VI. RESULT

Using the above methodology, we have found the following results for the single objective and multi-response optimization of ECG process.

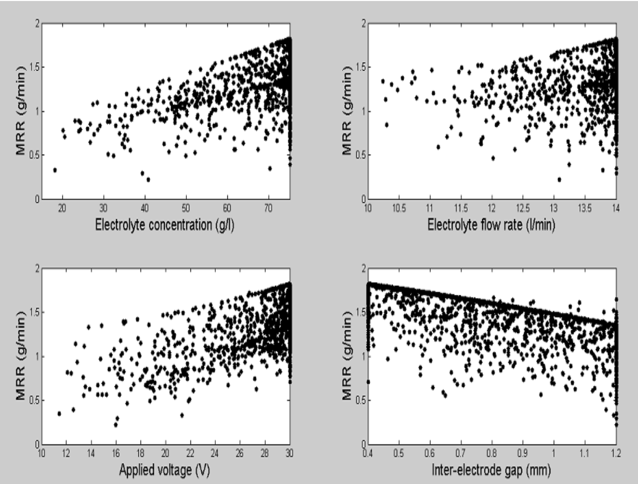

Figure 6 Variations of MRR with Respect to Different ECM process parameters

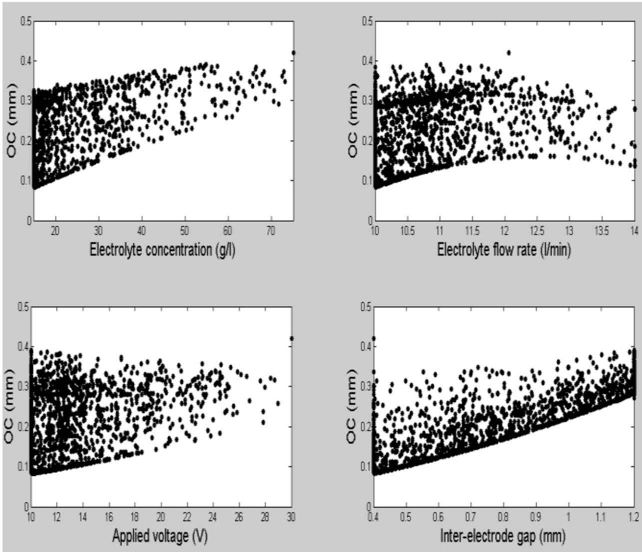

Figure 7 Variations of OC with Respect to Different ECM Process Parameters

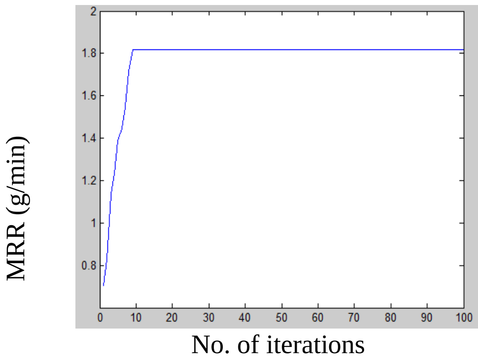

Figure 8 Convergence of PSO Algorithm for MRR

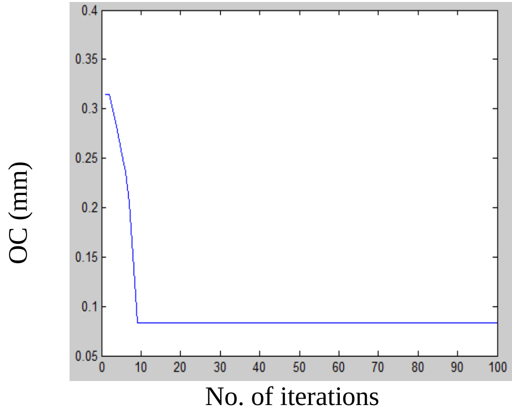

Figure 9 Convergence of PSO Algorithm for OC

VII. CONCLUSION

From the above results, we have following conclusions.

Table 1: Comparative Results for Single Response Optimization for ECM Process

Process parameters	Results obtained by Bhattacharya and Sorkhel [44]		PSO algorithm	
	MRR (g/min)	OC (mm)	MRR (g/min)	OC (mm)
Electrolyte concentration (g/l	57.88	17.55	75	15
Electrolyte flow rate (l/min)	11.98	11.05	14	10
Applied voltage (V)	22.04	21.65	30	10
Inter-electrode gap (mm)	0.001	0.87	0.4	0.5
Optimal value	0.7254	0.2702	1.8162	0.0835

Table 2 Multi-Response Optimization Results for ECM Process for Case 1

$w_1 = 0.1$ and $w_1 = 0.9$	
Process parameters and objective function	PSO algorithm
Electrolyte concentration (g/l)	75
Electrolyte flow rate (l/min)	14
Applied voltage(V)	30
Inter-electrode gap (mm)	0.4
MRR (g/min)	1.819
OC (mm)	0.4636
Z_1	-19.555

Table 3 Multi-Objective Optimization Results for ECM process for case 2

$w_1 = w_2 = 0.5$	
Process parameters and objective function	PSO algorithm
Electrolyte concentration (g/l)	75
Electrolyte flow rate (l/min)	14
Applied voltage (V)	30
Inter-electrode gap (mm)	0.4
MRR (g/min)	1.819
OC (mm)	0.4636
Z_1	-10.777

Table 4 Multi-Objective Optimization Results For ECM Process for Case 3

$w_1 = 0.9$ and $w_2 = 0.1$	
Process parameters and objective function	PSO algorithm
Electrolyte concentration (g/l)	15
Electrolyte flow rate (l/min)	14
Applied voltage(V)	10
Inter-electrode gap (mm)	0.4
MRR (g/min)	0.2942
OC (mm)	0.1356
Z_1	1.43165

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