Optimization of ED Machining of SiC Parameters

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Abstract

Silicon Carbide (SiC) machining by traditional methods with regards to its high hardness is not possible. Electro Discharge Machining, among non-traditional machining methods, is used for machining of SiC. The present work is aimed to optimize the surface roughness and material removal rate of electro discharge machining of SiC parameters simultaneously. As the output parameters are conflicting in nature, so there is no single combination of machining parameters, which provides the best machining performance. A multi-objective optimization method, non-dominating sorting genetic algorithm-II is used to optimize the process. Experiments have been conducted over a wide range of considered input parameters for training and verification of the model. Testing results demonstrate that the model is suitable for predicting the response parameters. A pareto-optimal set has been predicted in this work.

Keywords

Electro Discharge Machining, Non-Dominating Sorting Algorithm**,** REFEL SiC.

1. Introduction

Electrical discharge machining (EDM) is one of the most extensively used non-conventional material removal process. S. K. Pal, D. Mandal and P. Saha (2007) found the unique feature of using thermal energy to machine electrically conductive parts regardless of hardness has been its distinctive advantage in the manufacture of mould, die, automotive, aerospace and surgical component. G. K. M. Rao et al.(2009) according to the development of a hybrid model, recommended a selection method of appropriate parameters for maximum material removal rate and minimum surface roughness during the EDM process traditionally carried out by the operator's experience or conservative technological data provided by the EDM equipment manufacturers, which produced inconsistent machining performance.

Some researchers carried out various investigations to improve the stock material removal rate and surface finishing in EDM process. Proper selection of machining parameters for the best process performance is still a challenging job. Wang et al.(2003) used genetic algorithm (GA) with artificial neural network (ANN) to find out optimal main output parameters such as material removal rate and surface roughness. They used ANN to model the process and Hunter Software to solve multi-objective optimization problem. Su et al.(2004) by using ANN and GA, optimized EDM parameters, roughing and finishing machining stages. They utilized artificial neural network to establish the relationship between the process parameters and outputs. GA with properly defined objective functions was then adapted to the neural network to determine the optimal process parameters. They transformed material removal rate, tool wear and surface roughness into a single objective. Rao et al. (2007) used ANN and GA to optimize the surface roughness of die sinking electric discharge machining (EDM) by considering the simultaneous affect of various input parameters. Genetic algorithm concept was used to optimize the weighting factors of the network. Pal et al. (2007) used non dominating sorting genetic algorithm-II to optimize the process. They conducted some experiments on C40 Steel to generate input and output data for training an ANN model. Material removal rate and tool wear were two objectives to be optimized. So they predicted a Pareto-optimal set for outputs.

In this study material removal rate and surface roughness have been considered to produce a Pareto- optimal set for EDM of REFEL SiC. Some related properties of this material are shown in Table 1.

Table1. Some characteristics of REFEL SiC [5]

Density (gr/cm^3)	**Hardness** (HV)	**Young modulus** $(E)(GN/m)$	**thermal Expansion** 1×10^{-6}°C	**thermal conductivity** (k) at 100°C $(W/m\cdot°C$ at$)$ 1200°C	**Specific heat** $(J/g°C)$	**electrical resistance** (Ωcm)	**Thermal shock** $(cal/cm\ s)$ at 500°C
3.10	2500	413	4.3	83.6 38.9	670.710	0.42 (at25°C) 0.016(at1200°C)	59

2. Experimentations

In this study, Deckel CNC Spark, ISO frequency system, with gap control system was used to carry out the experiments. Copper electrode was selected to drill holes in the REFEL SiC blocks. For evaluating the EDM process the MRR and surface roughness (Ra) are mentioned with input machining parameters such as pulse on time (T_{on}), pulse off time (T_{off}), discharge current (I). Proper selection of the machining parameters can result a higher material removal rate and lower Ra. 81 experiments have been conducted covering wide range of current, pulse on time and off time settings to collect more number of data for better training of the neural network model. For each experiment, a new set of tool and work-piece has been used. For normal polarity the work-piece is connected to the negative terminal and the tool is connected to the positive terminal of the source, where as for reverse polarity it is just the opposite. Experiment has been performed with normal polarity. The current range is 0.1-5 A and the pulse on time and pulse off time ranges are 21-1100 μs.

3. Material Removal Rating (MRR)

Material removal rate and surface roughness have been used to evaluate machining performance. Material removal rate (MRR) is calculated from the difference of weight of work piece before and after experiment.

$$MRR = \frac{(w_i - w_f)}{\rho_{SiC}\, t}\ mm^3/min \qquad (1)$$

Where, w_i is the initial weight of work piece in g; w_f the weight of work piece after machining in g; t the machining time in minutes; ρ_{SiC} is the density of SiC (3.1×$10^{-3}\ g/mm^3$).

4. Surface Roughness

The surface roughness R_a is the arithmetic average of collected roughness data points and given by the sum of the absolute values of all the areas above and below the mean line (in integrally form). A mean line is found that is parallel to the general surface direction and divides the surface in such a way that the sum of the areas formed above the line is equal to the sum of the areas formed below the line. When sample points were taken, R_a is calculated as follows:

$$R_a = \frac{1}{n}\sum_{i=1}^{n}|y_i| \qquad (2)$$

Where y_i is the distance between the i^{th} sample point on the profile from the mean line, and n is the number of sample points.

4.1 NSGA II

A single objective optimization algorithm provides a single optimal solution. However, most of the multi-objective problems, in principle, give rise to a set of optimal solutions instead of a single optimal solution [1-9]. The set of solution is known as pareto-optimal solution. In the absence of any further information, none of these Pareto-optimal solutions cannot be said to be better than the other. Suitability of one solution depends on a number of factors including user's choice and problem environment and etc. Hence, this demands finding the entire set of optimal solutions. In this study two objectives that we considered are MRR and Ra. It is observed that when MRR is increasing the Ra increases too. But our goals are maximizing of MRR and minimizing of Ra. A single optimal solution will not serve our purpose, as these objectives are conflicting in nature. Optimization of both the output parameters requires multi-objective optimization. Genetic algorithm works with a population of feasible solutions and, therefore, it can be used in multi-objective optimization problems to capture a number of solutions simultaneously. NSGA-II is fast and elitist multi objective GA, proposed by Dev et al. [6] (See Figure 2).

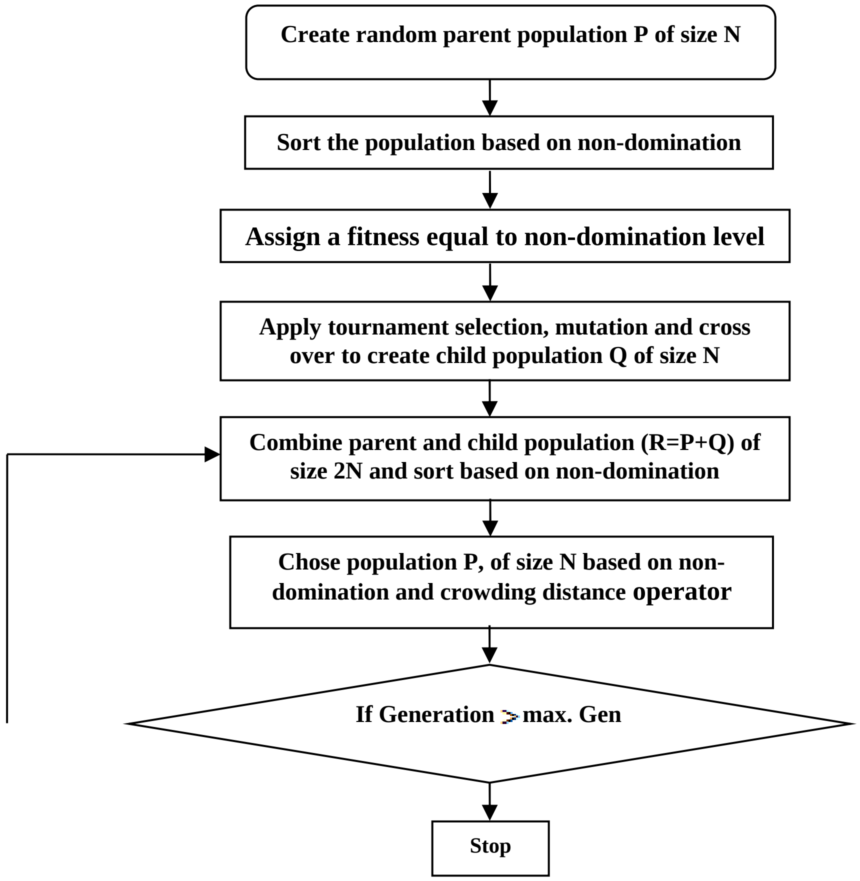

Fig. 2, Flow chart of NSGA II

5. Discussion

The objectives in this study, which are conflicting together, are MRR and surface roughness. In order to convert the first objective (MRR) for minimization, it is suitably modified. Two objective functions are given below:

$$objective\ 1 = 1/MRR \quad \text{and} \quad objective\ 2 = R_a \qquad (3)$$

The non-dominated solution set obtained over the entire optimization procedure as shown in Figure 3.This shows the formation of the pareto-optimal front leading to the final set of solutions.

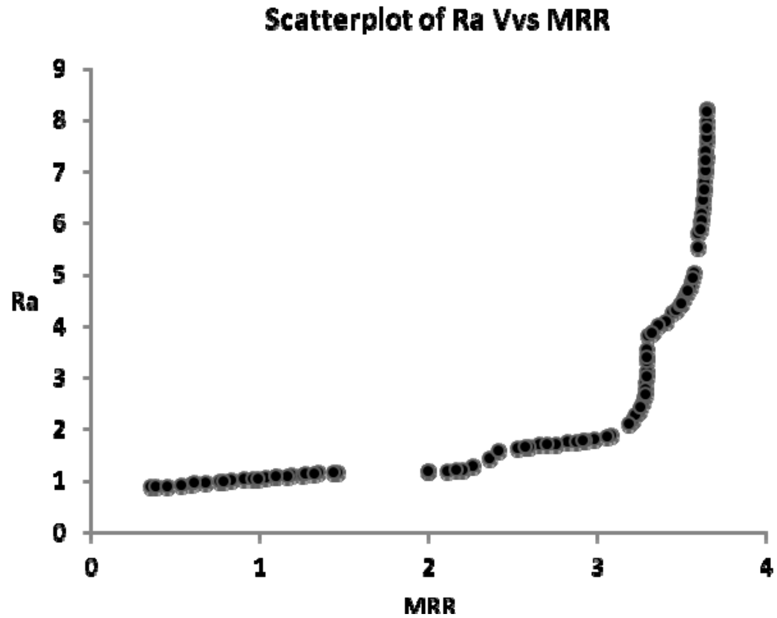

Figure 3: Pareto-Optimal set

Since none of the solutions in the Pareto-optimal front is absolutely better than any other, any one of them is an acceptable solution. The choice of one solution over the other depends on the requirement of the process engineer. If the situation or environment can permit a surface roughness rate of $3\mu m$ to maintain the accuracy of the product, the process engineer can chose the parameter setting according to that to obtain maximum MRR at the specified value of surface roughness.

From the experiments results, MRR and surface roughness are 3.58 mm^3/min and 7.34, where the pulse on time and pulse off time, current settings are 850 µs, 900 µs and 5A, respectively. For solution number 1 in Table 2, MRR and Surface roughness are 3.6446 mm^3/min and 7.2561 mm3/min, where the pulse on time and pulse off time, current settings are 858.9584, 924.463 µs and 4.8902, respectively. Choice of pulse on time and off time will help to achieve higher MRR with same tool wear. This indicates, values obtained from the optimization technique are in close agreement with the experimental values for more or less the same parameter settings.

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Biography

Ramezan Ali Mahdavinejad received his B.S., M.S., and Ph.D. in Mechanical Engineering from Tehran University, Iran in 1981, 1991 and 1999, respectively. Prof. Mahdavinejad is currently a Professor of the School of Mechanical Engineering, Engineering Faculty of Tehran University, Iran. His research fields are Advanced and Non-Traditional Manufacturing.