A CASE STUDY ON QUALITY AND PRODUCTIVITY OPTIMIZATION IN ELECTRIC DISCHARGE MACHINING (EDM)

H Dalai, S Dewangan, S Datta , SK Patel, SS Mahapatra
Department of Mechanical Engineering, National Institute of Technology, Rourkela-769008, Orissa, INDIA
Email: skpatel85@gmail.com

ABSTRACT

Quality and productivity are two important aspects have become great concerns in today's competitive global market. Every manufacturing/ production unit mainly focuses on these areas in relation to the process as well as product developed. Achieving high quality necessarily requires higher degree of skill, sophisticated machine/ tools, advanced technology, precise control, immense attention-inspection and considerable time. Improvement of quality results reduction in productivity and vice versa. Thus, optimality must be maintained between quality as well as productivity.
The case study highlights EDM of stainless steel in which best process environment (optimal) has been determined to satisfy productivity and quality requirements simultaneously. Material Removal Rate (MRR) during the process has been considered as productivity estimate with the aim to maximize it. Where as surface roughness i.e. (R_a value) of the machined surface has been chosen as surface quality estimate with the requirement to minimize it. These two contradicting requirements have been simultaneously satisfied by selecting an optimal process environment (optimal parameter setting). Desirability Function (DF) approach coupled with Taguchi method has been used to solve the problem.

KEY WORDS

EDM; Material Removal Rate (MRR); surface roughness; Desirability Function (DF); Taguchi method

INTRODUCTION: QUALITY VERSES PRODUCTIVITY

Product quality is described by some attributes; called quality indices. These can be treated as process response(s). Process response(s) can be represented as a function of process control parameters. Now, in the machine/ setup, a number of discrete points are available in the parameter domain in which the said factor(s)/ parameter(s) can be adjusted. A particular combination of factors setting is called a process environment. Depending on the availability of factors setting in the equipment, various factorial combinations are possible. Maximum number of factorial combination can be estimated by full factorial design of experiment depending on the total number of factors and their levels of variation. It is obvious that if number of factors and their levels increase, the total experimental run number in full factorial design also increases exponentially. As process responses (here, product quality indices) are likely to be influenced by the process control parameters; different parametric combination would likely to produce product quality different from each other. Moreover, there may be some parameter settings at which the product quality may become very unsatisfactory; the product may not be developed as well. The situation invites trial and error experimentation to select an appropriate parametric combination (process environment) in order to yield satisfactory quality product.

Quality of a process/ product is basically a cumulative performance index. The product quality can be described by multiple quality characteristics. These characteristics may be conflicting in nature from one another, depending on the requirement. There exist three types of quality requirements: Lower-the-Better (LB), Higher-the-Better (HB) and Nominal-the-Best (NB). A product is said to be conforming high quality, when all quality parameters are at desired level of satisfaction simultaneously.

In this context, it is indeed necessary to define an equivalent single quality index (representative of multi-quality features); based on which overall product quality can be assessed and the best one can be selected. The corresponding process environment is then said to be the most favorable process environment (optimal setting). For a mass production, this setting may be employed to avoid quality loss.

OVERVIEW OF EDM: PRIOR STATE OF ART

Basically Electric Discharge Machining (EDM) is a process for eroding and removing material by transient action of electric sparks on electrically conductive materials. This process is achieved by applying consecutive spark discharges between charged work piece and electrode immersed in a dielectric liquid and separated by a small gap. Usually, localized breakdown of the dielectric liquid occurs where the local electrical field is highest. Each spark melts and even evaporates a small amount of material from both electrode and work piece. Part of this material is removed by the dielectric fluid and the remaining part resolidifies rapidly on the surfaces of the electrodes. The net result is that each discharge leaves a small crater on both work piece and electrode. Application of consecutive pulses with high frequencies together with the forward movement of the tool electrode towards the work piece, results with a form of a complementary shape of the electrode on the work piece.

The material removal rate, electrode wear, surface finish, dimensional accuracy, surface hardness and texture and cracking depend on the size and morphology of the craters formed. The applied current, voltage and pulse duration, thermal conductivity, electrical resistivity, specific heat, melting temperature of the electrode and work piece, size and composition of the debris in dielectric liquid can be considered as the main physical parameters effecting to the process. Among them, applied current, voltage and pulse duration are the parameters which can be controlled easily.

Marafona and Wykes (2000) reported an investigation into the optimization of the process which used the effect of carbon which was migrated from the dielectric to tungsten–copper electrodes. This work led to the development of a two-stage EDM machining process where different EDM settings were used for the two stages of the process giving a significantly improved material removal rate for a given tool wear ratio.

Tzeng and Chen (2007) described the application of the fuzzy logic analysis coupled with Taguchi methods to optimize the precision and accuracy of the high-speed electrical discharge machining (EDM) process. Kumar and Singh (2007) compared the performance of copper-chromium alloy with copper and brass as EDM electrode materials for machining OHNS die steel using kerosene and distilled water as dielectric media. Saha (2008) reported parametric analysis of the dry EDM process on experimental results. Experiments based on the Central Composite Design (CCD) were conducted to develop empirical models of the process behavior. Process optimization was performed using Genetic Algorithms (GA). Surface roughness and MRR were optimized.

Rao et al. (2008) optimized the metal removal rate of die sinking electric discharge machining (EDM) by considering the simultaneous affect of various input parameters. The experiments were carried out on Ti6Al4V, HE15, 15CDV6 and M-250. Experiments were conducted by varying the peak current and voltage and the corresponding values of metal removal rate (MRR) were measured. Multi-perceptron neural network models were developed using Neuro solutions package. Genetic algorithm concept was used to optimize the weighting factors of the network.

Pradhan and Biswas (2008) investigated the relationships and parametric interactions between the three controllable variables on the material removal rate (MRR) using RSM method. Experiments were conducted on AISI D2 tool steel with copper electrode and three process variables (factors) as discharge current, pulse duration, and pulse off time. To study the proposed second-order polynomial mode for MRR, the authors used the central composite experimental design to estimation the model coefficients of the three factors, which are believed to influence the MRR in EDM process. Tebni et al. (2009) proposed a simple and easily understandable model for predicting the relative importance of different factors (composition of the steel and Electro Discharge Machining processing conditions) in order to obtain efficient pieces. Popa et al. (2009) reported the importance of the EDM technology in the industry of machine building.

Singh and Garg (2009) investigated the effects of various process parameters of WEDM like pulse on time (TON), pulse off time (TOFF), gap voltage (SV), peak current (IP), wire feed (WF) and wire tension (WT) to reveal their impact on material removal rate of hot die steel (H-11) using one variable at a time approach. The optimal set of process parameters was predicted to maximize the material removal rate. Pradhan and Biswas (2009) used Response Surface Methodology (RSM) to investigate the effect of four controllable input variables namely: discharge current, pulse duration, pulse off time and applied voltage Surface Roughness (SR) of on Electrical Discharge Machined surface. To study the proposed second-order polynomial model for SR, a Central Composite Design (CCD) was used to estimation the model coefficients of the four input factors, which were alleged to influence the SR in Electrical Discharge Machining (EDM) process. Experiments were conducted on AISI D2 tool steel with copper electrode. The response was modeled using RSM on experimental data. The significant coefficients were obtained by performing Analysis of Variance (ANOVA) at 5% level of significance. It was found that discharge current, pulse duration, and pulse off time and few of their interactions had significant effect on the SR.

Iqbal and Khan (2010) established empirical relations regarding machining parameters and the responses in analyzing the machinability of the stainless steel. The machining factors used were voltage, rotational speed of electrode and feed rate over the responses MRR, EWR and R_a. Response surface methodology was used to investigate the relationships and parametric interactions between the three controllable variables on the MRR, EWR and R_a.

The present study has been based on a case study in EDM. The goal is to search the best process environment (optimal parameters setting) to produce desired productivity as well as surface quality of the EDM product. The entire work has been based on the assumptions highlighted below.

1. Result of optimization/ prediction is valid only in the selected experimental domain.
2. There is no interaction effect of process control parameters.
3. Productivity has been interpreted in terms of MRR (Material Removal Rate) of the process and product quality has been described by the surface texture of the EDM machined surface.

EXPERIMENTATION

The selected work piece material for this research work is UTS 304 grade stainless steel (density 8030 Kg/m^3). Experiments have been conducted on Electronica Electraplus PS 50ZNC die sinking machine. An electrolytic pure copper with a diameter of 30 mm has been used as a tool electrode (positive polarity) and work piece materials used were stainless steel rectangular plates of dimensions $100 \times 50\,mm$ and of thickness $4\,mm$. Commercial grade EDM oil (specific gravity 0.763 and freezing point 94^0C) has been used as dielectric fluid. Lateral flushing with a pressure of 0.3 Kgf/cm^2 has been used. Discharge current (I_P), pulse on time (T_{ON}), duty factor (τ) of the machine and discharge voltage (V) have been treated as controllable process factors. Table 1 reveals domain of experiments. Design of Experiment (DOE) has been selected as per Taguchi's L_9 orthogonal array (Table 2), in which interactive effect of process parameters have been neglected. Experimental data have been furnished in Table 3.

DESIRABILITY FUNCTION APPROACH

In this approach, individual responses are transformed to corresponding desirability values. Desirability value depends of acceptable tolerance range as well as target of the response. If the response reaches its target value, which is the most desired situation, its desirability is assigned as unity. If the value of the response falls beyond the prescribed tolerance rage, which is not desired, its desirability value is assumed as zero. Therefore, desirability value may vary with zero to unity.

In this section individual desirability values related to each bead geometry parameters have been calculated using the formula proposed by Derringer and Suich, (1980). For bead width, reinforcement, area of reinforcement and bead volume Lower-the-better (LB); and for depth of penetration, area of penetration and dilution percentage Higher-the-better (HB) criterion has been selected.

Individual desirability value using Lower-the-better (LB) criterion is shown in Figure 1. The value of $\hat{y}$ is expected to be the lower the better. When $\hat{y}$ is less than a particular criteria value, the desirability value d_i equals to 1; if $\hat{y}$ exceeds a particular criteria value, the desirability value equals to 0. So, d_i can vary within the range (0, 1). The desirability function of the Lower-the-better (LB) criterion can be written as below (equations 1 to 3). Here, $y_{\min}$ denotes the lower tolerance limit of $\hat{y}$, the $y_{\max}$ represents the upper tolerance limit of $\hat{y}$ and r represents the desirability function index, which is to be assigned previously according to the consideration of the optimization solver. If the corresponding response is expected to be closer to the target, the index can be set to the larger value, otherwise a smaller value.

If $\hat{y} \le y_{\min}$, $d_i = 1$ (1)

If $y_{\min} \le \hat{y} \le y_{\max}$, $d_i = \left(\frac{\hat{y} - y_{\max}}{y_{\min} - y_{\max}} \right)^r$ (2)

If $\hat{y} \ge y_{\max}$, $d_i = 0$ (3)

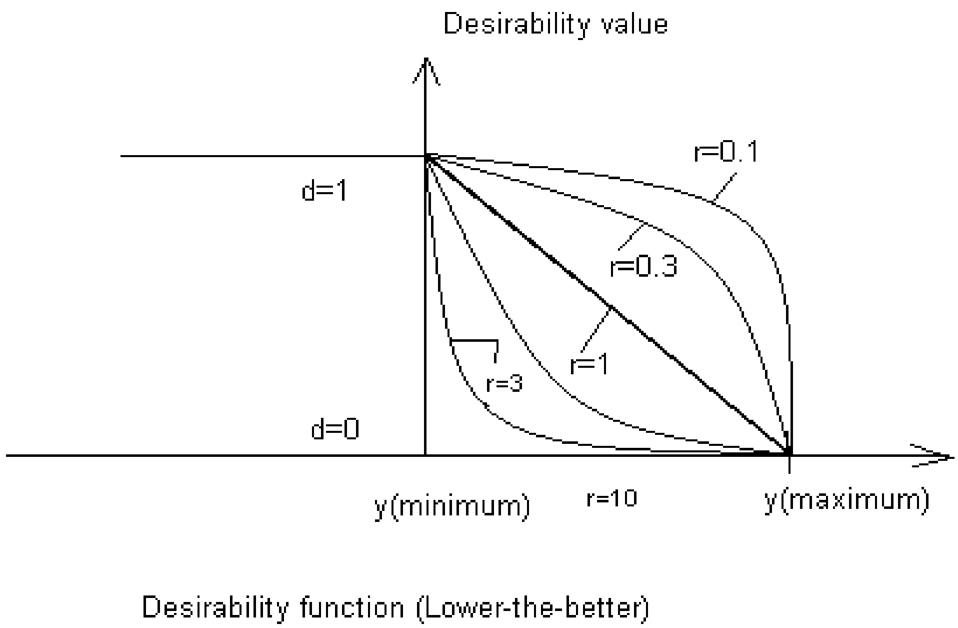

Figure 1: Desirability function (Lower-the-Better)

Individual desirability value using Higher-the-better (HB) criterion is shown in Figure 2. The value of $\hat{y}$ is expected to be the higher the better. When $\hat{y}$ exceeds a particular criteria value, according to the requirement, the desirability value d_i equals to 1; if $\hat{y}$ is less than a particular criteria value, i.e. less than the acceptable limit, the desirability value equals to 0. The desirability function of the Higher-the-better (HB) criterion can be written in the form as given in equations (4) to (6). Here, $y_{\min}$ denotes the lower tolerance limit of $\hat{y}$, the $y_{\max}$ represents the upper tolerance limit of $\hat{y}$ and r represents the desirability function index, which is to be assigned previously according to the consideration of the optimization solver. If the corresponding response is expected to be closer to the target, the index can be set to the larger value, otherwise a smaller value.

If $\hat{y} \le y_{\min}$, $d_i = 0$ (4)

If $y_{\min} \le \hat{y} \le y_{\max}$, $d_i = \left(\dfrac{\hat{y} - y_{\min}}{y_{\max} - y_{\min}} \right)^r$ (5)

If $\hat{y} \ge y_{\max}$, $d_i = 1$ (6)

The individual desirability values have been accumulated to calculate the overall desirability, using the following equation (7). Here D_O is the overall desirability value, d_i is the individual desirability value of ith quality characteristic and n is the total number of responses.

$$D_O = (d_1 d_2 .... d_n)^{\frac{1}{n}} \quad (7)$$

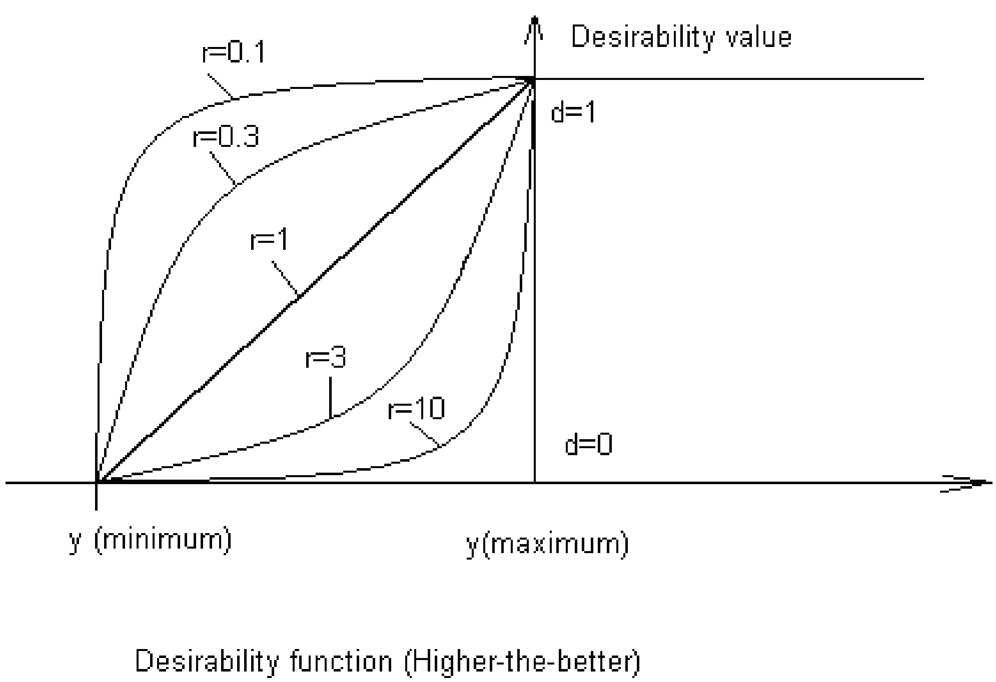

Figure 2: Desirability function (Higher-the-Better)

PARANETRIC OPTIMIZATION

Experimental data (Table 3) i.e. MRR and R_a (for each experiment) have been converted to corresponding desirability values. For MRR and R_a Higher-the-Better (HB) and Lower-the-Better (LB) criteria has been chosen respectively. For MRR, minimum limit has been selected- 7.72 mm^3/min and for R_a, maximum limit has been modified as 11.69 µm. This modification has been made to avoid difficulties in computing S/N ratio in Taguchi analysis. In this computation desirability function index has been assumed as unity. Individual desirability values have been aggregated to calculate overall desirability. Priority weight of each response has been assumed as 0.5. Table 4 represents individual desirability of responses, overall desirability value and corresponding S/N ratio. S/N ratio of overall desirability has been computed using HB criteria.

Table 1: Domain of Experiments

Factor(s)	Notation/ Units	Code	Levels of Factors		
			1	2	3
Discharge Current	I_P (A)	A	06	08	10
Pulse on Time	T_{ON} (µs)	B	300	400	500
Duty Factor	τ	C	8	10	12
Discharge Voltage	V (Volt)	D	40	45	50

Table 2: Design of Experiment (DOE)

Sl. No.	Design of Experiment (L_9 orthogonal array)			
	A	B	C	D
01	1	1	1	1
02	1	2	2	2
03	1	3	3	3
04	2	1	2	3
05	2	2	3	1
06	2	3	1	2
07	3	1	3	2
08	3	2	1	3
09	3	3	2	1

Figure 3 represents S/N ratio plot of overall desirability; S/N ratio has been calculated using Higher-the-Better (HB) criteria. Optimal setting has been evaluated from this plot. Predicted optimal combination becomes: A2 B1 C2 D1. Optimal result has been verified through confirmatory test. According to Taguchi' prediction predicted value of S/N ratio for overall desirability becomes 11.4134 (higher than all entries in Table 4) whereas in confirmatory experiment it is obtained a value of 13.4792. So quality has improved using the optimal setting. Mean response table for S/N Ratio of overall desirability has been shown in Table 5; which indicates that discharge current and discharge voltage are most important factors influencing overall desirability. Next important process factor seems to be the duty factor which influences both pulse on and pulse off time.

Table 3: Experimental Data

Sl. No.	Experimental Data	
	MRR (mm^3/min)	R_a (μm)
01	8.4682	8.66
02	8.7173	8.38
03	7.7210	8.42
04	13.4496	9.88
05	14.6949	10.72
06	11.7061	8.10
07	18.9290	11.22
08	15.4421	11.68
09	19.6762	9.02

Table 4: Calculation of Desirability Values

Sl. No.	Individual Desirability Values of		Overall Desirability	Corresponding S/N Ratio
	MRR	R_a		
01	0.0626	0.8440	0.2298	-12.7730
02	0.0834	0.9220	0.2773	-11.1410
03	0.0001	0.9109	0.0087	-41.2096
04	0.4792	0.5042	0.4915	-6.1695
05	0.5834	0.2702	0.3970	-8.0242
06	0.3334	1.0000	0.5774	-4.7705
07	0.9375	0.1309	0.3503	-9.1112
08	0.6459	0.0028	0.0424	-27.4527
09	1.0000	0.7437	0.8624	-1.2858

CONCLUSIONS

- Adaptation of Taguchi’s Orthogonal Array design of experiment provides a limited number of well balanced experimental runs resulting saving in experimental cost as well as experimentation time.
- Desirability function approach has been found fruitful which can take care of the constraints imposed by the fixation of target/tolerance limit of the individual responses.
- Desirability function approach has been found efficient to convert a multi-objective optimization problem to a single objective optimization problem.

- The said approach can be recommended for multi-response optimization and off-line quality control.

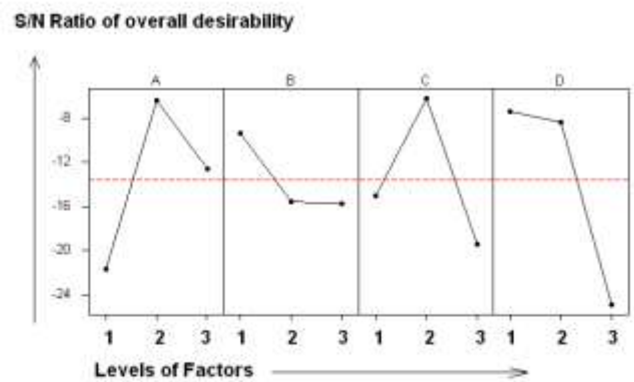

Figure 3: S/N Ratio plot of overall desirability (Prediction of Optimal Setting)

Table 5: Response Table for Signal to Noise Ratios

Level	A	B	C	D
1	-21.7079	-9.3512	-14.9987	-7.3610
2	-6.3214	-15.5393	-6.1988	-8.3409
3	-12.6166	-15.7553	-19.4483	-24.9439
Delta	15.3865	6.4041	13.2495	17.5829
Rank	2	4	3	1

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