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Optimization of multiple quality characteristics of EDM process for MRR and TWR using utility concept

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ABSTRACT

Electrical discharge machining (EDM) researchers have explored a number of ways to improve the material removal rate (*MRR*) in order to meet the industrial need for fulfilling market demand. Tool wear rate (*TWR*) is also one of the important performance measures in EDM amongst other measures such as metal removal rate and surface roughness. In most EDM operations, the contribution of the tool cost to the operational costs is more than 70 %. As a consequence, the wear of the tool should be carefully taken into consideration when planning and designing EDM operations. Despite a range of different approaches, this new research shares the same objective of achieving more efficient material removal coupled with a simultaneous reduction in tool wear. This study reports on an investigation into the optimization of the die sink EDM process on EN31 die steel. Taguchi's method with multiple performance characteristics has been adopted to obtain an overall utility value that represents the overall performance of die sink EDM. The six input parameters are optimized by considering multi-performance characteristics including *MRR* and *TWR*. The predicted optimal values for *MRR* and *TWR* obtained for die sink EDM are 0.2421 g/min and 0.0087 g/min, respectively. The results were verified by conducting confirmation experiments.

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1. Introduction

Electrical discharge machining (EDM) is a non-traditional machining method commonly used to produce die cavities via the erosive effect of electric current. This method is especially effective in machining hard die steels, complex cavities and small workpieces. EDM has various applications in automobile, aeronautic, mold and die manufacturing industries especially for manufacturing die for injection molding, forging, extraction, etc. The objective of research in area of advanced machining has been to enhance the efficiency and reliability of machine tools while designing them [1]. Electric discharge machining (EDM) is one of the most effective non-conventional machining processes for manufacturing of dies in forging/extrusion industries. High strength temperature resistant (HSTR) super alloys, composites and advanced ceramics can be machined with close precision and surface finish by EDM satisfactorily [2]. In spite of the remarkable process capabilities, the instability factor in EDM is slow material removal rate. The electrical parameters (current, pulse on time, voltage, duty cycle) and non-electrical parameters (spark gap and flushing pressure) of die sink EDM have great effect on process performance [3]. The governing characteristics (material removal rate, tool wear and surface roughness) need to be optimized for achieving efficient machining rate and accuracy. A single setting of process parameters may be optimal for one quality characteristic but same setting may yield detrimental results for other quality characteristics. Most of the operations need several quality characteristics for achieving efficient performance. In the present investigation, a simplified methodology based on Taguchi's approach and utility concept has been developed for determining optimal setting of process parameters for multi characteristic product [4, 6].

1.1 Literature survey

In the past, manufacturers have tried to quantify the control parameters to improve machining quality. Literature review indicates that a number of input parameters affect the quality of machined component in die sink EDM and the main interest of the researchers has been to identify the parameters affecting the surface roughness, material removal rate and tool wear [7-11]. It is desirable to obtain the maximum material removal rate with minimal electrode wear. Phase of sparking of material removal mechanism (breakdown, discharge and erosion) is highly influenced by the types of eroded electrode and workpiece elements together with disintegrated products of dielectric fluid [12]. Yu et al. introduced a uniform tool wear machining method compensating the longitudinal tool wear by applying an overlapping to-and-from machining motion [13]. Bleys et al. and Dauw have illustrated the development of tool wear and part geometry to provide good opportunity of understanding and compensating the tool wear through a geometrical simulation of EDM [14, 15]. Osyczka et al. addressed multi-criterion optimization in EDM process to improve the quality of metal removal rate, surface roughness and electrode wastage [16]. Lin et al. analyzed the best factors combination by using Taguchi method in conjunction with fuzzy logic to improve the quality features of *MRR* and electrode wastage [17, 18]. Lin et al. developed a set of algorithm to improve *MRR*, surface roughness and electrode wastage in electric discharge process through Taguchi method and grey relational analysis [19, 20]. Jangra, et al. [21] had applied Taguchi method along with grey relational analysis for optimization of Material Removal Rate (*MRR*) and Surface Roughness (*SR*) for wire electrical discharge machining (WEDM) of WC-Co composite simultaneously. Shandilya, et al. [22] had applied response surface methodology (RSM) and analysis of variance (ANOVA) to solve single response problem. Gadakh and Shinde [23] have discussed and applied the graph theory for selecting suitable process parameters and also have few multiple attribute decision-making (MADM) methods to rank and select the process parameters. Gadak had applied TOPSIS to solve the multiple objective optimization in wire electrical discharge machining process, and results obtained using TOPSIS method almost match with those obtained by the other researchers in the past with various techniques [24]. To find the percentage contribution of the drilling parameters to machine carbon-fibre-reinforced polymer (CFRP) composites with multiple performance characteristics, grey fuzzy analysis and ANOVA was applied [25]. Optimization of process parameters of electrochemical discharge machining (ECDM) using Taguchi with utility concept was applied and to find out that tool workpiece gap has the great impact on *MRR* and *TWR* [26]. Bose and Mitra made attempt to optimize the machining parameters of ECG process using grey-Taguchi methodology while machining AL_2O_3/Al interpenetrating phase composite [27].

1.2 Principle of die sink EDM

Sinker EDM is best suited for machining deep and thin cavities in hard materials [28]. The EDM removes material by electro-erosion based on the spark discharge between the electrode and the workpiece to meet the demand on dimension, shape and surface quality [29]. The material erosion mechanism primarily makes use of electrical energy turned into thermal energy through a series of discrete electrical discharges occurring between the electrode and workpiece immersed in a dielectric fluid [30]. The thermal energy generates a channel of plasma between the cathode and anode at a temperature in the range of 8000-12000 °C or as high as 20000 °C [31]. The volumetric material removal rate and the volume of material removed per discharge depend upon the application and *MRR* observed in the range of 2-400 mm^3/min [32]. EDM is a highly accurate and reproductive shaping process in which the shaped electrode is mirrored in the workpiece and defines the area where the spark erosion takes place [33].

2. Selection of process parameters

The process parameters that affect performance of die sink EDM are:

- Electrical parameters: current, pulse on time, duty cycle and supply voltage,
- Non-electrical parameters: electrode lift time, working time, spark gap, flushing pressure and gain, and
- Electrode based parameters: electrode material and electrode size.

The following six parameters were chosen for this study: current (A), pulse on time (B), spark gap (C), voltage (D), duty cycle (E), and flushing pressure (F). The ranges of the selected process parameters were decided by conducting the experiments using one variable at a time approach. The selected process parameters, their designated symbols and levels are given in Tables 1 and 2.

Table 1 Selected parameters and their ranges

#	Process parameters	Parameter designation	Units	Ranges
1	Discharge current (I)	Factor A	A	6-12
2	Pulse on time (T_{on})	Factor B	µs	100-200
3	Spark gap (X)	Factor C	mm	0.3-0.7
4	Voltage (V_{g})	Factor D	V	35-55
5	Duty cycle	Factor E	%	56-88
6	Flushing pressure (P)	Factor F	kgf/cm^2	0.4-0.8

Table 2 Selected fixed parameters for centre flushing

Base	Parameter	Description
Tool	Material	Copper rod
	Shape	Cylindrical with centre hole
	Size	Ø 20 mm by 30 mm with centre hole of Ø 3 mm
Workpiece	Material	EN31 (HRC 58)
	Shape	Cylindrical with centre hole
	Size	Ø 20 mm by 30 mm with centre hole of Ø 3 mm
Polarity	Electrode (tool)	Negative
	Workpiece (job)	Positive
Others	Dielectric	Kerosene
	Flushing	Centre flushing

Performance characteristics

For evaluating the performance of die sink EDM, the following output characteristics were selected:

- material removal rate (MRR),
- tool wear rate (TWR).

MRR should be higher and TWR should be lowest possible. A simplified multi-characteristic methodology based on Taguchi's approach and utility concept has been used to optimize the performance of die sink EDM.

3. Utility concept

The performance of a product is evaluated on various quality characteristics. The evaluations of different characteristics are combined to give a composite index. Such a composite index represents the utility of a product and is the sum of utilities of each of the quality characteristics. The joint utility function can be expressed as [34]:

$$U(x_1, x_2, \ldots, x_n) = f[U_1(x_1), U_2(x_2), \ldots, U_n(x_n)] \tag{1}$$

In linear case, the function becomes:

$$U(x_1, x_2, \dots, x_n) = \sum_{i=1}^{n} W_i U(x_i) \tag{2}$$

where W_i is the weightage assigned to the attribute i and the sum of the weightages for all attributes is equal to 1.

If the composite measure (the overall utility) is maximized, the quality characteristics considered for evaluation of utility will automatically be optimized (maximized or minimized whatsoever the case may be).

3.1 Determination of utility value

To determine the utility value for a number of quality characteristics, a preference scale for each quality characteristic is constructed. Later these scales are weighted to obtain a composite number (overall utility). The weighting is done to satisfy the test of indifference on the various quality characteristics. The preference scale should be a logarithmic one [35]. The minimum acceptable quality level for each quality characteristic is set out at 0 preference number and the best available quality is assigned a preference number of 9. If a log scale is chosen, the preference number (P_i) is given by [35]:

$$P_i = A \log \frac{x_i}{x_i'} \tag{3}$$

where:

x_i – any value of quality characteristic or attribute *i*
x_i' – minimum acceptable value of quality characteristic or attribute *i*
A – a constant

At optimum value (x_i') of attribute *i,* the preference number, $P_i = 9$, therefore:

$$A = \frac{9}{\log \frac{x_i^*}{x_i'}} \tag{4}$$

The next step is to assign weights or relative importance to the quality characteristics. This assignment is subjective and based on experience. Moreover, it depends on the end use of the product or it may depend on the customer's requirements. The weightage should be assigned such that the following condition holds:

$$\sum_{i=1}^{n} W_i = 1 \tag{5}$$

The overall utility can be calculated as:

$$U_j = \sum_{i=1}^{n} W_i P_i \tag{6}$$

4. Multi-characteristic optimization of quality characteristics

The optimal setting of process parameters and the optimal values of material removal rate, tool wear rate and surface roughness (optimized individually using Taguchi's approach) have been established. The summary results are reproduced in Table 3.

Table 3 Optimal setting of process parameters and optimal values of individual quality characteristics

Quality characteristics (individual)	Optimal setting of process parameters	Significant process parameters (at 95 % confidence level)	Predicted optimal value of quality characteristics
Material removal rate (g/min)	A_3, B_1, C_3, D_1, F_1	A, B, C, D, F	0.229 g/min
Tool wear rate (g/min)	A_1, B_3, C_3, D_3, F_1	A, B, C, D, F	0.0071 g/min

4.1 Preference scale construction

Material removal rate (MRR)
x^* – optimum value of MRR (when optimized individually)
x^* = 0.229 g/min (Table 3)

x' – minimum acceptable value of material removal rate
x' = 0.111 g/min (assumed)

Using these values and Eqs. 3 and 4, the following preference scale for material removal rate has been constructed:

$$P_{MRR} = 28.26 \log \frac{x}{0.111} \tag{7}$$

Tool wear rate (TWR)
x^* – optimum value of TWR (when optimized individually)
x^* = 0.0071 g/min (Table 3)

x' – minimum acceptable value of tool wear rate
x' = 0.065 g/min (assumed)

Using these values and Eqs. 3 and 4, the following preference scale for tool wear rate has been constructed:

$$P_{TWR} = -9.36 \log \frac{x}{0.065} \tag{8}$$

4.2 Weightage of quality characteristics

It has been assumed that the quality characteristics are equally important and hence equal weightage has been assigned. However, there is no constraint on weightage and it can be any value between 0 and 1 subjected to the conditions specified.

W_{TWR} = 0.5 (weightage for tool wear rate)
W_{MRR} = 0.5 (weightage for material removal rate)

4.3 Utility value calculation

The utility value of each machined part has been calculated using the following relation:

$$U(n,R) = P_{TWR}(n,R) \times W_{TWR} + P_{MRR}(n,R) \times W_{MRR} \tag{9}$$

where:
n – trial number, n = 1,2,...,27
R – repetition, R = 1,2,3

The utility values thus calculated are given in Table 4.

5. Determination of optimal settings of process parameters

The data (utility values) have been analyzed both for mean responses (mean of utility at each level of each parameter) and signal to noise ratio. Since utility is a higher-the-better (HB) type of quality characteristic, the signal to noise ratio for HB has been used. The S/N ratios are also given in Table 4. The mean responses and main effects (in terms of utility value) are given in Table 5. The average value of S/N ratios and S/N main effects are given in Table 7. The data from Tables 5 and 7 are plotted in Fig. 1, subfigures a), b), c), d), e), and f). The pooled version of ANOVA for raw data (utility) is given in Table 6. From Tables 6 and 8, it is seen that current (A), pulse on time (B), spark gap (C), voltage (D), and flushing pressure (F) significantly affect mean of utility values. The optimal setting of process parameters for optimization of Utility value based on the material removal rate and tool wear rate of EN31 steel EDM machined parts using copper electrode is as given as in Table 9.

Table 4 Utility data based on quality characteristics (MRR and TWR)

Raw data (Utility values) (MRR and TWR)			MSD (HB)	S/N ratio (dB)
R1	R2	R3		
4.234	4.210	4.225	0.056	12.512
0.251	4.247	3.736	0.061	12.160
3.263	3.789	2.677	0.101	9.955
4.327	4.321	4.315	0.054	12.711
3.823	3.796	3.832	0.069	11.634
2.438	2.437	2.439	0.168	7.740
8.413	8.037	8.037	0.015	18.230
4.477	4.880	5.299	0.042	13.717
7.316	7.300	7.305	0.019	17.275
3.220	2.277	3.223	0.129	8.909
3.380	2.921	3.852	0.091	10.423
6.083	6.343	5.806	0.027	15.657
2.666	2.826	3.328	0.119	9.253
4.448	4.425	4.439	0.051	12.943
4.559	4.555	4.556	0.048	13.173
2.143	2.138	2.142	0.218	6.612
4.939	5.171	5.183	0.039	14.141
4.611	4.942	4.844	0.044	13.612
2.264	2.259	2.265	0.195	7.093
4.175	4.499	4.173	0.055	12.617
4.837	4.709	4.810	0.044	13.596
4.844	5.598	5.599	0.035	14.501
5.423	5.093	4.748	0.039	14.093
6.703	6.687	6.710	0.022	16.521
6.664	6.658	6.658	0.023	16.470
6.128	6.213	6.060	0.027	15.753
5.338	5.324	5.334	0.035	14.538

$\bar{T}$= 3.586

R1, R2, R3 repetition of experiments against each of the trial conditions

Table 5 Average values and main effects [Raw data: Utility (MRR and TWR)]

Process parameter designation	Average utility values			Main effects	
	L1	L2	L3	L2-L1	L3-L2
A	4.7194	4.0378	5.1768	−0.6816	1.1390
B	3.9158	4.4050	5.6132	0.4892	1.2082
C	4.3293	4.5782	5.0265	0.2489	0.4483
D	4.3515	4.9779	4.6046	0.6264	−0.3732
E	4.3558	4.8287	4.7494	0.4728	−0.0793
F	5.2338	4.7875	3.9127	−0.4464	−0.8748
$A \times B$	4.5733	4.1674	5.1932	−0.4059	1.0258
$A \times C$	5.2270	4.4483	4.2587	−0.7787	−0.1896
$B \times C$	4.4098	4.6774	4.8468	0.2676	0.1694

L1, L2, L3 represent levels 1, 2, 3, respectively, of parameters / interactions

A, B, C, D, E, and F represents current, T_{on}, spark gap, voltage, duty cycle, and flushing pressure, respectively

Table 6 Pooled ANOVA [Raw data: Utility (*MRR* and *TWR*)]

Source	SS	DOF	V	F-ratio	SS'	P
A	17.7398	2	8.869898	73.5*	17.6135	9.409
B	41.2222	2	20.61111	170.8*	41.0959	21.954
C	6.74206	2	3.371028	27.9*	6.61576	3.534
D	5.36174	2	2.680872	22.2*	5.23545	2.797
E	3.46286	2	pooled	–	–	–
F	24.3891	2	12.19456	101.1*	24.2628	12.961
$A\times B$	43.9008	4	10.9752	90.9*	43.6482	23.317
$A\times C$	34.9595	4	8.73987	72.4*	34.7069	18.541
$B\times C$	5.8783	4	1.469575	12.2*	5.62571	3.005
T	187.193	80	–	–	–	100.000
e_p	6.99908	58	0.12067	–	8.3883	4.481

SS – sum of squares, DOF – degree of freedom, V – variance, SS' – pure sum of squares, P – percentage contribution, T – total, e – error, A – current, B – T_{on}, C – spark gap, D – voltage, E – duty cycle, F – flushing rate

Tabulated F-ratio at 95 % confidence level $F_{0.05}(2,58) = 3.56$, $F_{0.05}(4,58) = 2.53$

*Significant at 95 % confidence level

Table 7 Average S/N values and main effects [S/N data: Utility (*MRR* and *TWR*)]

Process parameter designation	Average S/N Values			Main Effect	
	L1	L2	L3	L2-L1	L3-L2
A	9.34	9.42	12.44	0.09	3.02
B	9.57	9.54	12.09	–0.03	2.56
C	9.42	10.72	11.06	1.30	0.35
D	10.22	11.28	9.70	1.06	–1.58
E	10.07	10.44	10.69	0.37	0.25
F	11.43	10.78	8.99	–0.65	–1.79
$A\times B$	9.94	9.50	11.77	–0.44	2.27
$A\times C$	11.74	10.11	9.35	–1.63	–0.76
$B\times C$	9.92	10.58	10.70	0.67	0.12

Table 8 Pooled ANOVA [S/N data: Utility (*MRR* and *TWR*)]

Source	SS	DOF	V	F-ratio	SS'	P
A	23.32	2.00	11.66	3.92*	22.16	12.04
B	43.01	2.00	21.50	7.23*	41.85	18.07
C	14.63	2.00	pooled	–	–	–
D	8.91	2.00	pooled	–	–	–
E	2.54	2.00	pooled	–	–	–
F	32.16	2.00	16.08	5.40*	31.01	15.65
$A\times B$	50.08	4.00	12.52	4.21*	47.76	20.48
$A\times C$	60.92	4.00	15.23	5.12*	58.61	24.90
$B\times C$	8.47	4.00	pooled	–	–	–
T	245.20	26.00	–	–	–	100.00
e_p	35.71	12.00	2.98	–	43.81	8.86

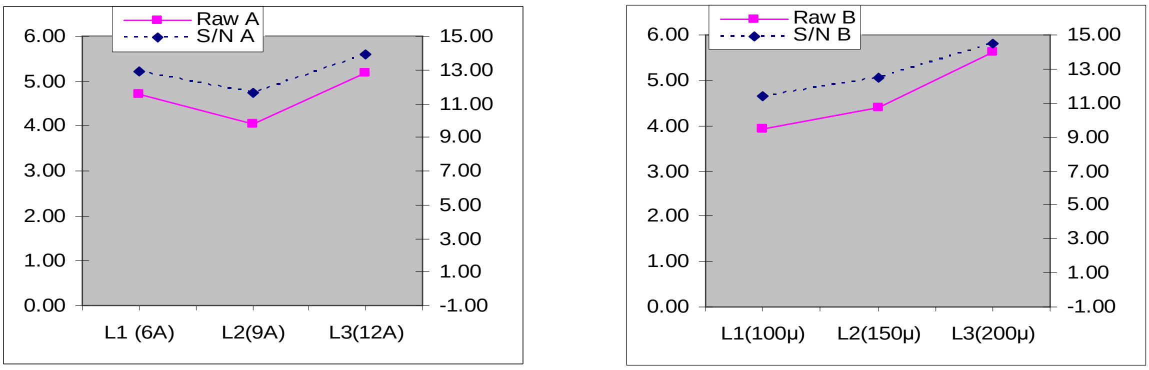
Tabulated F-ratio at 95 % confidence level $F_{0.05}(2,12) = 3.89$, $F_{0.05}(4,12) = 3.26$

*Significant at 95 % confidence level

Table 9 Optimal setting of process parameters

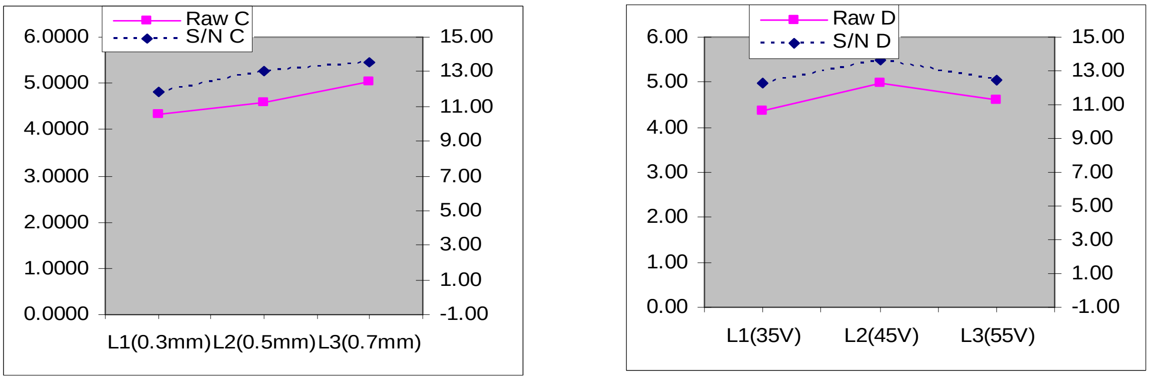
Parameter	Representation	Level	Values
Current	A	3	12 A
Pulse on time (T_{on})	B	3	200 μs
Spark gap	C	3	0.7 mm
Voltage	D	2	45 V
Flushing pressure	F	1	0.4 kgf/cm^2

Quality characteristic: UTILITY
Type of quality characteristic: Higher-the-better
Utility value based on *MRR* and *TWR*: $U_{MRR,TWR}$
Utility (Raw data): ___________
Utility (S/N ratio): - - - - - - -



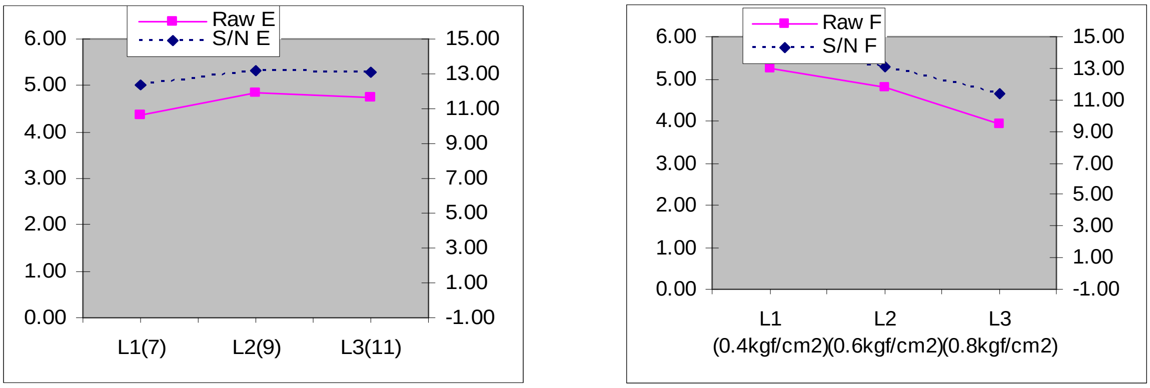
a) Current (A)

b) Pulse on time (μs)



c) Spark gap (mm)

d) Voltage (V)



e) Duty cycle

f) Flushing pressure (kgf/cm^2)

Fig 1 Effect of process parameters on utility values ($U_{MRR,\ TWR}$) and S/N ratio (the main effects)

5.1 Predicted mean (optimal)

From Table 5, the average utility values are:

- Third level of current, $\bar{A}_3$ = 5.1768
- Third level of pulse on time, $\bar{B}_3$ = 5.613
- Third level of spark gap, $\bar{C}_3$ = 5.026
- Second level of voltage, $\bar{D}_2$ = 4.9779

- First level of flushing pressure, $\bar{F}_1$ = 5.234
- Overall mean of material removal rate, $\bar{T}_{U(MRR,TWR)} = 3.586$.

The relative power of factors in controlling average and variation of utility is shown under column P of Table 6. By considering the interaction as one item which has good additivity to other non-interacting items, an estimate of mean value may be made [5].

$$\bar{A}_3\bar{B}_3 = 0.194 \tag{10}$$

$$\bar{B}_3\bar{C}_3 = 0.178 \tag{11}$$

$$\bar{A}_3\bar{C}_3 = 0.198 \tag{12}$$

The predicted optimal utility based on *MRR* and *TWR* is calculated as (Ross 1996, page 185):

$$\begin{aligned}\mu_{U_{(MRR,TWR)}} &= \bar{T} + (\bar{A}_3\bar{B}_3 - \bar{T}) + (\bar{B}_3\bar{C}_3 - \bar{T}) + (\bar{A}_3\bar{C}_3 - \bar{T}) + (\bar{D}_2 - \bar{T}) \\ &+(\bar{F}_1 - \bar{T}) - (\bar{B}_3 - \bar{T}) - (\bar{A}_3 - \bar{T}) - (\bar{C}_3 - \bar{T})\end{aligned} \tag{13}$$

$$\mu_{U_{(MRR,TWR)}} = \bar{A}_3\bar{B}_3 + \bar{B}_3\bar{C}_3 + \bar{A}_3\bar{C}_3 + \bar{D}_2 + \bar{F}_1 - \bar{B}_3 - \bar{A}_3 - \bar{C}_3 - \bar{T} \tag{14}$$

$$\begin{aligned}\mu_{U_{(MRR,TWR)}} &= 6.965 + 5.813 + 5.706 + 4.9779 + 5.234 \\ &-5.1768 - 5.613 - 5.0265 - 3.586\end{aligned} \tag{15}$$

$$\mu_{U_{(MRR,TWR)}} = 9.2936 \tag{16}$$

The 95 % confidence intervals for the mean of the population and three confirmation experiments (CI_{POP} and CI_{CE}) have been calculated as:

$$CI_{POP} = \sqrt{\frac{F_\alpha(1,f_e)V_e}{n_{eff}}} \tag{17}$$

$$CI_{CE} = \sqrt{F_\alpha(1,f_e)\left[\frac{1}{n_{eff}} + \frac{1}{R}\right]V_e} \tag{18}$$

The specific values as required are:

f_e – error; DOF = 58 (Table 6)
V_e – error variance is 0.12067 (Table 6)
N = 81: n_{eff} = 81/23 (calculated), R = 3
$F_{0.05}$(1.58) = 4; (tabulated value from F-Table)

So:

- CI_{POP} = ± 0.397
- CI_{CE} = ± 0.585

The 95 % confidence intervals are:

$$\left(\hat{\mu}_{U_{(MRR,TWR)}} - CI\right) < \mu_{U_{(MRR,TWR)}} < \left(\hat{\mu}_{U_{(MRR,TWR)}} + CI\right) \tag{19}$$

Hence:

$$CI_{\text{POP}} = 8.8966 < \mu_{U_{(MRR,TWR)}} < 9.6906 \tag{20}$$

$$CI_{\text{CE}} = 8.7086 < \mu_{U_{(MRR,TWR)}} < 9.8786 \tag{21}$$

5.2 Confirmation experiments

Three confirmation experiments have been conducted at the optimum setting (A_3, B_3, C_3, D_2, F_1) of the process parameters. The following average values have been found for the quality characteristics considered:

- average material removal rate is 0.2421 g/min,
- average tool wear rate is 0.0087 g/min.

The utility value of machined part has been calculated using the following relation:

$$U = P_{TWR} \times W_{TWR} + P_{MRR} \times W_{MRR} \tag{22}$$

$$\mu_{U_{(MRR,TWR)}} = 8.928 \tag{23}$$

6. Conclusion

In this work, an attempt is made to determine the optimal parameters for material removal rate, tool wear rate, and surface finish through the use of Taguchi approach and utility concept. The following conclusions have been drawn.

- A simplified model based on Taguchi approach and utility concept has been developed for determining optimal settings of the process parameters for multi-characteristic product. The model has been used to predict optimal settings of process parameters for combined quality characteristics. The predicted optimal values of the quality characteristics have been verified by machining specimens of EN31 die steel with copper electrode at the optimal settings recommended by the model.
- The percent contribution of the significant process parameters towards the utility index of the selected quality characteristics of machined parts are (Table 6):
  - current: 9.049 %,
  - pulse on time: 21.954 %,
  - spark gap: 3.534 %,
  - voltage: 2.797 %,
  - flushing pressure: 12.961 %,
  - interaction between current and pulse on time: 23.317 %,
  - interaction between current and spark gap: 18.541 %,
  - interaction between pulse on time and spark gap: 3.005 %.
- The optimal levels of various machining process parameters for optimization of utility based on material removal rate and tool wear rate from Eq. 16 while machining EN31 with copper are in Table 10.

Table 10 The optimal levels of various machining process parameters

Parameters		Level	
Current	A	3	12 A
Pulse on time (T_{on})	B	3	200 μs
Spark gap	C	3	0.7 mm
Voltage	D	2	45 V
Flushing pressure	F	1	0.4 kgf/cm^2

- The predicted optimal range of utility based material removal rate and of utility based tool wear rate is as in Eq. 20 and Eq. 21, respectively, at 95 % confidence level.
- The optimal values obtained using the multi-characteristic optimization models have been validated by confirmation experiments.
- The model can be extended to any number of quality characteristics provided proper utility scales for the characteristics are available from the realistic data.

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