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ScienceDirect

Procedia Engineering 64 (2013) 446 – 455

Procedia Engineering

www.elsevier.com/locate/procedia

International Conference On DESIGN AND MANUFACTURING, IConDM 2013

Comment [S1]: Elsevier to update with volume and page numbers.

Optimization of surface roughness and MRR in EDM using WPCA

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Abstract

The objective of the present study is to find out the optimum combination of process parameters in EDM process so that surface roughness reaches a minimum value and the metal removal rate (MRR) reaches a maximum value. In this study, five roughness parameters (viz. center line average roughness, root mean square roughness, mean line peak spacing, skewness and kurtosis) along with MRR have been considered. To optimize the multi-response problems, Taguchi method alone is unable to solve the problem. Thus, the multi-response characteristics must be converted to a single performance index. In this study weighted principal components analysis (WPCA) method is used for this conversion. For the experimentation, Taguchi L_{27} orthogonal design with four process parameters, viz., pulse on time, pulse off time, discharge current and voltage at three different levels is used. The optimum combination of process parameters has been found out and verified through the confirmation test. The result of the confirmation test shows a good agreement with the predicted value. This indicates the utility of the WPCA technique as multi-objective optimizer in the field of EDM. In addition, the surface morphology is studied with the help of scanning electron microscopy (SEM) analysis.

Keywords: EDM; Multiple-response; Weighted Principal Component Analysis (WPCA); Optimization

1. Introduction

Electrical discharge machining (EDM) is a controlled metal-removal process that is used to remove metal by means of electric spark erosion. In this process, an electric spark is used as the cutting tool to cut (erode) the work piece to produce the finished product to the desired shape. The metal-removal process is performed by applying a pulsating (ON/OFF) electrical charge of high-frequency current through the electrode to the work piece. This

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doi:10.1016/j.proeng.2013.09.118

removes (erodes) very tiny pieces of metal from the work piece at a controlled rate. The dielectric oil, that provides a means of flushing, is pumped through the arc gap. This removes suspended particles of work piece material and electrode from the work cavity.EDM process is popular non-conventional machining process and there are many researchers who have studied the performance characteristics of EDM process. Zhang et al. [1] have investigated the effects on material removal rate, surface roughness and diameter of discharge points in electro-discharge machining (EDM) on ceramics. From the experimental results, they have shown that the material removal rate, surface roughness and the diameter of discharge point all increase with increasing pulse-on time and discharge current. Lin and Lin [2] have studied an approach for the optimization of the electrical discharge machining process (work-piece polarity, pulse on time, duty factor, open discharge voltage, discharge current, and dielectric fluid) with multiple performance characteristics viz. MRR, surface roughness and electrode wear ratio using grey relational analysis. Haron et al. [3] have studied the effect of MRR and tool wear on AISI 1045 tool steel, which shows the maximum MRR is obtained when copper or graphite electrode is used, also current and electrode diameter have effects on MRR. Singh et al. [4] have concluded that pulse on-time and current have significant effect on the multiple response characteristics. Gao et al. [5] have used artificial neural network (ANN) to represent the relationship between material removal rate (MRR) and input parameters, and genetic algorithm (GA) is used to optimize parameters. George et al. [6] have shown that pulse current is the most significant machining parameter on MRR followed by gap voltage and pulse on time. Pradhan and Biswas [7] have used response surface methodology (RSM) to investigate the effect of four controllable input variables viz. discharge current, pulse duration, pulse off time and applied voltage on surface roughness and the results show that surface roughness is directly proportional to linear effect of pulse current and pulse on time. Patel et al. [8] have studied the surface integrity and material removal mechanisms associated with EDM of Al_2O_3 ceramic composite and shown that surface roughness increases with discharge current and pulse-on time.

The present study deals with the optimization of multiple responses: centre line average roughness (R_a), root mean square roughness (R_q), skewness (R_{sk}), kurtosis (R_{ku}), mean line peak spacing (R_{sm}) and MRR in EDM of EN31 tool steel. Experiments are conducted based on L_{27} orthogonal array of Taguchi design for four process parameters (factors) viz. discharge current, pulse on time, pulse off time and voltage with three levels for each factor. To optimize the multi-responses problem, weighted principal component analysis (WPCA) is applied for the current study. Finally, a confirmation test is carried out to validate the result. Also, surface morphology is investigated for the material before and after the test using SEM images.

2. Weighted principal component (WPC) method

Su and Tong [9] and Antony [10] have proposed a new method called principal component analysis (PCA) to optimize the multi-response problem. They have used a PCA method to transform the normalized multi-response value into uncorrelated linear combinations. After obtaining the linear combinations, the principal components can be formed. In the application of PCA method, this selected component is regarded as an index in order to conveniently optimize the multi-response problem and to gain the best combination of factors/levels. However, there are still two shortcomings in the PCA method. First, when more than one principal component is selected whose Eigen value is greater than 1, the required trade-off for a feasible solution is unknown; and second, the multi-response performance index cannot replace the multi-response solution when the chosen principle component can only be explained by total variation. In order to overcome these two main shortcomings in the PCA method, the present study deals with weighted principal components (WPC) method. In this WPC method, all components are taken into consideration in order to completely explain variation in all responses. The WPC method uses the explained variation as the weight to combine all principal components in order to form a multi-response performance index (MPI). Then, the best combination of factors/levels will easily be obtained.

The WPC method for multi-response optimization can be described in the following steps:

Step 1: Computation of loss function

Based on the objective of the study, the Taguchi loss function can be categorized in to three types:

Lower-the-better (LB),

$$L_{ij} = \frac{1}{n}\sum_{k=1}^{n} y_{ijk}^2 \tag{1}$$

Higher-the-better (HB),

$$L_{ij} = \frac{1}{n}\sum_{k=1}^{n}\frac{1}{y_{ijk}^2} \quad (2)$$

Nominal-the-best (NB),

$$L_{ij} = \left(\frac{\mu^2}{\sigma^2}\right) \quad (3)$$

Where, $\mu = \frac{1}{n}\sum_{k=1}^{n} y_{ijk}$, $\sigma^2 = \frac{1}{n-1}\sum_{k=1}^{n}(y_{ijk} - \mu)^2$

n represents the number of repeated experiments, y_{ijk} is the experimental value of j^{th} response variable in i^{th} trial at k^{th}test and L_{ij} is the computed quality loss for j^{th} response in i^{th} trial.

Step 2: Computation of the signal-to-noise (S/N) ratio for each response

The S/N ratio can be calculated using Equation (4).The quality loss (L_{ij})of j^{th} response corresponding to i^{th} trial can be taken according to the objective of the experiment using Equation (1) or (2) or (3),

$$\alpha_{ij} = -10log_{10}L_{ij} \quad (4)$$

Step 3: Transformation of the S/N ratio values for each response into (0, 1) interval:

The S/N ratio values is transformed into scaled S/N ratio using Equation (5)

$$Y_{ij} = \frac{\alpha_{ij} - \alpha_j^{min}}{\alpha_j^{max} - \alpha_j^{min}} \quad (5)$$

Where, Y_{ij} = scaled S/N ratio value for j^{th} response at i^{th} trial. $\alpha_j^{min} = min\{\alpha_{1j}, \alpha_{2j}, ..., \alpha_{mj}\}$ and $\alpha_j^{max} = max\{\alpha_{1j}, \alpha_{2j}, ..., \alpha_{mj}\}$.

Step 4: Pearson's correlation coefficient:

The correlation coefficient between two response variables is calculated by the following equation

$$\rho_{jk} = \frac{Cov(Q_j, Q_k)}{\sigma_{Q_j} \times \sigma_{Q_k}} \quad (6)$$

Where, ρ_{jk} is the correlation coefficient between response variables j and k

$Cov\left(Q_j, Q_k\right)$ is the covariance of response variables j and k.

$\sigma_{Q_j} and \sigma_{Q_k}$ are the standard deviation of response variables j and k respectively.

The correlation is checked by testing the following hypothesis:

There will be no correlation between the responses, if $\rho_{jk} = 0$; and the correlation exists if $\rho_{jk} \neq 0$.

Step 5: Principal component calculation

The principal components for each trial is computed as follows

$$z_l^i = a_{l1}Y_{i1} + a_{l2}Y_{i2} + ... + a_{lp}Y_{ip}; (l = 1,2,.....,q) \quad (7)$$

Where, $Z_l^i (l = 1,2,....,q)$ is q principal components corresponding to a trial i.

Step 6: Computation of the multi-response performance index (MPI) corresponding to each trial.

The multi-response performance index (MPI) is essentially the weighted sum of all the principal components.

The MPI value for i[th] trial, therefore, can be computed using the following equation:

$$MPI^i = \sum_{l=1}^{q} W_l Z_l^i \tag{8}$$

where, W_i is the proportion of overall variance of the response explained by l[th] principal component, Z_l^i is the computed value of l[th] principal component corresponding to i[th] trial and $\sum W_l = 1$. It may be noted that since all the principal components are independent of each other, the additive model is appropriate here. A large value of MPI will imply better quality.

3. Experimental details

3.1. Machine used

The experiments are performed on CNC EDM (EMT 43, Electronica) machine. Electrolytic Copper (25mm X 25 mm, 99.9% Purity) is used as electrode and EDM Oil is used as electrolyte. The polarity of electrode is kept positive.

3.2. Work-piece material

EN31tool steel (22 mm X 22 mm X 15 mm size) is taken as work piece having following chemical composition: C- 1.07%; Mn- 0.57%; Si- 0.32%; P- 0.04%; S- 0.03%; Cr- 1.13% and Fe- 96.84%. Other properties are given in Table 1.

Table 1. Mechanical properties of EN 31 tool steel

Thermal Conductivity (w/mk)	46.6
Density (gm/cc)	7.81
Electrical Resistivity (ohm-cm)	0.0000218
Specific heat capacity (j/gm-◦c)	0.475

3.3. Design of experiment (DOE)

DOE technique is a very powerful tool for the modelling and analysis of the influence of process variables on the response variables. The response variable is an unknown function of the process variables, which are known as design factors. There are a large number of factors that can be considered for control of EDM process. However, the review of the literature shows that the following four parameters are the most widespread among the researchers to control MRR and surface roughness: pulse on time (A), pulse off time (B), current (C) and voltage (D).These four factors are considered as main design factors along with their interactions in this study. Table 2 shows the design factors along with their levels. Three levels, having equal spacing, within the operating range of the parameters are selected for each of the factors. By selecting three levels, the curvature or non-linearity effects can be studied. On the basis of Taguchi method [11], an orthogonal array (OA) is employed to reduce the number of experiments for determining the optimal machining parameters. An OA provides the shortest possible matrix of combinations in which all the parameters are varied to consider their direct effect as well as interactions simultaneously. In the present investigation, an L_{27} OA, which has 27 rows corresponding to the number of tests [26 degrees of freedom (DOFs)] with 13 columns at three levels, is chosen. To check the DOFs in the experimental design, for the three-level test, the four main factors take 8 [3 × (3 − 1)] DOFs. The DOF for three second- order interactions (A × B, A ×C, B×C) is 12 [3 × (3 −1) × (3 − 1)] and the total DOFs required is 20. As per the Taguchi method, the total DOFs of selected OA must be greater than or equal to the total DOFs required for the experiment and hence the L_{27} OA has been selected. Table 3 shows the OA with design factors and their interactions assigned.

Table 2.Design factors and their levels

Design factors	Unit	Notation	Levels		
			1	2	3
Pulse on time (T_{on})	µs	A	200	300	400
Pulse off time (T_{off})	µs	B	1800	1700	1600
Discharge Current (I_p)	Amp	C	8	12	16
Voltage (V)	Volt	D	40	60	80

3.4. Response variables

The response variables considered in the present study are surface roughness characteristics (R_a, R_q, R_{sk}, R_{ku}, R_{sm}) and metal removal rate (MRR).

3.5. Measurement of responses

Roughness measurement is done using a stylus-type profilometer, Talysurf (Taylor Hobson, Surtronic 3+). The profilometer is set to a cut-off length of 0.8 mm, Gaussian filter and traverse speed 1mm/second with 8 mm evaluation length. Roughness measurements, on the work pieces are repeated five times and average of five measurements of surface roughness parameter values is recorded in the transverse direction.

Table 3. L27 Orthogonal Array with design factors and interactions assigned

	Column numbers												
Trial no	1 (A)	2 (B)	3 (A x B)	4 (A x B)	5 (C)	6 (A x C)	7 (A x C)	8 (B x C)	9	10	11 (B x C)	12	13
1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2	2	2	2	2	2	2
3	1	1	1	1	3	3	3	3	3	3	3	3	3
4	1	2	2	2	1	1	1	2	2	2	3	3	3
5	1	2	2	2	2	2	2	3	3	3	1	1	1
6	1	2	2	2	3	3	3	1	1	1	2	2	2
7	1	3	3	3	1	1	1	3	3	3	2	2	2
8	1	3	3	3	2	2	2	1	1	1	3	3	3
9	1	3	3	3	3	3	3	2	2	2	1	1	1
10	2	1	2	3	1	2	3	1	2	3	1	2	3
11	2	1	2	3	2	3	1	2	3	1	2	3	1
12	2	1	2	3	3	1	2	3	1	2	3	1	2
13	2	2	3	1	1	2	3	2	3	1	3	1	2
14	2	2	3	1	2	3	1	3	1	2	1	2	3
15	2	2	3	1	3	1	2	1	2	3	2	3	1
16	2	3	1	2	1	2	3	3	1	2	2	3	1
17	2	3	1	2	2	3	1	1	2	3	3	1	2
18	2	3	1	2	3	1	2	2	3	1	1	2	3
19	3	1	3	2	1	3	2	1	3	2	1	3	2
20	3	1	3	2	2	1	3	2	1	3	2	1	3
21	3	1	3	2	3	2	1	3	2	1	3	2	1
22	3	2	1	3	1	3	2	2	1	3	3	2	1
23	3	2	1	3	2	1	3	3	2	1	1	3	2
24	3	2	1	3	3	2	1	1	3	2	2	1	3
25	3	3	2	1	1	3	2	3	2	1	2	1	3
26	3	3	2	1	2	1	3	1	3	2	3	2	1
27	3	3	2	1	3	2	1	2	1	3	1	3	2

The measured profile is digitized and processed through the dedicated advanced surface finish analysis software Talyprofile for evaluation of the roughness parameters. MRR is expressed as the ratio of weight difference of the work piece before and after machining to the machining time and in the present study it is measured by weight loss of the material and expressed by gm/min. Table 4 shows the experimental results.

Table 4. Experimental results for roughness parameters and MRR

Exp. Nos.	R_aµm	R_qµm	R_{sk}	R_{ku}	R_{sm}mm	MRR gm/min
1	09.51	11.54	0.49	3.58	0.21	0.14187
2	11.57	14.10	0.38	3.962	0.22	0.19778
3	11.98	14.38	0.31	2.862	0.24	0.21207
4	09.07	11.04	0.41	3.34	0.19	0.15370
5	10.63	12.96	0.25	3.112	0.22	0.20833
6	12.04	14.46	0.31	3.108	0.25	0.38095
7	09.24	11.26	0.38	3.002	0.20	0.15353
8	11.02	13.44	0.45	3.426	0.24	0.38889
9	11.31	13.50	0.39	3.586	0.22	0.40667
10	09.62	11.72	0.34	3.494	0.22	0.10370
11	12.22	14.58	0.26	3.036	0.24	0.16250
12	11.97	14.49	0.32	3.81	0.24	0.29305
13	10.77	12.94	0.30	3.24	0.18	0.12273
14	11.96	14.48	0.11	3.282	0.23	0.31759
15	11.71	14.06	0.21	2.958	0.22	0.32667
16	11.14	13.52	0.28	3.084	0.22	0.22578
17	10.43	12.72	0.30	3.894	0.25	0.31000
18	12.30	14.78	0.15	3.05	0.25	0.34167
19	10.39	12.52	0.19	3.846	0.22	0.08880
20	11.38	13.52	0.01	3.348	0.24	0.23985
21	12.54	15.08	0.08	3.062	0.24	0.26538
22	10.75	13.07	0.20	3.406	0.24	0.17778
23	12.36	14.92	0.19	3.07	0.24	0.25909
24	12.68	15.32	0.20	3.66	0.26	0.29063
25	09.272	11.20	0.21	3.346	0.21	0.17536
26	11.74	14.02	0.14	3.212	0.24	0.25278
27	13.14	15.86	0.14	3.116	0.25	0.51667

4. Result and discussion

As a first step, the experimental results (Table 4) for surface roughness parameters and MRR have been normalized within the range of 0 to 1. For all surface roughness parameters, lower-the-better (LB) criterion and for material removal rate (MRR) higher-the-better (HB) criterion have been selected. Normalized experimental data are shown in Table 5.

The Pearson's correlation coefficient between individual responses has been computed using Equation (6). Table 6 represents Pearson's correlation coefficients. It has been observed that all the responses are correlated.

Now, weighted principal component analysis (WPCA) has been employed to find the explained variation as a result of these six responses and the eigenvector of each principal component. The results are shown in Table 7.

$$Z_1^i = -0.429\times Y_{i1} + 0.513\times Y_{i2} + 0.512\times Y_{i3} - 0.243\times Y_{i4} - 0.149\times Y_{i5} + 0.455\times Y_{i6} \quad (9)$$

$$Z_2^i = 0.163\times Y_{i1} - 0.018\times Y_{i2} - 0.047\times Y_{i3} - 0.380\times Y_{i4} - 0.870\times Y_{i5} - 0.260\times Y_{i6} \quad (10)$$

$$Z_3^i = -0.256\times Y_{i1} + 0.078\times Y_{i2} + 0.101\times Y_{i3} + 0.863\times Y_{i4} - 0.398\times Y_{i5} - 0.112\times Y_{i6} \quad (11)$$

$$Z_4^i = -0.735\times Y_{i1} - 0.444\times Y_{i2} - 0.440\times Y_{i3} - 0.146\times Y_{i4} - 0.097\times Y_{i5} + 0.190\times Y_{i6} \quad (12)$$

$$Z_5^i = 0.426\times Y_{i1} - 0.188\times Y_{i2} - 0.171\times Y_{i3} + 0.166\times Y_{i4} - 0.225\times Y_{i5} + 0.821\times Y_{i6} \quad (13)$$

$$Z_6^i = 0.003\times Y_{i1} - 0.705\times Y_{i2} + 0.708\times Y_{i3} - 0.023\times Y_{i4} - 0.008\times Y_{i5} - 0.014\times Y_{i6} \quad (14)$$

where, $Y_{i1,}Y_{i2,}Y_{i3,}Y_{i4,}Y_{i5} and Y_{i6}$ are the scaled S/N ratio values of MRR and surface roughness respectively, for ith trial.

Table 5. Scaled S/N ratio of multiple responses

Exp. Nos.	Scaled S/N ratio					
	R_a	R_q	R_{sk}	R_{ku}	R_{sm}	MRR
1	0.87055	0.87819	0.00001	0.31174	0.58658	0.26604
2	0.34352	0.32486	0.06923	0.00000	0.44005	0.45471
3	0.24917	0.27055	0.11944	1.00000	0.17571	0.49432
4	0.99999	1.00001	0.04959	0.52510	0.79079	0.31154
5	0.57100	0.55769	0.16743	0.74250	0.39691	0.48423
6	0.23570	0.25523	0.12159	0.74646	0.14093	0.82696
7	0.94991	0.94602	0.06883	0.85316	0.63813	0.31092
8	0.47486	0.45726	0.02050	0.44694	0.23770	0.83867
9	0.40434	0.44495	0.05877	0.30659	0.40167	0.86405
10	0.84123	0.83544	0.09914	0.38651	0.48882	0.08809
11	0.19570	0.23241	0.16158	0.81853	0.18667	0.34314
12	0.25188	0.24989	0.10986	0.12029	0.23322	0.67800
13	0.53573	0.56196	0.12645	0.61857	1.00000	0.18373
14	0.25368	0.25142	0.38945	0.57897	0.27832	0.72366
15	0.31063	0.33271	0.21518	0.89855	0.46433	0.73966
16	0.44517	0.44087	0.14512	0.77029	0.42079	0.52984
17	0.62220	0.60932	0.12575	0.05323	0.06009	0.70992
18	0.17810	0.19478	0.29728	0.80438	0.06218	0.76515
19	0.63412	0.65308	0.23332	0.09137	0.45216	0.00000
20	0.38770	0.44087	1.00001	0.51775	0.18887	0.56424
21	0.12600	0.13929	0.45058	0.79231	0.25117	0.62168
22	0.54175	0.53435	0.22572	0.46494	0.24218	0.39417
23	0.16498	0.16875	0.23464	0.78428	0.22429	0.60805
24	0.09607	0.09568	0.22896	0.24379	0.00000	0.67327
25	0.94001	0.96078	0.22200	0.51959	0.62256	0.38640
26	0.30373	0.34057	0.32043	0.64526	0.24667	0.59404
27	0.00000	0.00001	0.32866	0.73855	0.03921	1.00000

Table 6. Correlation among response variables

Sl. No.	Correlation between responses	Pearson correlation coefficient	Comment
1	R_a and R_q	0.998	Both are correlated
2	R_a and R_{sk}	-0.342	Both are correlated
3	R_a and R_{ku}	-0.241	Both are correlated
4	R_a and R_{sm}	0.713	Both are correlated
5	R_a and MRR	-0.653	Both are correlated
6	$R_q$andR_{sk}	-0.313	Both are correlated
7	$R_q$andR_{ku}	-0.224	Both are correlated
8	$R_q$andR_{sm}	0.722	Both are correlated
9	$R_q$and MRR	-0.661	Both are correlated
10	R_{sk}andR_{ku}	0.163	Both are correlated
11	R_{sk} and R_{sm}	-0.333	Both are correlated
12	R_{sk} and MRR	0.173	Both are correlated
13	R_{ku}andR_{sm}	-0.025	Both are correlated
14	R_{ku} and MRR	0.165	Both are correlated
15	R_{sm} and MRR	-0.646	Both are correlated

Table 7. Eigen values, eigen vectors, accountability proportion (AP) and cumulative accountability proportion (CAP) computed

	MRR	R_a	R_q	R_{sk}	R_{ku}	R_{sm}
Eigen values	3.4103	1.0154	0.8489	0.4338	0.2899	0.0015
Eigenvector	-0.4296 0.1635 -0.2566 -0.7357 0.4261 0.0038	0.5131 -0.0186 0.0784 -0.4441 -0.1888 -0.7053	0.5125 -0.0471 0.1011 -0.4404 -0.1710 0.7083	-0.2436 -0.3800 0.8638 -0.1469 0.1669 -0.0233	-0.1496 -0.8708 -0.3985 -0.0979 -0.2257 -0.0081	0.4558 -0.2609 -0.1129 0.1909 0.8215 -0.0141
AP	0.5684	0.1692	0.1415	0.0723	0.0483	0.0003
CAP	0.5684	0.7376	0.8791	0.9514	0.9998	1.0000

Table 8. Calculated MPI values

Exp.No.	A	B	C	D	MPI
1	1	1	1	1	0.427555
2	1	1	1	1	0.147943
3	1	1	1	1	-0.279400
4	1	2	2	2	0.461362
5	1	2	2	2	0.011406
6	1	2	2	2	-0.312960
7	1	3	3	3	0.293921
8	1	3	3	3	-0.077790
9	1	3	3	3	-0.025140
10	2	1	2	3	0.403918
11	2	1	2	3	-0.204940
12	2	1	2	3	-0.051270
13	2	2	3	1	0.282868
14	2	2	3	1	-0.216000
15	2	2	3	1	-0.221520
16	2	3	1	2	-0.064850
17	2	3	1	2	0.103381
18	2	3	1	2	-0.378010
19	3	1	3	2	0.398737
20	3	1	3	2	-0.141610
21	3	1	3	2	-0.326130
22	3	2	1	3	0.064793
23	3	2	1	3	-0.290970
24	3	2	1	3	-0.236550
25	3	3	2	1	0.359291
26	3	3	2	1	-0.165700
27	3	3	2	1	-0.529440

The weighted sum of the principal components, i.e. multi-response performance index (MPI) corresponding to a trial i, is then calculated using Equation (8):

$$MPI^i = 0.5684 \times Z_1^i + 0.1692 \times Z_2^i + 0.1415 \times Z_3^i + 0.0723 \times Z_4^i + 0.0483 \times Z_5^i + 0.003 \times Z_6^i \quad (15)$$

The computed MPI values corresponding to 27 trials are listed in the last column of Table 8. Table 9 summarizes the level average on MPI, i.e. average MPI values corresponding to different levels of the control factors. For example, the level average on MPI for factor A at level 1 is calculated taking the average of the MPI values corresponding to level 1 of factor A. Larger value of MPI implies better quality. Consequently, the optimal condition for the factors A, B, C and D can be set as A1B1C1D2.

Table 9. Level average on MPI

Factor	Level 1	Level 2	Level 3
A	0.0719	-0.0385	-0.0964
B	0.0416	-0.0508	-0.0538
C	0.2919	-0.0927	-0.2623
D	-0.0216	0.068	-0.0309

Table 10. ANOVA on MPI

Source	Degree of freedom	Sum of squares	Mean Square	F-ratio	Contribution (%)
A	2	0.13155	0.06578	1.98	6.314713
B	2	0.05302	0.02651	0.8	2.545086
C	2	1.45163	0.72582	21.88*	69.6817
D	2	0.12861	0.0643	1.94	6.173586
A*B	4	0.01762	0.00441	0.13	0.845802
A*C	4	0.04689	0.01172	0.35	2.250832
B*C	4	0.05489	0.01372	0.41	2.634851
Error	6	0.19901	0.03317		9.552954
Total	26	2.08323			100

*Significant at 95% confidence level ($F_{0.05,2,6} = 5.14$)

Analysis of variance (ANOVA) is carried out to find out the significant effects of design parameters on the MPI. Table 10 shows the result of ANOVA test. From the ANOVA table, it is observed that the parameter C (discharge current) is the most significant factor for controlling the multiple responses, which is approximately 70% significant.

5. Confirmation test

After the optimal level of process parameters has been found, a verification test needs to be carried out in order to check the accuracy of the analysis. Table 11 shows the comparison of the initial S/N ratio with the actual S/N ratio using the optimal parameters. The increase in the S/N ratio from the initial process parameters to the optimal process parameters is 1.6554 dB. In other words, the experimental results confirm the prior design and analysis for optimizing the machining parameters.

Table 11. Results of confirmation test

	Initial parameter combination	Optimal parameter combination
level	A2B2C2D2	A1B1C1D2
		Experimental
R_a	10.496	9.514
R_q	13.26	11.54
R_{sk}	0.4096	0.4952
R_{ku}	3.628	3.280
R_{sm}	213	195
MRR	0.2479	0.2519
S/N ratio	-44.4509	-42.7955
Improvement of S/N ratio = 1.6554 dB		

6. Surface morphology analysis

Scanning electron microscopy (SEM) (JEOL, JSM-6360) images are used to investigate the surface morphology (Fig.1). Before machining, the work piece surface has no globular spot. After machining, the surface becomes rougher and the machined surface contains plenty of globules which are unevenly distributed. This is because at high temperature gradient produced due to the thermal energy in the work-piece surface, erosion occurs from the surface and the debris particles remain attached to the work-piece surface.

a b

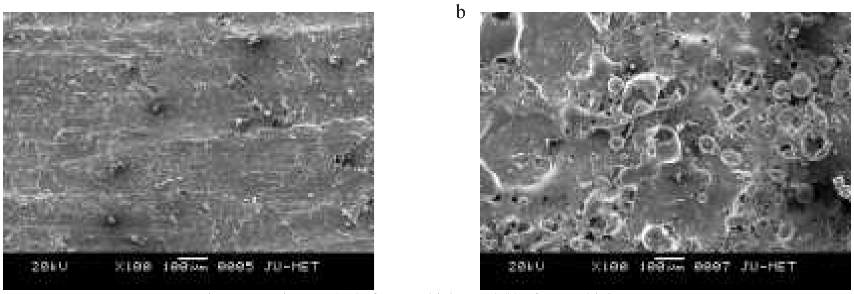

Fig. 1. SEM images (a) before machining and (b) after machining

7. Conclusion

In this study, the multiple responses (surface roughness parameters and MRR) are efficiently optimized using the weighted principal component analysis (WPCA) along with Taguchi design in EDM of EN31 tool steel. The optimum parameter combination is obtained as A1B1C1D2 (the lowest levels of pulse on time, pulse off time and discharge current and mid-level of voltage) by considering the maximum MPI level average. ANOVA result shows that the discharge current is the most influencing parameter that significantly affects the roughness and MRR characteristics at a confidence level of 95%. The confirmation test ensures the improvement of S/N ratio (1.6554 dB) from the initial to optimal condition. From this study, it can be concluded that the proposed methodology can be treated as a very effective and powerful approach to tackle multiple response problems in industrial experiments.

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