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Optimization of WEDM process parameters on EN31steel by weighted principal component analysis

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ABSTRACT : *The aim of the present experimental investigation is to optimize the machining parameters of wire electrical discharge machining (WEDM) for multiple performance characteristics on EN 31 tool steel using weighted principal component analysis (WPCA). The experiments are conducted based on Taguchi's L_{27} orthogonal array (OA) with combinations of four machining parameters viz. discharge current, voltage, pulse on time and pulse off time. The responses are metal removal rate (MRR) and surface roughness (centre line average roughness: R_a, root mean square roughness: R_q, skewness: R_{sk}, kurtosis: R_{ku} and mean line peak spacing: R_{sm}). WPCA has been aggregated to compute a multi-response performance index (MPI). MPI has been optimized (maximized) finally by Taguchi method. Analysis of variance (ANOVA) is also carried out and it is seen that current, pulse off time and interaction between voltage and pulse on time are significant factors affecting metal removal rate and surface roughness parameters. An optimal setting of process parameters is found out for maximization of MRR and minimization of roughness parameters. Finally, the optimal result is verified through confirmatory test and it is found that the improvement of S/N ratio at the optimal condition is about 21%.*
Keywords: *MRR, Optimization, Surface Roughness, WEDM, WPCA*

I. INTRODUCTION

Wire Electrical discharge machining (WEDM) is a nontraditional, thermoelectric process which erodes material from the work piece by a series of discrete sparks between a work and tool electrode immersed in a liquid dielectric medium. These electrical discharges melt and vaporize minute amounts of the work material, which are then ejected and flushed away by the dielectric fluid [1]. This is a popular non-conventional machining process used in industries. As surface roughness and material removal rate (MRR) are very important parameters in any machining operation, many researchers have studied these parameters using different statistical, optimization tools. Shah et al. [2] have studied the effects process parameters in addition to varying the material thickness on the machining responses such as material removal rate, kerf and surface roughness of tungsten carbide samples. Manna and Bhattacharyya [3] have established mathematical models relating the machining performances like MRR, surface roughness, spark gap and gap current using Gauss elimination method. Kumar et al. [4] have developed a quadratic model in WEDM of pure titanium material and optimized process parameters for MRR and surface roughness. Datta and Mahapatra [5] have utilized the response surface methodology (RSM) coupled with grey-based Taguchi technique to optimize surface roughness, kerf and MRR. Han et al. [6] have reported that the surface finish is improved by decreasing pulse duration and discharge current in WEDM of alloy steel (Cr12). Ramakrishnan and Karunamoorthy [7] have described the multi-objective optimization of WEDM process using parametric design of Taguchi methodology. Mahapatra and Patnaik [8] have attempted to optimize process parameters for better metal removal rate and surface finish simultaneously using genetic algorithm. Sarkar et al. [9] have developed a second order mathematical model using RSM in trim cutting operation of γ-titanium aluminide and optimized machining process parameters by desirability function approach and Pareto optimization algorithm. Esme et al. [10] and Saha et al. [11] have developed neural network (NN) and regression analysis models for WEDM process and shown that NN model is better than regression analysis in predicting surface roughness. Tosun et al. [12] have attempted to optimize WEDM process parameters using Taguchi method for minimum kerf and maximum MRR. Gauri and Chakraborty [13] have utilized principal component analysis (PCA) for multi-response optimization in WEDM process.

In this paper, an attempt has been made to optimize the process parameters in WEDM for the multiple responses viz. MRR and surface roughness parameters (centre line average roughness: R_a, root mean square roughness: R_q, skewness: R_{sk}, kurtosis: R_{ku} and mean line peak spacing: R_{sm}) using weighted principal component analysis (WPCA). Four process parameters viz. current, voltage, pulse on time and pulse off time are considered for the study. As a work-piece material, EN 31 tool steel is used. It is a high carbon steel with high degree of hardness with compressive strength and abrasion resistance. Experiments are conducted based on L_{27}

orthogonal array (OA). Analysis of variance (ANOVA) is also carried out to observe the level of significance of factors and their interactions. Finally, the optimal result is verified through a confirmation test.

Experimental Details

The experiments have been conducted on 5-axis CNC type WEDM (ELEKTRA, MAXICUT 434). A 0.25 mm diameter zinc coated brass wire is selected as the tool electrode. Rectangular block (22 mm X 22 mm X 15 mm) of EN 31 tool steel is chosen as work piece. The chemical composition of the work-piece materials are C-1.07%; Mn-0.57%; Si-0.32%; P-0.04%; S-0.03%; Cr-1.13%; and Fe-96.84%. The work piece and electrode are separated by dielectric medium (deionized water). As seen from literature review, the following four machining parameters are the most important parameters: current (A), voltage (B), pulse on time (C) and pulse off time (D). Table 1 shows the design factors along with their levels. Taguchi's design [14] for the partial factorial is based on specially developed orthogonal array (OA). As it is a four factor three level experiment, total degrees of freedom considering the individual factors and their interactions are 20. Hence, L_{27} orthogonal array is chosen as it has 26 degrees of freedom which is higher than 20.

Table 1. Input Parameters and their levels

Parameters	Coding	Level		
		1	2	3
Discharge Current (I_p) in A	A	4	6	8
Voltage (V) in V	B	45	50	55
Pulse on time (T_{on}) in µs	C	2	3	4
Pulse off time (T_{off}) in µs	D	2	3	4

The response variables chosen are MRR and surface roughness characteristics (centre line average roughness: Ra, root mean square roughness: R_q, skewness: R_{sk}, kurtosis: R_{ku} and mean line peak spacing: R_{sm}) in the present case. 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. Roughness measurement is done using a stylus-type profilometer, Talysurf (Taylor Hobson, Surtronic 3+). Roughness measurements, in the transverse direction, on the work pieces are repeated five times and average of five measurements of surface roughness parameter values are recorded. The measured profile is digitized and processed through the dedicated advanced surface finish analysis software Talyprofile for evaluation of the roughness parameters.

Weighted Principal Component Analysis (WPCA) Method

Principal component analysis (PCA) method is used to optimize the multiple response problems [15, 16]. In the application of PCA method, the 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. 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 analysis (WPCA) method [17]. In WPCA method, all components are taken into consideration in order to completely explain variation in all responses. WPCA method uses the explained variation as the weight to combine all principal components in order to form a multi-response performance index (MPI). Thus, multi-response problem is converted into a single response problem and Taguchi analysis may be applied with MPI as the response.

II. RESULT AND DISCUSSION

The experimental data is analyzed, using the WPCA method with the aim to determine the optimum combination of machining parameters. For MRR, higher-the-better criterion and for all surface roughness parameters lower-the-better criterion have been selected. Then, S/N ratios are scaled into (0, 1) interval. After data normalization, a check has to be made whether responses are correlated or not using Pearson's correlation coefficient. Here, all the correlation coefficients have non-zero value so all the responses are correlated to each other. For the brevity of the paper, the table showing the correlation coefficients is omitted. In order to eliminate response correlation, PCA has been applied. Eigen value, Eigen vector, accountability proportion (AP) and cumulative accountability proportion (CAP) are shown in Table 2, which represents results of PCA. Finally, multi-response performance index (MPI) for each trail is computed and shown in Table 3.

The level average of MPI for all levels of each parameter is shown in Table 4. Larger value of MPI signifies better quality, so the optimal combination of machining process parameters can be obtained as A2B1C3D2.

Table 5 shows ANOVA results for MPI. From this, it is seen that discharge current, pulse off time and the interaction between voltage and pulse on time have the major contribution in controlling MRR and surface roughness in WEDM.

A confirmation test is carried out in order to validate the result and shown in Table 6. From the table, it is clear that the total S/N ratio of optimum combination is higher than the initial parameter combination. The improvement of S/N ratio is 5.5914 dB. It is well known that regardless of the category of the performance characteristics, a higher S/N ratio always corresponds to a better performance. Hence the result of confirmation test ensures the better performance of the optimum design.

Table 2. Eigen values, Eigen vectors, AP and CAP computed

	MRR	R_a	R_q	R_{sk}	R_{ku}	R_{sm}
Eigen values	2.5277	1.2806	1.0006	0.8218	0.3666	0.00779
Eigenvector	-0.0699 -0.2284 0.9522 -0.0289 0.1879 0.0088	0.5629 0.3702 0.0852 -0.0053 0.1938 0.7079	0.5585 0.3813 0.1033 0.0128 0.1830 -0.7059	0.2565 -0.5569 -0.1788 0.6422 0.4237 -0.0025	-0.4858 0.3566 -0.1073 -0.0474 0.7893 -0.0036	0.2539 -0.4776 -0.1785 -0.7644 0.3017 -0.0189
AP	0.4204	0.2134	0.1667	0.1369	0.0611	0.0013
CAP	0.4204	0.6339	0.8006	0.9376	0.9987	1.0000

Tables 3. Calculated MPI values.

Exp. No	A	B	C	D	MPI	Exp. No	A	B	C	D	MPI
1	1	1	1	1	0.0949	15	2	2	3	2	0.4641
2	1	1	2	2	0.2313	16	2	3	1	1	0.2109
3	1	1	3	3	0.1525	17	2	3	2	2	0.5629
4	1	2	1	2	0.0748	18	2	3	3	3	0.1523
5	1	2	2	3	0.2577	19	3	1	1	3	0.0985
6	1	2	3	1	0.1819	20	3	1	2	1	0.1538
7	1	3	1	3	0.2150	21	3	1	3	2	0.1371
8	1	3	2	1	0.0334	22	3	2	1	1	0.0176
9	1	3	3	2	0.1907	23	3	2	2	2	0.0279
10	2	1	1	2	0.7416	24	3	2	3	3	0.1455
11	2	1	2	3	0.2829	25	3	3	1	2	0.1297
12	2	1	3	1	0.0909	26	3	3	2	3	0.1004
13	2	2	1	3	0.0287	27	3	3	3	1	0.2659
14	2	2	2	1	0.0184						

Table 4. Level average on MPI

	Level 1	Level 2	Level 3
A	0.159138	0.283634	0.115684
B	0.22040	0.131253	0.206804
C	0.17517	0.185406	0.19788
D	0.114726	0.284459	0.159272

Table 5. ANOVA on MPI

Source of variation	DOFs	Sum of squares	Mean Square	F	% Contribution
A	2	0.13191	0.06596	1.78	17.892
B	2	0.03775	0.01887	0.51	5.120
C	2	0.00165	0.00082	0.02	0.224
D	2	0.13446	0.06723	1.82	18.238
A*B	4	0.04287	0.01072	0.29	5.815
A*C	4	0.03346	0.00837	0.23	4.539
B*C	4	0.13309	0.03327	0.9	18.052
Error	6	0.22206	0.03701		
Total	26	0.73724			

III. CONCLUSION

In the present study, weighted principal component analysis (WPCA) is used to optimize the machining process parameters (discharge current, voltage, pulse on time and pulse off time) in order to optimize MRR and surface roughness in WEDM of EN 31 tool steel. The optimal combination of parameters is found to be A2B1C3D2. Also through ANOVA, it is revealed that current and pulse off time have the maximum contribution in controlling MRR and surface roughness of WEDM. A confirmation test is carried out to validate the analysis. The improvement of the S/N ratio from the initial condition to the optimal condition is about 21%. This WPCA technique can be effectively applied for the optimization of multi-responses.

Table 6. Results of confirmation test

	Initial parameter combination		Optimal parameter combination	
level	A2B2C2D2		A2B1C3D2	
	S/N ratio		Experimental S/N ratio	
MRR	0.05183	-25.70831	0.05881	-24.61097
R_a	5.940	-15.45730	5.535	-14.86235
R_q	7.065	-16.98224	6.86	-16.72648
R_{sk}	0.085	21.41162	0.067	23.47851
R_{ku}	3.135	-9.92475	2.613	-8.34278
R_{sm}	0.106	19.49388	0.103	19.47014
Total S/N ratio	-27.18548		-21.59407	
Improvement of S/N ratio = 5.5914 dB				

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