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Modeling and multi-objective optimization of WEDM of spark plasma sintered boron carbide considering preferences of users

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Abstract: In this research work, development of a multi-response optimization technique was performed, using Genetic Algorithm (GA) optimization technique in wire electrical discharge machining (WEDM) keeping in mind about the priorities of multiple users. Boron carbide has been selected as work piece for experiment. The effect of five process parameters such as pulse on time (T_{on}), pulse off time (T_{off}), peak current (IP), water pressure (WP), servo feed (SF), were investigated on the responses such as machining speed and surface roughness (R_a) in WEDM operation. Further, two responses were modeled empirically through regression analysis. The developed models can be used by the machinists to predict the machining as well as the surface characteristics over a wide range of machining input parameters. The analysis of variance (ANOVA) is also applied to investigate the effect of influential input parameters. Finally, the confirmation experiments were conducted with optimal set of machining parameters and minor deviations have been found.

1 Introduction

Ceramics and its composites that possess high hardness, toughness and corrosion resistance are increasingly needed for applications such as manufacturing of light aircraft, submarines, valve systems, heat exchangers and other high temperature applications etc. Boron carbide (B_4C) among the advanced engineering ceramics possesses specific remarkable properties like low weight, high melting point ~ 2475^{o}C; coefficient of thermal expansion is 5.73x10^{-6}/K and having Vickers hardness >30 GPa after sintering [1,2]. B_4C exhibits good mechanical properties at room temperature flexural strength, fracture toughness, and Young's modulus range from 375 to 525 MPa, 2.9–3.7 MPam$^{1/2}$, and 360–460 GPa respectively [3-5]. The uses of conventional machining techniques are unable to remove material from very hard ceramic as B_4C. So the non-conventional machining processes like WEDM which can be used for effective manufacturing of the components of B_4C [6]. WEDM can produce a precise, corrosion and wear resistant surface [7]. The dimensional accuracy, surface finish and generation of complex shapes can be achieved by machining through WEDM process. This process consists of a number of control factors due to which it is a challenging task to achieve optimal performance against the required output response. This problem can be solved by establishing a relation between the control factors of the process and quality characteristics by design of experiments [8]. WEDM is a thermo-electric non-conventional machining process to reshape hard but electrically conductive ceramics. Many researchers tried to optimize the machining performance by adapting different optimization techniques among which response surface methodology (RSM) is an effective technique in carrying out the analysis of experiments with the least experimental efforts and subsequently to develop suitable mathematical models of responses [9-11]. Genetic algorithm (GA) possesses advantages that do not require any gradient information and inherent parallelism in searching the

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design space, thus making it a robust adaptive optimization technique. A multiple regression model to represent the relationship between input and output variables and multi-objective optimization method based on a Non-Dominated Sorting Genetic Algorithm to optimize Wire-EDM process [12]. In this work RSM and GA are used together to establish parameter optimization model. RSM model has been established with the help of MINITAB software to represent the relationship between R_a and machining speed with input variables. Multi response genetic algorithm has been used to obtain a Pareto optimal combination of parameters using MATLAB toolbox.

2 Methodology

2.1 Design of Experiments(DOE)

The WEDM process of boron carbide work-piece was studied corresponding to 3 selected levels and values of five input process parameters are shown in Table 1 and experimental design was prepared according to the Box-Behnken design (BBD). Table 3 shows the experimental results of the 43 experiments conducted in this work along with the order, combinations and design of experiments based on the coded surfaces. The two mathematical models were developed for two responses to obtain the optimized input process parameters in order to achieve the desired responses i.e. R_a and machining speed. Generally, these mathematical models are polynomials with a structure having relationship of responses with the inputs so the corresponding experiments are designed only for every particular problem. Table 2 shows the results of analysis of variance (ANOVA) of two mathematical models.

2.2 Wire Electrical Discharge Machining of B_4C

All machining operations were performed using a WEDM machine (*EUROCUT Mark-I, 734, Elctronica, India)*. In this machining operation, material removal occurred by repetitive spark discharge between the workpiece and the soft brass wire electrode. The wire diameter was kept constant at 0.25 mm, so, the width of cut was also constant. Therefore, the machining speed for WEDM operation was calculated using the following expression:

$$machining\ speed = C.L(mm^2/min) \tag{1}$$

where, C is the cutting rate in mm/min and L is the thickness of the material in mm. R_a values of machined samples having 5 mm cut length, were measured using a portable profilometer (Mitutoyo, *Japan*) with cut off length 2.5 mm.

2.3 Experimental method and process parameters selection

The experiments were carried out on a WEDM machine (Euro cut Mark I-734 of Electronica Machine Tools Ltd., India). The test sample of Ø 20 mm was prepared by sintering of B_4C powder using spark plasma sintering furnace at 2050^oC, 50 MPa pressure, in argon atmosphere, within graphite mould.

Table 1: Wire EDM parameters and their levels

Level	**T_{on}** (µsec)	**T_{off}** (µsec)	**IP** (Amp)	**WP** (kg/cm^2)	**SF** (mm/min)
1	27	49	160	6	2050
2	29	51	180	8	2150
3	31	53	200	10	2250

3 Results and discussions

ANOVA table was generated at 95% confidence level and the p-value represented the significance of machine input parameters. It may be visualized from Table 2 that among the linear effects, for all the input parameters found to be significant ('*' marked) as the P-values i.e. >0.05 for both the responses. R-square terms described the variation in the observed responses that explained by the model. As shown in Table2, the R-square value was found to be 99.79 for machining speed and 96.25 for R_a. This suggested the adequacy to fit the data in the model very well. Adjusted R-square represented the adjusted number of terms in the model. R-square adjusted terms also represented good agreement with the R-square value as 97.69 and 92.84 for R_a and machining speed, respectively. The input parameter T_{on}, T_{off}, IP, WP, SF is also represented by A, B, C, D, E respectively.

Table 2: ANOVA results of machining speed and surface roughness

	Machining speed (mm^2/min)				**R_a (μm)**			
Source	**DF**	**Adj SS**	**Adj MS**	**P-Value**	**DF**	**Adj SS**	**Adj MS**	**P-Value**
Model	20	3.38941	0.16947	0.000*	20	12.0891	0.60446	0.000*
A	1	0.65206	0.65206	0.000*	1	0.4160	0.41603	0.000*
B	1	0.04101	0.04101	0.000*	1	1.2355	1.23547	0.000*
C	1	1.82250	1.82250	0.000*	1	0.3136	0.31360	0.001*
D	1	0.73531	0.73531	0.000*	1	5.3130	5.31302	0.000*
E	1	0.02176	0.02176	0.003*	1	2.6033	2.60333	0.000*
A*A	1	0.00441	0.00441	0.141	1	0.0087	0.00866	0.531
B*B	1	0.00107	0.00107	0.460	1	0.0485	0.04849	0.146
C*C	1	0.00093	0.00093	0.489	1	0.0924	0.09235	0.050*
D*D	1	0.00441	0.00441	0.141	1	0.2227	0.22270	0.004*
E*E	1	0.00093	0.00093	0.489	1	0.0310	0.03102	0.241
A*B	1	0.00810	0.00810	0.050*	1	0.0506	0.05063	0.138
A*C	1	0.02403	0.02403	0.002*	1	0.0056	0.00562	0.613
A*D	1	0.00040	0.00040	0.650	1	0.0812	0.08123	0.064
A*E	1	0.00090	0.00090	0.497	1	0.0702	0.07023	0.084
B*C	1	0.00010	0.00010	0.820	1	0.0036	0.00360	0.686
B*D	1	0.00360	0.00360	0.181	1	0.0676	0.06760	0.089
B*E	1	0.02723	0.02723	0.001*	1	0.0027	0.00270	0.726
C*D	1	0.02250	0.02250	0.002*	1	1.1342	1.13423	0.000*
C*E	1	0.00063	0.00063	0.571	1	0.0001	0.00010	0.946
D*E	1	0.01562	0.01562	0.009*	1	0.0400	0.04000	0.185
Lack-of-Fit	20	0.02989	0.00149	0.963	20	0.4339	0.02170	0.558
R^2(%)	98.79				96.25			
Adj-R^2 (%)	97.69				92.84			

Mathematical models of machining responses were developed by regression analysis from the experimental observations. Each of the response function can be expressed [11] as:

$$Y = C_O + \sum_{i-1}^{n} C_i * X_i + \sum_{i-1}^{n} C_j * X_j + \sum_{i-1}^{n-1}\sum_{j-2}^{n} C_{ij} * X_{ij} \quad (2)$$

where, Y is the response characteristic. Regression models were utilized to correlate the x_i (1, 2,…., n) are coded levels of n quantitative input process variables i.e. machining parameters, the terms C_0, C_i, and C_{ij} are the regression coefficients. By regression analysis, two mathematical models for two responses i.e. R_a and Machining speed were derived as follows:

$$R_a = 102 - 1.95 * A - 3.29 * B - 0.011 * C - 2.98 * D + 0.0258 * E - 0.0092 * A * A + 0.0218 * B * B - 0.0003 * C * C + 0.0466 * D * D - 0.000007 * E * E + 0.0281 * A * B - 0.00094 * A * C - 0.0356 * A * D + 0.000662 * A * E + 0.00075 * B * C + 0.0325 * B * D - 0.00013 * B * E + 0.01331 * C * D - 0.000002 * C * E - 0.0005 * D * E \quad (3)$$

$$\text{Machining speed} = -14.7 - 1.06 * A + 0.22 * B - 0.072 * C - 0.12 * D + 0.029 * E + 0.0065 * A * A + 0.00323 * B * B + 0.00003 * C * C + 0.00656 * D * D - 0.000001 * E * E + 0.01125 * A * B + 0.00194 * A * C + 0.0025 * A * D - 0.000075 * A * E - 0.000125 * B * C + 0.0075 * B * D - 0.000413 * B * E + 0.00188 * C * D + 0.000006 * C * E - 0.000313 * D * E \quad (4)$$

The predicted results has been derived from the mathematical models is shown in Table 3. The percentage error of experimental responses with predicted responses was calculated and found to be satisfactory with maximum error in the case of machining speed is 2.79 and R_a is 13.86 respectively. The responses obtained from the Table 3 has been compared with available literatures and was found to be adequate enough by considering the variations present in fabrication of sintered B_4C and WEDM machining conditions [6].

Table 3: Experimental setup with response parameters

Sl. No.	T_{on} (μs)	T_{off} (μs)	IP (A)	WP (kg/cm)	SF (mm/min)	Experimental R_a (μm)	Predicted R_a (μm)	Error (%)	Experimental machining speed (mm^2/min)	Predicted machining speed (mm^2/min)	Error (%)
1	27	49	180	8	2150	3.06	3.13	2.26	3.58	3.63	1.26
2	31	49	180	8	2150	2.49	2.58	3.60	3.91	3.93	0.51
3	27	53	180	8	2150	2.44	2.36	-3.26	3.66	3.64	-0.65
4	31	53	180	8	2150	2.32	2.26	-2.57	4.17	4.12	-1.18
5	29	51	160	6	2150	3.84	3.82	-0.41	3.36	3.36	-0.03
6	29	51	200	6	2150	2.26	2.53	11.79	3.86	3.87	0.36
7	29	51	160	10	2150	1.66	1.61	-3.28	3.65	3.63	-0.54
8	29	51	200	10	2150	2.21	2.44	10.28	4.45	4.45	-0.09
9	29	49	180	8	2050	2.38	2.40	1.19	3.76	3.66	-2.79
10	29	53	180	8	2050	1.69	1.91	13.16	3.95	3.92	-0.73
11	29	49	180	8	2250	3.18	3.24	1.82	3.83	3.83	-0.06
12	29	53	180	8	2250	2.39	2.64	10.54	3.69	3.76	2.00
13	27	51	160	8	2150	2.50	2.62	4.66	3.41	3.37	-1.03
14	31	51	160	8	2150	2.26	2.37	4.73	3.64	3.61	-0.71
15	27	51	200	8	2150	2.43	2.46	1.18	3.94	3.88	-1.41
16	31	51	200	8	2150	2.04	2.06	0.91	4.48	4.43	-1.02
17	29	51	180	6	2050	2.79	2.73	-1.99	3.62	3.53	-2.54
18	29	51	180	10	2050	1.88	1.78	-5.29	4.14	4.07	-1.57
19	29	51	180	6	2250	3.57	3.72	4.10	3.64	3.66	0.57
20	29	51	180	10	2250	2.26	2.36	4.52	3.91	3.96	1.21
21	29	49	160	8	2150	2.96	2.92	-1.43	3.43	3.43	-0.12
22	29	53	160	8	2150	2.14	2.31	8.12	3.51	3.54	0.77
23	29	49	200	8	2150	2.58	2.62	1.73	4.15	4.10	-1.18
24	29	53	200	8	2150	1.88	2.14	13.86	4.21	4.19	-0.43
25	27	51	180	6	2150	3.19	3.28	2.78	3.42	3.44	0.67
26	31	51	180	6	2150	3.17	3.24	2.16	3.84	3.82	-0.58
27	27	51	180	10	2150	2.23	2.41	8.04	3.83	3.84	0.38
28	31	51	180	10	2150	1.64	1.80	9.74	4.29	4.26	-0.71
29	29	51	160	8	2050	1.90	2.06	8.62	3.49	3.47	-0.67
30	29	51	200	8	2050	1.77	1.84	3.88	4.12	4.11	-0.30
31	29	51	160	8	2250	2.86	2.85	-0.23	3.44	3.45	0.30
32	29	51	200	8	2250	2.71	2.61	-3.61	4.12	4.14	0.47
33	27	51	180	8	2050	2.13	2.33	9.35	3.65	3.59	-1.68
34	31	51	180	8	2050	1.54	1.74	12.96	4.05	4.01	-0.90
35	27	51	180	8	2250	2.81	2.85	1.28	3.61	3.63	0.45
36	31	51	180	8	2250	2.75	2.79	1.31	3.95	3.99	1.04
37	29	49	180	6	2150	3.61	3.78	4.84	3.59	3.60	0.19
38	29	53	180	6	2150	3.02	2.98	-1.30	3.67	3.64	-0.88
39	29	49	180	10	2150	2.21	2.37	7.27	3.98	3.96	-0.54
40	29	53	180	10	2150	2.14	2.09	-2.50	4.18	4.12	-1.45
41	29	51	180	8	2150	2.31	2.53	9.61	3.82	3.79	-0.81
42	29	51	180	8	2150	2.47	2.53	2.51	3.72	3.79	1.86
43	29	51	180	8	2150	2.58	2.53	-1.86	3.87	3.79	-2.09

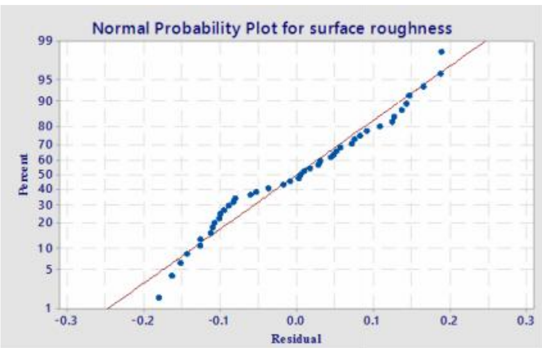

Fig. 1 Normal probability plot for R_a

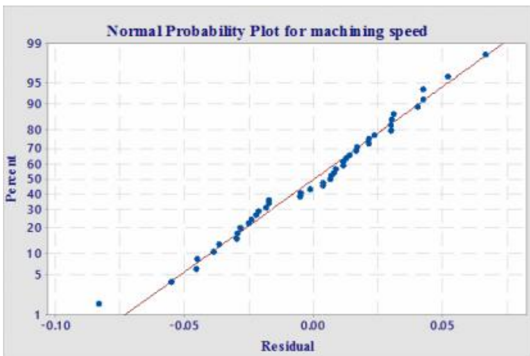

Fig. 2 Normal probability plot for machining speed

In the Fig. 1 and 2 the residuals (i.e. difference between the observed response values and the fitted response values) has been appeared to follow the straight line which indicated as normal distribution.

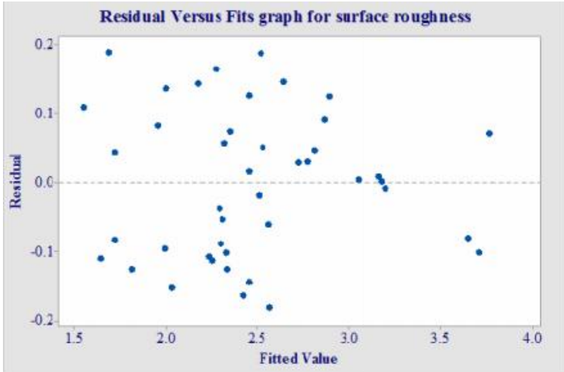

Fig. 3 Residual vs fits plot for R_a

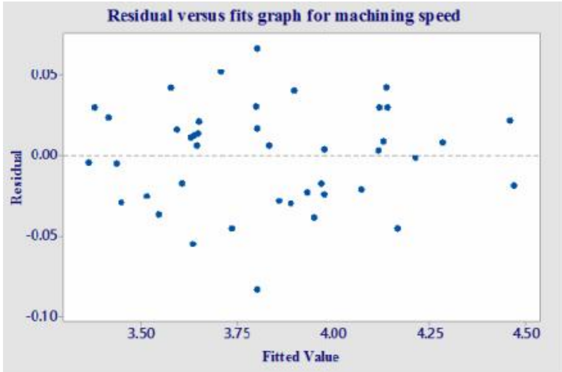

Fig. 4 Residual vs fits plot for machining speed

Figs. 3 and 4 provide the scatter plot of residuals on the *y* axis with fitted estimated response values on the *x*-axis. The constant variance is acquired by the residuals, as the values appear to be randomly scattered in both axes of plot around zero line (in x-axis). Among the scattered points, not any single point is plotted far away from zero line in y-direction means no presence of outliers.

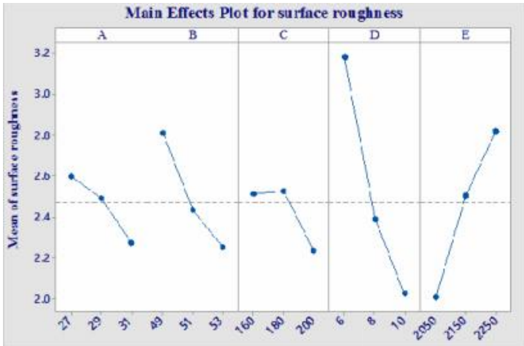

Fig. 5 Main effects plot for R_a

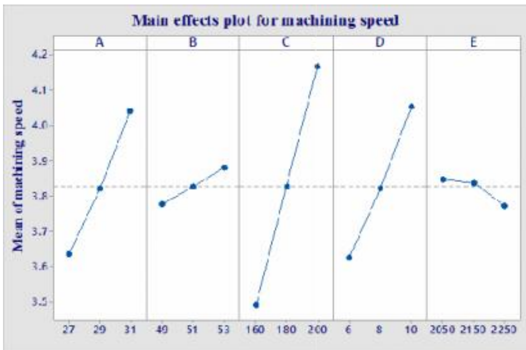

Fig. 6 Main effects plot for machining speed

The individual main effect plots for R_a and machining speed of WEDM input parameters are shown in Fig. 5 and 6. From the figures the most to least significant parameter has been identified, which is given as follows: water pressure, servo feed, pulse off time, pulse on time and pulse peak current for R_a and pulse peak current, pulse on time, water pressure, pulse off time and finally servo feed rate for machining speed. The most significant effect for R_a is water pressure which can be inferred as B_4C possesses low electrical conductivity than metals which requires more uniform current conduction between job and brass wire and also the residue part of the removed material need to be washed out properly for producing good surface quality. The main effect plot for machining speed shows that pulse peak current having most significant effect as the physical phenomena for Wire EDM machining is melting and vaporization so that without sufficient current conduction the proper machining speed could not be achieved.

4 Optimization by genetic algorithm based analysis

Optimization is the selection of a major and important constituent with related to some criterion from some set of selected alternatives. In optimization of a design, objective could be simply to minimize or maximize the responses i.e. to minimize the surface roughness or to maximize the machining speed in terms of enhance productivity. The optimization tool is used instead of coding which was executed iteratively by comparing various solutions till an optimum or a satisfactory solution is found [12].

The general approach of using genetic algorithm is to determine an entire Pareto optimal solution set as which are non-dominated with respect to each other and the process is known as non-dominated sorting algorithm NSGA-II [10]. Generating the Pareto set has several advantages as it allows the user to make an informed decision by viewing a wide range of options. From set of solutions single optimal solution was obtained by the technique for order of preference by similarity to ideal solution (TOPSIS) and the values are: T_{on}=31 (µs), T_{off}=51(µs), IP=160 (A), WP=10 (kg/cm^2) and SF=2050 (mm/min) respectively. The Pareto optimal solution is shown in Fig. 7.

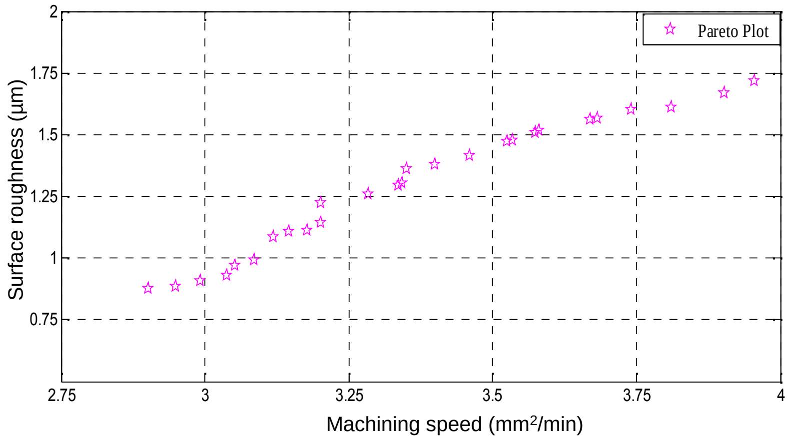

Fig. 7 Multi objective optimization plot of genetic algorithm for machining speed and surface roughness

Conclusions

In this paper RSM and GA have been implemented to statistically analyze as well as optimize the WEDM process parameters during WEDM of B_4C. The developed mathematical model was further coupled with a developed GA to find out the optimum conditions aiming to the maximum machining speed and minimum surface roughness value. The predicted optimum machining conditions using mathematical modeling were validating with 43 experimental measurements. The four confirmatory experiments were conducted using Pareto optimum input parameter set and the maximum error of 6.68% for machining speed and 9.32% for surface roughness generated. The results shows good agreement with the mathematical model based genetic algorithm and its applicability for end users.

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