Parametric Optimization of Wire Electrical Discharge Machining (WEDM) Process using Taguchi Method

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Wire electrical discharge machining (WEDM) is a specialized thermal machining process capable of accurately machining parts of hard materials with complex shapes. Parts having sharp edges that pose difficulties to be machined by the main stream machining processes can be easily machined by WEDM process. Technology of the WEDM process is based on the conventional EDM sparking phenomenon utilizing the widely accepted non-contact technique of material removal with a difference that spark is generated at wire and work piece gap. Since the introduction of the process, WEDM has evolved as a simple means of making tools and dies to the best alternative of producing micro-scale parts with the highest degree of dimensional accuracy and surface finish. This paper outlines the development of a model and its application to optimize WEDM machining parameters. Experiments are conducted to test the model and satisfactory results are obtained. The methodology described here is expected to be highly beneficial to manufacturing industries, and also other areas such as aerospace, automobile and tool making industries.
***Keywords**: WEDM, metal removal rate, surface finish, taguchi method, genetic algorithm*

Introduction

Electrical discharge machining (EDM) is a non-traditional, thermo-electrical process, which erodes materials from the work piece by a series of discrete sparks between the 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. A wire EDM generates spark discharges between a small wire electrode and a work piece with de-ionized water as the dielectric medium and erodes the work piece to produce complex two and three dimensional shapes according to a numerically controlled (NC) path. The main goals of WEDM manufacturers and users are to achieve a better stability and higher productivity of the WEDM process. As newer and more exotic materials are developed, and more complex shapes are presented, conventional machining operations will continue to reach their limitations and the increased use of the WEDM in manufacturing will continue to grow at an accelerated rate (Guitrau, 1991). Wire electrical discharge machining manufacturers and users emphasize on achievement of higher machining productivity with a desired accuracy and surface finish. However, due to a large number of variables even a highly skilled operator with a state-of-the-art WEDM is rarely able to achieve the optimal performance (Williams and Rajurkar, 1991). An effective way to solve this problem is to determine the relationship between the performance measures of the process and its controllable input parameters.

Investigations into the influences of machining input parameters on the performance of WEDM have been widely reported (Rajurkar and Royo, 1989 Williams and Rajurkar 1991, Sone and Masui, 1991, Matsuo and Oshima, 1992, Soni and Chakraverti, 1994). Several attempts have been made to develop mathematical model of the process by Scott, Boyina and Rajurkar (1991), Indurkhya and Rajurkar (1992), and Rajurkar and Wang (1993). In these reports, productivity of the process and the surface roughness of the machined work piece are used as measures of the process performance. Neural network models on material removal rate in EDM has been studied by Tsai and Wang (2001) whereas Lee and Li (2001) concentrated on effects of process parameters in EDM using tungsten carbide as work material. Hocheng et al. (1997) investigated the correlation between current and spark on-time with the crater size produced by a single spark of SiC/Al work materials. Qu et al. (2002) have, through examination of literature, concluded that research has not been directed towards EDM applications in the area of newly developed engineering materials and the boundaries that limit the material removal rate (MRR). Hence, investigations were carried out to study the effect of spark on-time duration and spark on-time ratio, two important EDM process parameters, on the surface finish characteristics and integrity of the four types of advanced engineering material such as porous metal foams, metal bond diamond grinding wheels, sintered Nd-Fe-B magnets, and carbon-carbon bipolar plates. Scott, Boyina and Rajurkar (1991), used a factorial design method, to determine the optimal combination of control parameters in WEDM considering the measures of machining performance as metal removal rate and the surface finish. The study concludes that discharge current, the pulse duration and the pulse frequency are significant control factors. Tarng and Chung (1995) used a neural network model to estimate cutting speed and surface finish using input settings as pulse duration, pulse interval, peak current, open circuit voltage, servo reference voltage, electric capacitance and table speed. Trezise (1982) suggests that fundamental limits on machining accuracy are dimensional consistency of the wire and the positional accuracy of the work table. However, other factors conspire to prevent this theoretical precision from being achieved. Most of the uncertainties arise because of the wire remote from the guides. The detailed section of the working region of the wire electrode is shown in Fig.1. It is evident from Fig.1 that it is absolutely essential to hold the wire in a designated position against the object because the wire repeats complex oscillations due to electro-discharge between the wire and work piece. Normally, the wire is held by a pin guide at the upper and lower parts of the work piece. In most cases the wire, once used, will be discarded. However, there are problematic points that should be fully considered in order to enhance working accuracy.

Paper accepted July, 2005. Technical Editor: Anselmo Eduardo Diniz.

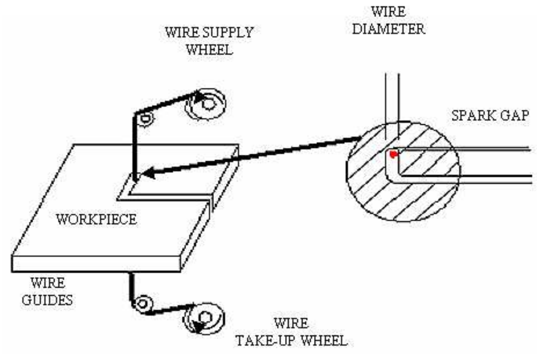

Figure 1. Details of WEDM Cutting Gap.

The most important performance measures in WEDM are metal removal rate, work piece surface finish, and cutting width. Discharge current, pulse duration, pulse frequency, wire speed, wire tension, dielectric flow rate are the machining parameters which affect the performance measures. The gap between wire and work piece usually ranges from 0.025 to 0.075 mm and is constantly maintained by a computer controlled positioning system. The material removal rate (g/min) is calculated by weight difference of the specimens before and after machining. The surface finish value (µm) is obtained by measuring the mean absolute deviation, R_a, from the average surface level. In WEDM operations, material removal rate determine the economics of machining and rate of production. In setting the machining parameter, the main goal is to maximize MRR and SF (surface finish). In order to investigate the effects of various process parameters on MRR and SF and then to suggest the optimal process settings, statistically designed experiments are used in this study. Generally, the machine tool builder provides machining parameter table to be used for setting machining parameter. This process relies heavily on the experience of the operator. In practice, it makes very difficult to utilize the optimal functions of a machine owing to there being too many adjustable machining parameters. The Taguchi method, a powerful experimental design tool, uses simple, effective, and systematic approach for deriving of the optimal machining parameters. Further, this approach requires minimum experimental cost and efficiently reduces the effect of the source of variation. An inexpensive and easy to operate methodology must be evolved to modify the machined surfaces as well as maintain accuracy. The methodology uses Taguchi's experimental design for setting suitable machining parameters in order to effectively control the amount of removed materials and to produce complicated precise components.

Experimental Method

The experiments were performed on Robofil 100 high precision five axis CNC WEDM, which is manufactured by Charmilles Technologies Corporation. The basic parts of the WEDM machine consists of a wire, a work table, a servo control system, a power supply and dielectric supply system. The Robofil 100 allows the operator to choose input parameters according to the material and height of the work piece and tool material from a manual provided by the WEDM manufacturer. The Robofil 100 WED machine has several special features. The pulse power supply uses a transistor controlled RC circuit. The discharge energy is determined by the value of the capacitor that is parallel to the machining gap. The experimental set-up for the data acquisition of the sparking frequency and machine table speed is illustrated in the Fig. 2. The WEDM process generally consists of several stages, a rough cut phase, a rough cut with finishing stage, and a finishing stage. During the rough cut phase metal removal rate is of primary importance. Only during the rough cut with finishing stage are metal removal rate and surface finish both of primary importance. This means that the rough cut with finishing phase is the most challenging phase because two goals must simultaneously be considered. We shall therefore consider the rough cut with finishing phase here.

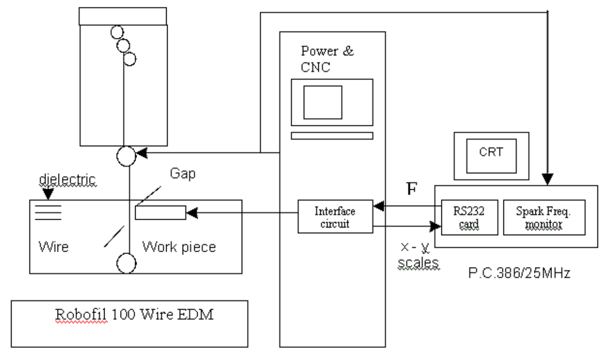

Figure 2. Experimental Set-up of Robofil 100 WEDM.

Material, Test Conditions, and Measurement

The experimental studies were performed on a Robofil 100 WEDM machine tool. Settings of control parameters of the machine are listed as Table 1. Few other factors, which can be expected to have an effect on the measures of performance, are also listed in Table 1. In order to minimize their effects, these factors were held constant as for as practicable. The control factors were chosen based on review of literature, experience, and some preliminary investigations. Different settings of six controllable factors such as discharge current, pulse duration, pulse frequency, wire speed, wire tension, and dielectric flow rate were used in the experiments as shown in Table 2 whereas pulse interval time and

Table 1. Parameters of Robofil 100 WEDM.

Control Factors	Symbols	Fixed Parameters	
Discharge Current	Factor A	Wire	Zinc coated copper wire
Pulse Duration	Factor B	Shape	Rectangular product
Pulse Frequency	Factor C	Location of work piece on working table	At the center of the table
Wire Speed	Factor D	Angle of cut	Vertical
Wire Tension	Factor E	Thickness of work piece	10 mm
Dielectric Flow Rate	Factor F	Stability	Servo control
		Height of work piece	25 mm
		Wire type	Stratified, copper, diameter 0.25 mm

Table 2. Levels for Various Control Factors.

	Level			
Control Factor	I	II	III	Unit
A. Discharge Current	16.00	24.00	32.00	amp
B. Pulse Duration	3.20	6.40	12.80	µsec
C. Pulse Frequency	40.00	50.00	60.00	KHz
D. Wire Speed	7.60	8.60	9.20	m/min
E. Wire Tension	1000.00	1100.00	1200.00	g
F. Dielectric Flow Rate	1.20	1.30	1.40	Bars

table feed rate were kept constant throughout the experiment. Zinc coated copper wire with 0.25 mm diameter was used in the experiment. Each time the experiment was performed, a particular set of input parameters was chosen and the work piece, a block of D2 tool steel (1.5%C, 12%Cr, 0.6%V, 1%Mo, 0.6%Si, 0.6%Mn and balance Fe), was cut completely through 10 mm length of the cut. The gap between wire and work piece usually ranges from 0.025 to 0.075 mm and is constantly maintained by a computer controlled positioning system. The most important performance measures in WEDM are metal removal rate, and work piece surface finish. The material removal rate (g/min) was calculated by weight difference of the specimens before and after machining, using a type E-12005 sartorius precision scale (maximum capacity =1210g, precision = 0.001g). The surface finish value (µm) was obtained by measuring the mean absolute deviation from the average surface level using a type C3A Mahr Perthen Perthometer (stylus radius of 5 µm). In this investigation, the height of the work piece was chosen to be 25 mm so that the cross-section of the cut made was 10 mm $\times$ 25 mm. A 0.25 mm diameter stratified wire (zinc coated copper wire) with vertical configuration was used.

Design of Experiment based on Taguchi Method

By using Robofil 100 WEDM, the input parameters are to be chosen from a limited set of possible values. The values of input parameters which are of interest in the rough cut with finishing phase are recorded. To evaluate the effects of machining parameters on performance characteristics (MRR and SF), and to identify the performance characteristics under the optimal machining parameters, a specially designed experimental procedure is required. Classical experimental design methods are too complex and difficult to use. Additionally, large numbers of experiments have to be carried out when number of machining parameters increases. Therefore, Taguchi method, a powerful tool for parameter design, was used to determine optimal machining parameters for maximum MRR and SF in WEDM. The control factors are used to select the best conditions for stability in design of manufacturing process, whereas the noise factors denote all factors that cause variation. Taguchi proposed to acquire the characteristic data by using orthogonal arrays, and to analyze the performance measure from the data to decide the optimal process parameters. In this work, it is planned to study the behavior of six control factors viz., A, B, C, D, E, and F and two interactions viz.,

A×B and A×F, based on past experience and extensive literature review. The experimental observations are further transformed into a signal-to-noise (S/N) ratio. There are several (S/N) ratios available depending on objective of optimization of the response. The characteristic with higher value represents better machining performance, such as MRR, is called 'higher is better, HB'. Inversely, the characteristic that has lower value represents better machining performance, such as SF. Therefore, "HB" for the MRR, and "LB'' for the SF were selected for obtaining optimum machining performance characteristics. The loss function (L) for objective of HB and LB is defined as follows, where y_{MRR} and y_{SF} represent response for metal removal rate and surface finish respectively and 'n' denotes the number of experiments.

$$L_{HB} = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_{MRR}^{2}} \tag{1}$$

$$L_{LB} = \frac{1}{n}\sum_{i=1}^{n} y_{SF}^{2} \tag{2}$$

The S/N ratio can be calculated as a logarithmic transformation of the loss function as shown below.

$$\text{S/N ratio for MRR} = -10\log_{10}(L_{HB}) \tag{3}$$

$$\text{S/N ratio for SF} = -10\log_{10}(L_{LB}) \tag{4}$$

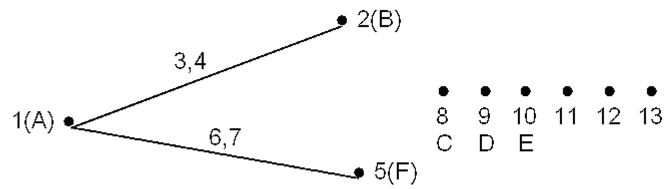

Figure 3. Modified Linear Graphs for L27 Array.

The standard linear graph is modified using line separation method, as shown in Fig.3, to assign the factors and interactions to various columns of the orthogonal array (Glen, 1993, Madhav, 1989) The array chosen was the L_{27} (3^{13}) which have 27 rows corresponding to the number of experiments with 13 columns at three levels. The factors and their interaction are assigned to the columns using modified linear graph. The plan of experiments is as follows: the first column was assigned to discharge current (A), the second column to pulse duration (B), the eighth column to pulse frequency (C), the ninth column to wire speed (D), the tenth column to wire tension (E), the fifth column to dielectric flow rate (F), the third and fourth columns are assigned to A×B for estimating interaction between discharge current (A) and pulse duration (B) respectively. The sixth and seventh columns are assigned to A×F for estimating interaction between discharge current (A) and dielectric flow rate (F) respectively. The L_{27} orthogonal array with assignment of factors and interactions is shown in Table 3. The experiments were conducted for each combination of factors (rows) as per selected orthogonal array. The number of observation under each combination of factors is one i.e. number of replications is one. The experimental results are shown in Table 4.

Table 3. Orthogonal Array for L27(313) Design with Factor Assignment to Columns.

$L_{27}(3^{13})$	1 A	2 B	3 $(AxB)_1$	4 $(AxB)_2$	5 F	6 $(AxF)_1$	7 $(AxF)_1$	8 C	9 D	10 E	11	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

Table 4. Experimental Design using L27 Orthogonal Array.

Expt. No.	A	B	C	D	E	F	MRR (g/min)	S/N Ratio (db)	Surface Roughness (R_a) (µm)	S/N Ratio (db)
1	1	1	1	1	1	1	0.139939	-17.0812	3.68	88.6820
2	1	1	2	2	2	2	0.127569	-17.8851	3.61	88.8514
3	1	1	3	3	3	3	0.115264	-18.7661	3.53	89.0493
4	1	2	2	2	2	1	0.169761	-15.4032	3.82	88.3584
5	1	2	3	3	3	2	0.150028	-16.4766	3.77	88.4805
6	1	2	1	1	1	3	0.156325	-16.1195	3.70	88.6461
7	1	3	3	3	3	1	0.182900	-14.7557	3.86	88.2607
8	1	3	1	1	1	2	0.166973	-15.5471	3.83	88.3468
9	1	3	2	2	2	3	0.146937	-16.6574	3.77	88.4688
10	2	1	1	2	3	1	0.141560	-16.9812	3.64	88.7723
11	2	1	2	3	1	2	0.132273	-17.5706	3.63	88.8088
12	2	1	3	1	2	3	0.151855	-16.3714	3.67	88.7120
13	2	2	2	3	1	1	0.222566	-13.0508	3.89	88.1925
14	2	2	3	1	2	2	0.219497	-13.1714	3.87	88.2436
15	2	2	1	2	3	3	0.220792	-13.1203	3.90	88.1698
16	2	3	3	1	2	1	0.165344	-15.6322	3.86	88.2722
17	2	3	1	2	3	2	0.156703	-16.0985	3.83	88.3295
18	2	3	2	3	1	3	0.165329	-15.6330	3.86	88.2722
19	3	1	1	3	2	1	0.168143	-15.4864	3.73	88.5755
20	3	1	2	1	3	2	0.174135	-15.1823	3.75	88.5098
21	3	1	3	2	1	3	0.170947	-15.3428	3.73	88.5688
22	3	2	2	1	3	1	0.161285	-15.8481	3.80	88.4047
23	3	2	3	2	1	2	0.169096	-15.4373	3.84	88.3123
24	3	2	1	3	2	3	0.169818	-15.4004	3.83	88.3353
25	3	3	3	2	1	1	0.188897	-14.4755	3.99	88.9833
26	3	3	1	3	2	2	0.155701	-16.1542	3.89	88.2038
27	3	3	2	1	3	3	0.174034	-15.1873	3.89	88.1982

Analysis

The S/N ratio for MRR and SF is computed using Eqs. (3) and (4) respectively for each treatment as shown in Table 4. Then, overall mean for S/N ratio of MRR and SF is calculated as average of all treatment responses. The overall mean for S/N ratio of MRR is found to be -15.04 db whereas overall mean for S/N ratio of SF is obtained as 88.45 db. The graphical representation of the effect of the six control factors on MRR and SF is shown in Fig. 4 and Fig. 5 respectively. The analysis was made using the popular software specifically used for design of experiment applications known as MINITAB 14. Before any attempt is made to use this simple model as a predictor for the measures of performance, the possible interactions between the factors must be considered. The factorial design incorporates a simple means of testing for the presence of interaction effects. The S/N ratio response tables for MRR and SF are shown in Table 5 and 6 respectively.

The purpose of the analysis is to determine the factors and their interactions that have strong effects on the machining performance. It is evident from Table 5 that factor A, B and F can be treated as significant factors whereas factor C, D and E are less significant factors for maximization of MRR. The interaction of factors A and B presents the strongest significant effects as evident from Fig. 6. Before determining the recommended levels for factors A and F, the interaction between the factors A and F must be analyzed. As such factor F is a weak factor by itself, its preferred level should be determined purely based on the interaction AxF. It is observed from Fig. 7 that the interaction between AxF shows significant effect on MRR. Hence factor F can not be neglected. So, for maximization of MRR, the significant effects observed for factors A, B and F along with interactions are AxB and AxF.

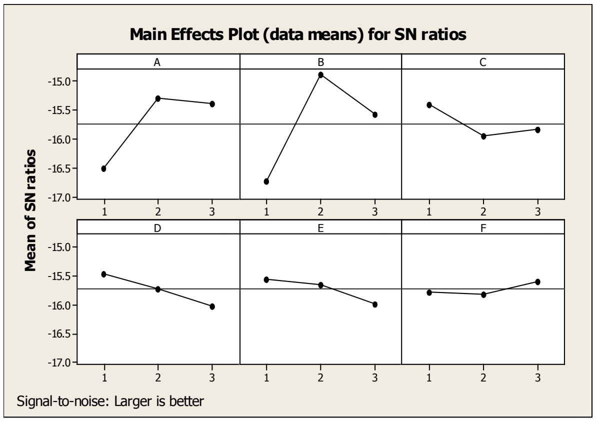

Figure 4. Effect of Control Factors on MRR.

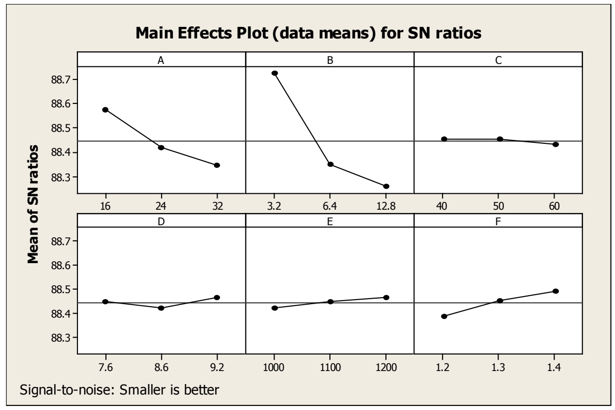

Figure 5. Effect of Control Factors on SF.

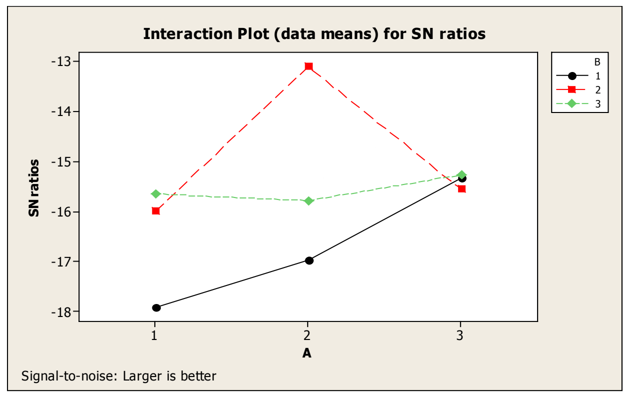

Figure 6. Interaction Graph of AxB for MRR.

Table 5. S/N Ratio Response Table for MRR.

	A	B	$(AXB)_1$	$(AXB)_2$	F	$(AXF)_1$	$(AXF)_2$	C	D	E
Level 1	-16.52	-16.74	-16.42	-15.43	-15.78	-15.46	-15.56	-15.41	-15.46	-15.56
Level 2	-15.29	-14.89	-16.08	-15.71	-15.82	-15.72	-15.65	-15.95	-15.72	-15.65
Level 3	-15.39	-15.57	-14.70	-16.06	-15.60	-16.02	-15.99	-15.84	-16.02	-16.00
Delta	1.23	1.85	1.72	0.63	0.22	0.56	0.43	0.53	0.56	0.44

Table 6. S/N Ratio Response Table for SF.

	A	B	$(AXB)_1$	$(AXB)_2$	F	$(AXF)_1$	$(AXF)_2$	C	D	E
Level 1	88.57	88.72	88.50	88.40	88.39	88.39	88.42	88.45	88.44	88.42
Level 2	88.42	88.35	88.46	88.44	88.45	88.45	88.42	88.45	88.43	88.45
Level 3	89.34	89.26	88.37	89.49	88.49	88.50	88.49	88.43	88.46	88.47
Delta	0.23	0.46	0.13	0.09	0.10	0.11	0.07	0.02	0.04	0.05

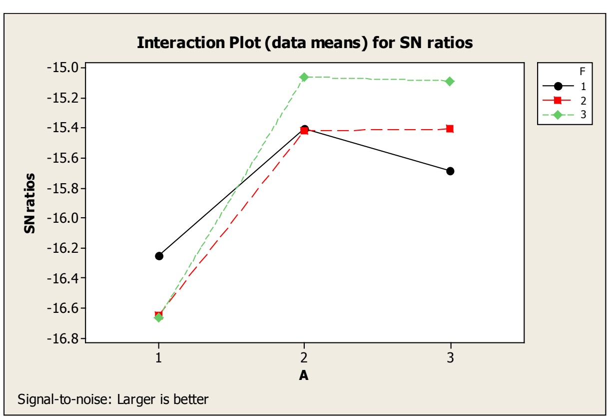

Figure 7. Interaction Graph of AxF for MRR.

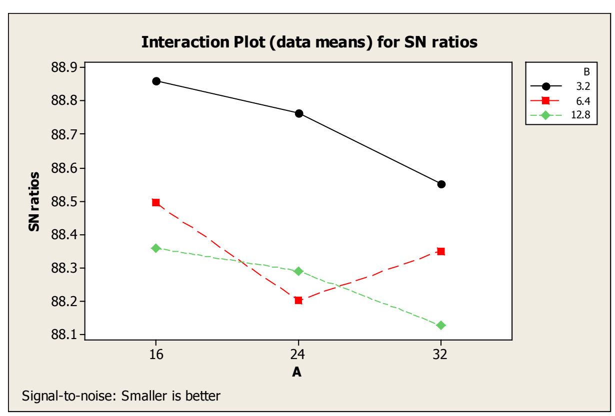

Figure 8. Interaction Graph of AxB for SF.

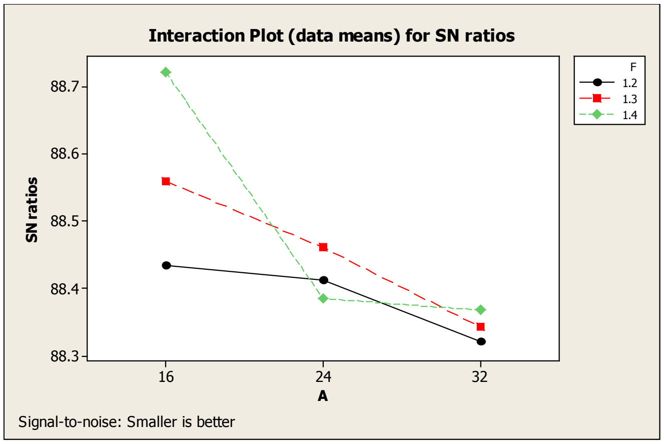

Figure 9. Interaction Graph of AxF for SF.

Similarly, Table 6 indicates that factors A, B and F have significant effect whereas factor C, D and E have least significant effect on maximization of SF. Factors A and B not only shows significant effect individually but also their interaction shows strong effect on SF as shown in Fig. 8. Similarly, Factor F as such has also no significant effect on SF but its interaction with factor A shows significant effect on SF as shown in Fig. 9. Therefore, it is suggested that interaction of factors A and F can not be neglected.

Analysis of the results leads to conclusion that factors at level A_2, B_2 and F_3 can be set for maximization of MRR. Similarly, it is recommended to use the factors at levels such as A_1, B_1 and F_3 for maximization of SF. It has been observed that the optimal settings of parameters for MRR and SF are quite different but the factors are essentially same. It is to be noted that the optimal levels of factors differ widely for both the objectives.

Confirmation Experiment

The confirmation experiment is the final step in any design of experiment process. The purpose of the confirmation experiment is to validate the conclusions drawn during the analysis phase. The confirmation experiment is performed by conducting a test with specific combination of the factors and levels previously evaluated. In this study, a new experiment was designed with combinations of control factors A_2, B_3 and F_3 to obtain MRR. An experiment was conducted with new combination of factors and the result was noted down. The estimated S/N ratio is calculated with the help of the prediction equation shown below:

$$\hat{\eta}_1 = \bar{T} + (\bar{A}_2 - \bar{T}) + (\bar{B}_3 - \bar{T}) + (\bar{A}_2\bar{B}_3 - \bar{T}) - [(\bar{A}_2 - \bar{T}) - (\bar{B}_3 - \bar{T})] + (\bar{F}_3 - \bar{T})[(\bar{A}_2\bar{F}_3 - \bar{T}) - (\bar{A}_2 - \bar{T}) - (\bar{F}_3 - \bar{T})] \quad (5)$$

$\hat{\eta}_1$ Predicted Average

$\bar{T}$ Overall experimental average

$\bar{A}_2, \bar{B}_3$ *and* $\bar{F}_3$ Mean response for factors and interactions at designated levels.

By combining like terms, the equation reduces to

$$\hat{\eta}_1 = \bar{A}_2\bar{B}_3 - \bar{A}_2 + \bar{A}_2\bar{F}_3 \quad (6)$$

Substituting values from response table and interaction matrix for MRR, $\hat{\eta}_1$ is estimated as

$$\hat{\eta}_1 = -15.5558 \ db$$

The estimated S/N ratio for SF can be calculated with the help of the following prediction equation for new combinations A_1, B_2 and F_2.

$$\hat{\eta}_2 = \bar{T} + (\bar{A}_1 - \bar{T}) + (\bar{B}_2 - \bar{T}) + [(\bar{A}_1\bar{B}_2 - \bar{T}) - (\bar{A}_1 - \bar{T}) - (\bar{B}_2 - \bar{T})] + (\bar{F}_2 - \bar{T}) + (\bar{A}_1\bar{F}_2 - \bar{T}) - (\bar{A}_1 - \bar{T}) - (\bar{F}_2 - \bar{T})] \quad (7)$$

$\hat{\eta}_2$ Predicted Average

$\bar{T}$ Overall experimental average

$\bar{A}_1, \bar{B}_2$ *and* $\bar{F}_2$ Mean response for factor and interactions at designated levels

$$\hat{\eta}_2 = \bar{A}_1\bar{B}_2 - \bar{A}_1 + \bar{A}_1\bar{F}_2 \quad (8)$$
$$\eta_2 = 88.4731 db$$

Table 7 and Table 8 show the comparison of the predicted value with the new experimental value for the selected combinations of the machining parameters. As shown in these tables, the experimental values agree reasonably well with predictions because an error of 4.062 % for the S/N ratio of MRR and 1.53 % for the S/N ratio SF is observed when predicted results are compared with experimental values. Hence, the experimental result

Table 7. Results of the Confirmation Experiment for MRR.

	Optimal machining parameter	
	Prediction	Experimental
Level	$A_2B_3F_3$	$A_2B_3F_3$
S/N ratio for MRR	-15.5558	-16.2145

Table 8. Results of the Confirmation Experiment for SF.

	Optimal machining parameter	
	Prediction	Experimental
Level	$A_1B_2F_2$	$A_1B_2F_2$
S/N ratio for SF	88.4731	87.1194

confirms the optimization of the machining parameters using Taguchi method for enhancing the machining performance. The resulting model seems to be capable of predicting both the MRR and SF to a reasonable accuracy. However, the error in MRR can be further expected to reduce if the number of measurements is increased.

Multi-objective Optimization of WEDM Parameters

In this study, main objective is to derive machining parameter settings for maximization of MRR and SF. The multi-objective optimization requires quantitative determination of the relationship between the metal removal rate and surface finish with combination of machine setting parameters. In order to express, metal removal rate and surface finish in terms of machining parameter settings, a mathematical model in the following form is suggested.

$$Y = K_0 + K1 \times A + K_2 \times B + K_3 \times F + K_4 \times A \times B + K_5 \times A \times F \quad (9)$$

Here, Y is the performance output terms and K_i (i = 0,1 .5) are the model constants. The constant are calculated using non-linear regression analysis with the help of MINITAB 14 software and the following relations are obtained.

$$MRR = 1.011-0.580\times A+0.362\times \mathbf{B}-0.659\times F-0.371\times A\times B+1.046\times A\times F \quad r^2 = 0.98 \tag{10}$$

$$SF = 0.927-0.001\times A+0.095\times B-0.066\times F-0.031\times A\times B+0.081\times A\times F \quad r^2 = 0.99 \tag{11}$$

The correctness of the calculated constants is confirmed as high correlation coefficients (r^2) in the tune of 0.9 are obtained for equations (10) and (11) and therefore, the models are quite suitable to use for further analysis. A weighting method is followed to assign weights to performance outputs in the multi-objective optimization function. In order to overcome the large differences in numerical values between two different objects such as MRR and SF, the function corresponding to every machining performance output is normalized. The weighting method enables to express normalized performance output of MRR and SF as a single objective. Here, the resultant weighted objective function to be maximized is given as:

$$\text{Maximize} \quad Z = (w_1 \times f1 + w_2 \times 1/f_2) \times (1- K \times C) \tag{12}$$

f_1 Normalized function for MRR
f_2 Normalized function for SF
C violation coefficient
K a penalty parameter, usually the value is 1 0
Subjected to constraints:

$$A_{min} \leq A \leq A_{max} \tag{13}$$

$$B_{min} \leq B \leq B_{max} \tag{14}$$

$$F_{min} \leq F \leq F_{max} \tag{15}$$

w_1 and w_2 are the weighting factors applied to the normalized MRR and SF functions used in the objective function of optimization process. The weighting factors are selected in such a manner that their sum is equal to one. A higher value of weighting factor w_1 indicates that more emphasis is put on the objective of MRR. The min and max in Eqs.13-15 shows the lowest and highest control factors settings (machining parameters) used in this study (Table 2).

Genetic algorithm (GA) is used to obtain the optimum machining parameters for multi-objective outputs by using the several combinations of the weight. The values of the weights are assigned randomly in such a way that their sum should be equal to one. The larger the weighting factor, greater improvement in corresponding machining performance output can be achieved. To optimize the multi-objective function, the GA parameters are summarized in Table 9. The computational algorithm is implemented in Turbo C^{++} code and run on an IBM Pentium IV machine. Genetic algorithms (GAs) are mathematical optimization techniques that simulate a natural evolution process. They are based on the Darwinian Theory, in which the fittest species survives and propagate while the less successful tend to disappear. The concept of genetic algorithm is based on the evolution process and was introduced by Holland (1975). Genetic algorithm mainly depends on three types of operator's viz., reproduction, crossover and mutation. Reproduction is accomplished by copying the best individuals from one generation to the next, in what is often called an elitist strategy. The best solution is monotonically improving from one generation to the next. The selected parents are submitted to the crossover operator to produce one or two children. The crossover is carried out with an assigned probability, which is generally rather high. If a number randomly sampled is inferior to the probability, the crossover is performed. The genetic mutation introduces diversity in the population by an occasional random replacement of the individuals. The mutation is performed based on an assigned probability. A random number is used to determine if a new individual will be produced to substitute the one generated by crossover. The mutation procedure consists of replacing one of the decision variable values of an individual, while keeping the remaining variables unchanged. The replaced variable is randomly chosen, and its new value is calculated by randomly sampling within its specific range.

Table 9. Genetic Algorithm Parameters for Case 1, 2 and 3.

Population size	50
Maximum number of generation	500
Number of problem variables	3
Probability of crossover	75%
Probability of mutation	5%

Table 10. Optimum Machining Conditions for Multi-performance with Different Weighting Factors.

Control Factors and Performance Characteristics	Optimum Machining Conditions		
	Case-1 (w_1=0.9,w_2=0.1)	Case-2 (w_1=0.5,w_2=0.5)	Case-3 (w_1=0.1,w_2=0.9)
A: Discharge Current (amp.)	32.0000	32.0000	16.0000
B: Pulse Duration (μsec)	4.0300	3.4800	3.2400
F: Dielectric Flow Rate (bars)	1.3400	1.3700	1.3118
MRR (g/min)	0.1512	0.1605	0.0947
SF (μm)	3.6524	3.7404	3.6187

The pseudo-code for standard genetic algorithm is presented below.

Where S_a is initial population.

The Standard Genetic Algorithm

{
Generate initial population S_a
Evaluate population S_a
While stopping criteria not satisfied **repeat**
{
Select elements from S_a to put into S_{a+1}
Crossover elements of S_a and put into S_{a+1}
Mutate elements of S_a and put into S_{a+1}
Evaluate new population S_{a+1}
$S_a = S_{a+1}$
}
}

The process parameters with higher MRR (or SF) can be obtained by increasing the respective weighting factor in the objective function. Table 10 shows the optimum conditions of the machining parameters for multi-performance outputs with different combinations of the weighting factors. From this study Case-2 gives optimal machining performance with maximization of MRR and SF under equal importance of the weighting factors ($w_1 = 0.5$, $w_2 = 0.5$).

Conclusions

In this work, it is intended to study factors like discharge current, pulse duration, pulse frequency, wire speed, wire tension and dielectric flow rate and few selected interactions both for maximizations of MRR and minimization of surface roughness in WEDM process using Taguchi Method. The analysis shows that factors like discharge current (A), pulse duration (B), dielectric flow rate (F) and interactions AxB and AxF have been found to play significant role in cutting operations. Analysis of the results leads to conclude that factors at level A_2, B_2 and F_3 can be set for maximization of MRR. Similarly, it is recommended to use the factors at levels such as A_1, B_1 and F_3 for maximization of SF. In any process, few interactions play vital role in defining the optimal performance measures. A study without considering interaction effects seems to lack in-depth analysis. Hence, in this study, not only the factor but also few selected interactions have been considered. The results of confirmation experiment agree well the predicted optimal settings as an error of 4.062 % is found with MRR. Similarly, an error of 1.53 % was observed for SF. It is expected that errors can be reduced if more number of replications are taken during experimental stage. It is to be noted that the optimal levels of the factors for both the objectives differ widely. In order to optimize for both the objectives, mathematical models are developed using non-linear regression method. The optimum search of machining parameter values for the objective of maximizing both MRR and SF are formulated as a multi-objective, multi-variable, non-linear optimization problem. This study also evaluates the performance measures with equal importance to weighting factors, since high MRR and high SF are equally important objectives in WEDM application. The rationale behind the use of genetic algorithm lies in the fact that genetic algorithm has the capability to find the global optimal parameters whereas the traditional optimization techniques are normally stuck up at the local optimum values. The algorithm is tested to find optimal values of parameters varying weighting factors for different objectives. In future, the study can be extended using more than two objectives, different work materials, and hybrid optimization techniques.

Acknowledgments

The authors would like to sincerely express their gratitude to the anonymous reviewers for their valuable comments that helped to improve the quality of this paper.

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