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Optimization of Process Parameters of Wire Electrical Discharge Machining Using Fuzzy logic Integrated with Taguchi Method

Rajyalakshmi.G[1], Venkata Ramaiah. P[2]

[1]School of Mechanical and Building Sciences, Vellore Institute of Technology, Vellore, Tamilnadu, India.

[2] Department of Mechanical Engineering, Sri VenkateswaraUniversity, Tirupati, Andhrapradesh, India.

[1]rajyalakshmi@vit.ac.in

Abstract— ***In this paper, fuzzy logic integrated with the Taguchi method is used to optimize Wire Electro Discharge Machining (WEDM) process with multiple quality characteristics. Rough machining with EDM gives poor surface finish and has micro cracks and pores. Finish machining gives better surface finish but with very poor machining speed (MRR). Spark gap width is one of the important performance measures in WEDM. Spark gap width is the measure of the amount of the material that is wasted during machining. It determines the dimensional accuracy of the finishing part. In setting the machining parameters, the main goal is the maximum MRR with the minimum surface roughness and minimum spark gap width. Hence achieving higher MRR along with lower SR and SG can be considered as a multi-objective optimization problem.***

This paper discusses the application of the Taguchi method with fuzzy logic to optimize the machining parameters for Wire electrical discharge machining of Inconel 825 with multiple characteristics. A multi-response performance index (MRPI) was used for optimization. The machining parameters viz., pulse on time, pulse off time, corner servo voltage, flushing pressure, wire feed, wire tension, spark gap voltage, servo feed were optimized with consideration of multiple performance characteristics. The results from confirmation runs indicated that the determined optimal combination of machining parameters improved the performance of the machining process.

Keywords— WEDM, Inconel 825, Taguchi method, Fuzzy logic, Multi objective optimization.

I. INTRODUCTION

The recent trend of manufacturing industries in achieving larger quantities with good quality product is embarked by employing non traditional machine tools in order to obtain tight tolerances and accurate dimensions in shortest time possible to make their products timely in the market. One of the ways to achieve these instant manufacturing practices is by simulating the processes to its actual conditions before they are put onto the actual production floor. High number of simulation tools are being employed for this reasons as the method is seen to be more reliable as compared to the traditional trial and error methods.

Optimization of process parameters is an important criterion in the machining process to achieve high quality. Normally, the Taguchi method is used to optimize the performance characteristics of process parameters to achieve high quality [1, 2]. However, most reports on Taguchi applications to date have been concerned with the optimization of a single performance characteristic [3]. Handling the more demanding multiple performance characteristics are still an interesting research problem. Optimization of multiple response characteristics is more complex compared to optimization of single performance characteristics [4, 5]. The theory of fuzzy logics, initiated by Zadeh [6] has proven to be useful for dealing with uncertain and vague information. This theory has proved to be an effective means for dealing with objectives that are linguistically specified. Linguistic terms, such as 'low,' 'medium and 'high' may be defined by fuzzy sets [7]. Since its introduction, fuzzy set theory has attracted the attention of researchers in mathematical and engineering fields [8].

The Taguchi method can optimize performance characteristics through the settings of process parameters and reduce the sensitivity of the system performance to sources of variation. As a result, the Taguchi method has become a powerful tool in the design of experiment methods [9]. However, most published Taguchi applications to date have been concerned with the optimization of a single performance characteristic. Handling the more demanding multiple performance characteristics is still an interesting research problem[10] The theory of fuzzy logics, initiated by Zadeh in 1965 [11]. [Klir *et al 2002*] has proven to be useful for dealing with uncertain and vague information. In fact, the definition of performance characteristics such as lower-the-better, higher-the-better, and nominal-the-better contains a certain degree of uncertainty and vagueness. Therefore, optimization of the performance characteristics with fuzzy logic has been considered in this study

In this study, a fuzzy reasoning of the multiple performance characteristics has been developed based on fuzzy logic. As a result, optimization of complicated multiple performance characteristics can be transformed into the optimization of a single multi-response performance index (MRPI). In this paper, the optimization of the electrical discharge machining process with multiple performance characteristics has been investigated to illustrate this approach. Electrical discharge machining (EDM) has been used effectively in the machining of hard, high-strength, and temperature resistant materials. Material is removed by means of rapid and repetitive spark discharges across the gap between the tool and the work piece. In electrical discharge machining, it is important to select machining parameters for achieving optimal machining performance [12][Pandey *et al 1999*]. Usually, the desired machining parameters are determined based on experience or handbook values. However, this does not ensure that the selected machining parameters result in optimal or near optimal machining performance for that particular electrical discharge machine and environment. To solve this task in the present study, the Taguchi method with fuzzy logic is used as an efficient approach to determine the optimal machining parameters in the electrical discharge machining process. In the following, optimization of multiple performance characteristics with fuzzy logic is introduced briefly and the electrical discharge machining process is then described, after which the experimental details of using the Taguchi method with fuzzy logic to optimize the electrical discharge machining process to secure low surface roughness (SR) and high material removal rate (MRR) are given. Finally, the paper concludes with a summary

II. MULTI-RESPONSE OPTIMIZATION USING FUZZY LOGIC

In the present work, a multiple performance characteristics optimization method is introduced for a composite machining process. Optimization of the multiple performance characteristics is concerned with optimizing a vector of objectives. For the composite machining process, the material removal rate has the higher-the-better performance characteristic. However, surface roughness and tool wear have the lower the- better performance characteristics. As a result, improving one performance characteristic may require degrading another performance characteristic. Hence, optimization of such multiple performance characteristics is much more complicated than optimization of a single performance characteristic [13]. In this work, the Taguchi method with fuzzy logic is used to investigate the multiple performance characteristics in the composite machining process.

The optimization procedure adopted is as follows:

(i) Conduct the experiments using Taguchi's orthogonal array.
(ii) Transform the experimental results into a signal-to noise (S/N) ratio. The S/N ratio can be used to measure the deviation of the performance characteristics from the desired values.
(iii) Development of fuzzy rules. The loss function corresponding to each performance characteristics is fuzzified, and then a single MRPI is obtained through fuzzy reasoning on the fuzzy rules. The MRPI is used to optimize the machining process.
(iv) Analyze the experimental results using the MRPI and statistical analysis of variance
(v) Select the optimal levels of process parameters
(vi) Verify the optimal parameters through experiment.

III. THE WIRE CUT ELECTRICAL DISCHARGE MACHINING PROCESS

Wire-cut electrical discharge machining (WEDM) has grown tremendously since it was first applied more than twenty years ago. Its broad capabilities have allowed it to encompass the production, aerospace/aircraft and medical industries and virtually all areas of conductive material machining. 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 wire EDM in manufacturing will continue to grow at an accelerated rate [14].. In the WEDM process, a small wire is engaged as the tool electrode. The dielectric medium, which is usually de ionized water, does not immerse the wire. The work piece is mounted on the table of the machine and the dielectric medium is ejected to the sparking area. The movement of the wire is controlled numerically to achieve the desired complex two- and three-dimensional shapes for the work piece. What wire-cut EDM manufacturers and users want is to achieve higher machining productivity with a desired accuracy and surface finish? However, due to a large number of variables and the stochastic nature of the process, even a highly skilled operator with a state-of the- art WEDM is rarely able to achieve the optimal performance [15]. An effective way to solve this problem is to determine the relationship between the performance of the process and its controllable input parameters (i.e. model the process through suitable mathematical techniques). Investigations into the influences of machining input parameters on the performance of EDM and WEDM have been reported widely [15 -19] and several attempts [20-22] have been made to model the process.

In wire-cut EDM process the spark is occurring between continuous travelling wire and work piece. Here wire acts like a band saw, but sparks instead of teeth do the cutting. The variations in the machining parameters, such as the pulse on time, pulse off time, flushing pressure, wire tension, gap voltage, wire feed rate, and servo feed, greatly affect the measures of the machining performance, for example, the SR, MRR and the SG. Therefore, proper selection of the machining parameters can result in better machining performance in the electrical discharge machining process.

A. Experimental Setup and Experimental Procedure

The experiments were carried out on Ultra Cut 843/ ULTRA CUT f2 CNC WEDM machine. In this machine, all the axes are servo controlled and can be programmed to follow a CNC code which is fed through the control panel. All three axes have an accuracy of 1μm. The electrode material used was a 0.25 mm diameter brass wire. A small gap of 0.025 mm to 0.05 mm is maintained in between the wire and work-piece. Wire-cut electrical discharge machining of Inconel825 alloy has been considered in the present set of research work.

The size of the work piece considered for experimentation on the wire-cut EDM is 10 mm width, 10 mm length and 15 mm depth of cut. According to the Taguchi method based on robust design a L36 (21X37) mixed orthogonal array is employed for the experimentation.

In setting the machining parameters, particularly in rough cutting operation, the goal is threefold - the maximization of MRR, minimization of SR and minimization of gap width. 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 operators. In practice, it is very difficult to utilize the optimal functions of a machine owing to there being too many adjustable machining parameters. With a view to alleviate this difficulty, a simple but reliable method based on statistically designed experiments is

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Volume No.2, Issue No.6, pp : 600-606 1 June 2013

suggested for investigating the effects of various process parameters on MRR, SR and Gap width and determines optimal process settings. Finally, Fuzzy-based Taguchi technique has been adopted to evaluate the optimal process environment.

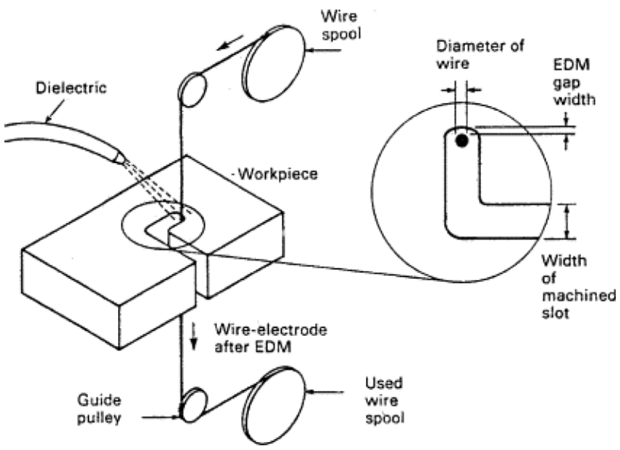

Fig 1. Schematic diagram of WEDM

B. Machining Parameter selection and performance evaluation

The selection of optimum machining parameters in WEDM is an important step. Improperly selected parameters may result in serious problems like short-circuiting of wire, wire breakage and work surface damage which is imposing certain limits on the production schedule and also reducing productivity. As Material Removal Rate (MRR), Surface Roughness (Ra) and Spark gap (SG) are most important responses in WEDM; various investigations have been carried out by several researchers for improving the MRR, Surface Finish and kerf width [3–7]. However, the problem of selection of machining parameters is not fully depending on machine controls rather material dependent.

To perform the experimental design, the levels of machining parameters are selected as in Table I.

TABLE I

Experimental factors and their levels for Wire Electrical Discharge Machining process

Factor	Parameter	Symbol	Level-1	Level-2	Level-3
A	Pulse On Time	T ON(μs)	105	115	-
B	Pulse Off Time	T OFF(μs)	50	55	60
C	Corner servo	CS(volts)	50	60	70
D	Flushing pressure Of Dielectric Fluid	WP(Kg/cm^2)	8	10	15
E	Wire feed rate	WF(m/min)	2	5	6
F	Wire tension N	WT(Kg-f)	9	10	11
G	Spark gap voltage	SV(volts)	20	25	30
H	Servo Feed	SF(mm/min)	1050	1100	1150

C. Experimental Results and Discussions

The multiple responses from the experiment were calculated as follows

Material removal rate is calculated as

MRR = V_c * b* h mm^3/min

Where: V= Cutting speed in mm/min

b = Width of cut in mm

h = Height of the work piece in mm and Surface roughness is measured with surfcorderSE3500 in µm and spark gap is measured with micrometer in mm

D. Signal-To-Noise Ratio

In the Taguchi method, a loss function is defined to calculate the deviation between the experimental value and the desired value. Usually, there are three categories of the performance characteristics in the analysis of the signal-to- noise ratio, i.e., the lower-the-better, the higher the- better, and the nominal-the-better. To obtain optimal machining performance, the minimum SR and the maximum MRR are desired. Therefore, the lower-the-better SR and the higher-the better MRR should be selected. The loss function *Lij* of the lower-the-better performance characteristic can be expressed as

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

Where *Lij* is the loss function of the *i*th performance characteristic in the *j*th experiment, *n* is the number of tests, and *yijk* is the experimental value of the *i*th performance characteristic in the *j*th experiment at the *k*th test. The loss function of the higher-the-better performance characteristic can be expressed as.

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

The loss function is further transformed into an S/N ratio. In the Taguchi method, the S/N ratio is used to determine the deviation of the performance characteristic from the desired value. The S/N ratio Z*ij* for the *i*th performance characteristic in the *j*th experiment can be expressed as

$$Zij = -10\log_{10}(L_{ij})$$

To consider the three different performance characteristics in the Taguchi method, the S/N ratios corresponding to the SG, SR and MRR are processed by the fuzzy logic unit.

E. Fuzzy Logic:

A fuzzy logic unit comprises a fuzzifier, membership functions, a fuzzy rule base, an inference engine, and a defuzzifier. First, the fuzzifier uses membership functions to fuzzify the S/N ratios. Next, the inference engine performs a fuzzy reasoning on fuzzy rules to generate a fuzzy value. Finally, the defuzzifier converts the fuzzy value into a MRPI. In the following, the concept of fuzzy reasoning is described briefly based on the three input-one-output fuzzy logic unit. The fuzzy rule base consists of a group of if-then control rules with the three inputs, x_1, x_2 and x_3, and one output *y*, i.e.

Rule 1: if x_1 is A_1 and x_2 is $B_1$and x_3 is C_1 then *y* is D_1 else
Rule 2: if x_1 is A_2 and x_2 is $B_2$and x_3 is C_2 then *y* is D_2 else
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……………………………………………………………
Rule n: : if x_1 is A_n and x_2 is B_n and x_3 is C_n then *y* is D_n .

Ai, Bi, Ci, and Di are fuzzy subsets defined by the corresponding membership functions, i.e., μ_{Ai}, μ_{Bi}, μ_{Ci}, and μ_{Di}.

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Volume No.2, Issue No.6, pp : 600-606 1 June 2013

In the present work, three fuzzy subsets are assigned to the three inputs, as shown in Fig. 2-4.

TABLE II
EXPERIMENTAL LAYOUT USING AN L36 ORTHOGONAL ARRAY

Exp. No.	TON	TOFF	CS	WP	WF	WT	SV	SF	MRR	SR	SG
1	1	1	1	1	1	1	1	1	120.3	1.54	0.02
2	1	2	2	2	2	2	2	2	143.2	1.86	0.03
3	1	3	3	3	3	3	3	3	182.2	1.41	0.03
4	1	1	1	1	1	2	2	2	119.6	1.68	0.01
5	1	2	2	2	2	3	3	3	139.5	1.66	0.04
6	1	3	3	3	3	1	1	1	183.7	1.75	0.01
7	1	1	1	2	3	1	2	3	112.8	1.47	0.04
8	1	2	2	3	1	2	3	1	142.5	1.17	0.05
9	1	3	3	1	2	3	1	2	195.7	1.99	0.04
10	1	1	1	3	2	1	3	2	114.7	1.86	0.04
11	1	2	2	1	3	2	1	3	147.7	1.54	0.04
12	1	3	3	2	1	3	2	1	202.1	1.94	0.04
13	1	1	2	3	1	3	2	1	115.8	1.86	0.03
14	1	2	3	1	2	1	3	2	127.1	1.85	0.01
15	1	3	1	2	3	2	1	3	144.3	1.61	0.04
16	1	1	2	3	2	1	1	3	123.3	1.94	0.04
17	1	2	3	1	3	2	2	1	131.6	1.38	0.04
18	1	3	1	2	1	3	3	2	187.1	1.47	0.04
19	2	1	2	1	3	3	3	1	371.2	1.91	0.05
20	2	2	3	2	1	1	1	2	315.3	1.88	0.01
21	2	3	1	3	2	2	2	3	325.5	2.58	0.04
22	2	1	2	2	3	3	1	2	277.8	2.03	0.04
23	2	2	3	3	1	1	2	3	294.3	2.30	0.01
24	2	3	1	1	2	2	3	1	309.3	1.91	0.03
25	2	1	3	2	1	2	3	3	267.3	1.94	0.01
26	2	2	1	3	2	3	1	1	329.2	1.95	0.03
27	2	3	2	1	3	1	2	2	325.8	2.25	0.03
28	2	1	3	2	2	2	1	1	264.7	2.23	0.05
29	2	2	1	3	3	3	2	2	247.8	2.04	0.04
30	2	3	2	1	1	1	3	3	352.2	2.44	0.01
31	2	1	3	3	3	2	3	2	401.2	2.05	0.01
32	2	2	1	1	1	3	1	3	348.7	2.94	0.03
33	2	3	2	2	2	1	2	1	360.0	2.32	0.03
34	2	1	3	1	2	3	2	3	322.5	1.90	0.04
35	2	2	1	2	3	1	3	1	352.5	1.82	0.03
36	2	3	2	3	1	2	1	2	274.8	2.30	0.04

Five fuzzy subsets are assigned to the output, as shown in Fig. 5. Thirty-six fuzzy rules were developed based on the fact that a higher S/N ratio gives better performance. By taking the max-min compositional operation, the fuzzy reasoning of these rules yields a fuzzy output. Suppose that x_1, x_2, and x_3 are the three input values of the fuzzy logic unit; then, the membership function of the output of fuzzy reasoning can be expressed as [3]

$\mu_{Do}(y) = [\mu_{A1}(x_1) \wedge \mu_{B1}(x_2) \wedge \mu_{C1}(x_3) \wedge \mu_{D1}(y)] \vee \ldots\ldots\ \mu_{An}(x_1) \wedge \mu_{Bn}(x_2) \wedge \mu_{Cn}(x_3) \wedge \mu_{Dn}(y)]$

Where $\wedge$ is the minimum operation and $\vee$ is the maximum operation. Finally, a defuzzification method called centre of gravity [3, 18] is used to transform the fuzzy output into a non-fuzzy value y_0,

$$y_0 = \frac{\sum y \mu_{D_o}(y)}{\sum \mu_{D_o}(y)}$$

The non-fuzzy value y_0 gives MRPI. Invariably, a larger MRPI is preferred, which gives a better performance characteristic. Table II shows the results of the S/N ratios and MRPI for different experiments.

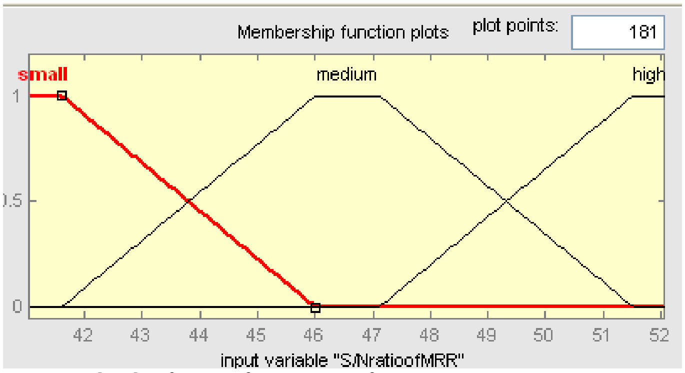

Fig 2 Membership function for S/N ratio of MRR

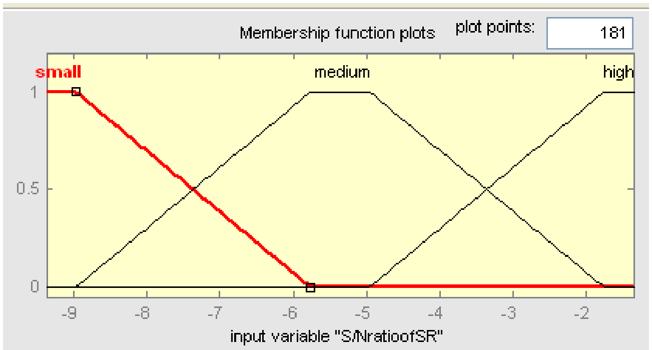

Fig 3 Membership function for S/N ratio of SR

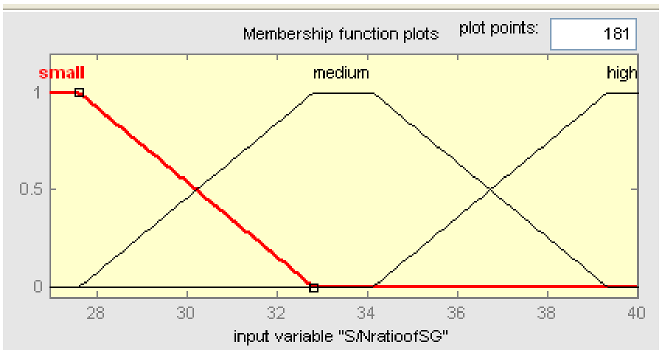

Fig 4 Membership function for S/N ratio of SG

International Journal of Scientific Engineering and Technology (ISSN : 2277-1581)
Volume No.2, Issue No.6, pp : 600-606 1 June 2013

TABLE III

S/N RATIOS AND MRPI

Exp. No.	S/N Ratio MRR	S/N Ratio Surface Roughness	S/N Ratio Spark Gap	MRPI
1	41.6107	-3.75041	32.0412	0.415
2	43.1219	-5.39026	29.1186	0.26
3	45.2134	-2.98438	28.5194	0.375
4	41.5564	-4.50619	36.4782	0.398
5	42.8915	-4.40216	26.9357	0.486
6	45.2845	-4.86076	36.4782	0.5
7	41.052	-3.34635	26.9357	0.5
8	43.0763	-1.36372	26.0206	0.337
9	45.834	-5.97706	26.9357	0.445
10	41.1951	-5.39026	27.9588	0.398
11	43.3905	-3.75041	26.9357	0.5
12	46.1124	-5.75603	26.9357	0.375
13	41.2798	-5.39026	29.1186	0.448
14	42.0846	-5.34343	36.4782	0.399
15	43.1898	-4.13652	27.9588	0.518
16	41.8245	-5.75603	26.9357	0.444
17	42.3868	-2.79758	27.9588	0.395
18	45.4426	-3.34635	27.9588	0.446
19	51.3933	-5.62067	26.0206	0.428
20	49.9765	-5.48316	40	0.34
21	50.251	-8.23239	27.9588	0.333
22	48.877	-6.14992	27.9588	0.354
23	49.378	-7.23456	36.4782	0.578
24	49.8097	-5.62067	29.1186	0.58
25	48.5424	-5.75603	40	0.328
26	50.3505	-5.80069	30.4576	0.5
27	50.261	-7.04365	29.1186	0.382
28	48.4567	-6.9661	26.0206	0.64
29	47.8847	-6.1926	27.9588	0.564
30	50.937	-7.7478	36.4782	0.614
31	52.0683	-6.23508	40	0.625
32	50.8503	-9.36695	30.4576	0.625
33	51.1261	-7.30976	29.1186	0.63
34	50.1706	-5.57507	26.9357	0.53
35	50.9432	-5.20143	29.1186	0.624
36	48.7827	-7.23456	26.9357	0.596

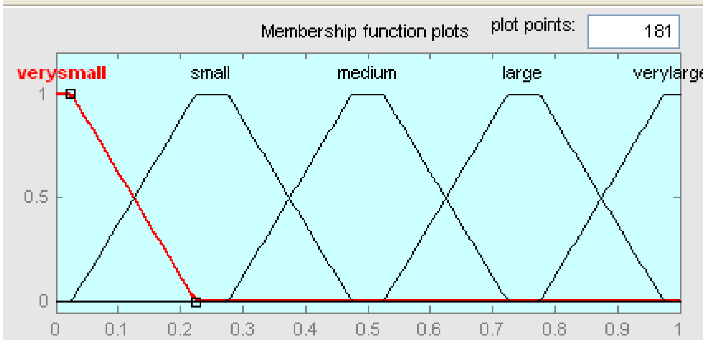

Fig 5 Membership function for MRPI

TABLE IV

S/N RATIOS AND MRPI

Parameter	Symbol	MRPI		
		Level-1	Level-2	Level-3
Pulse On Time	T ON(µs)	0.424389	0.515056	
Pulse Off Time	T OFF(µs)	0.45766	0.468667	0.482833
Corner servo	CS(volts)	0.49308	0.456583	0.459500
Flushing pressure Of Dielectric Fluid	WP(Kg/cm^2)	0.47592	0.469083	0.474833
Wire feed rate	WF(m/min)	0.45833	0.457833	0.481750
Wire tension N	WT(Kg-f)	0.48666	0.449417	0.464667
Spark gap voltage	SV(volts)	0.488417	0.449417	0.471333
Servo Feed	SF(mm/min)	0.48933	0.433917	0.485917
Mean Value of MRPI		0.46972		

IV. ANALYSIS AND DISCUSSION ON EXPERIMENTAL RESULTS USING MRPI AND ANOVA

The experimental scheme used in this work is based on Taguchi's orthogonal array, by which it is possible to separate the effect of each machining parameter on the MRPI at different levels. The mean MRPI at each level for the different machining parameters are presented in Table IV, which is referred to as a response table. In addition, the total mean of the MRPI was also calculated and is given in Table III.

The influence of each machining parameter can be more clearly presented by means of the MRPI response graph. The MRPI graph shows the change in the response when a given factor goes from level 1 to level 3. The response graph for the machining parameters of the wire edm machining process is presented in Fig. 6. Based on the response graph and response table, the optimal machining parameters for the Wire EDM machining process can be achieved. Basically, the larger the MRPI, the better the multiple performance characteristics. It was found from experimental results that the settings for experiment number 28 had the highest MRPI, as seen in Table III. Therefore, experiment 28 machining parameter settings are optimal for attaining multiple performances simultaneously among 36 experiments. However, the relative importance among the machining parameters for the multiple performance characteristics still needs to be analyzed so that the optimal combinations of the machining parameter levels can be

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Volume No.2, Issue No.6, pp : 600-606 1 June 2013

determined more clearly [9]. The relative importance among the factors can be analyzed through an analysis of variance (ANOVA). ANOVA is used to analyze which machining parameters significantly affect the performance characteristics. This is accomplished by separating the total variability of the MRPI, which is measured by the sum of the squared deviations from the total mean of the MRPI, into contributions by each machining parameter and the error.

Based on the results of analysis of variance (Table v), it was determined that pulse on time and servo feed were the most significant machining parameters affecting multiple performance characteristics. Referring to the average response table and average response graph, the variable settings for optimal machining parameters are the pulse on time at level2, pulse of time at level 3, corner servo voltage at level 1, flushing pressure at level1, wire feed at level3, wire tension at level1, spark gap voltage at level1 and servo feed at level 1.

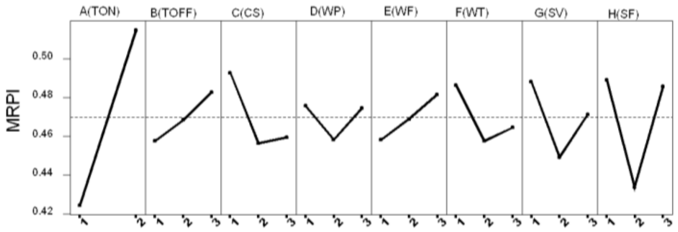

Fig 6: Response graph for MRPI

V. CONFIRMATION TEST

The final step of the optimization process was to predict and verify the improvement in the performance characteristic for machining of inconel 825 alloys by a wire electrical discharge machining process with respect to the chosen initial parameter setting. The estimated MRPI, using the optimal level of the machining parameters, can be calculated from following equation.

$$\hat{M} = M_m + \sum_{i=1}^{n} (M_o - M_m)$$

Where *Mm* is the total mean of the MRPI, *Mo* is the mean MRPI at optimal level, and *n* is the number of main design parameters that affect the multiple performance characteristics. Table VI shows the comparisons of predicted and actual machining performance for multiple performance characteristics using their optimal machining parameters. Based on the confirmation experiment results, the final optimal setting for parameters are pulse on time at level2, pulse of time at level 3, corner servo voltage at level 1, flushing pressure at level1, wire feed at level3, wire tension at level1, spark gap voltage at level1 and servo feed at level 1

TABLE V
RESULTS OF ANOVA

Parameter	Degree of Freedom	Sum of square	Mean sum of square	F-Value	% Contribution
Pulse On Time	1	0.07398	0.07398	7.95	18.95
Pulse Off Time	2	0.0038	0.0019	0.16	0.9736
Corner servo	2	0.0099	0.0049	0.43	0.655
Flushing pressure Of Dielectric Fluid	2	0.0023	0.0012	0.10	2.56
Wire feed rate	2	0.0033	0.0016	0.14	0.845
Wire tension N	2	0.0054	0.0027	0.23	1.38
Spark gap voltage	2	0.0092	0.0046	0.40	2.36
Servo Feed	2	0.0231	0.0116	1.04	5.91
Error	20	0.25932	0.012966		
Total	35	0.39029			

TABLE VI
RESULTS OF THE CONFIRMATION EXPERIMENT

	Initial machining parameters	Optimal machining parameters	
		Prediction	Experimental
Setting level	A1B2C2D2E2F2G2H2	A2B1C3D2E2F2G1H1	
Material removal rate	143.25		264.75
Surface roughness	1.86		2.23
Spark gap	0.0350		0.05
MRPI	0.26	0.46972	0.4727182
Improvement in MRPI		0.212	

VI. CONCLUSIONS

This paper has presented the use of fuzzy logics to the Taguchi method for the optimization of the wire-cut electrical discharge machining process on inconel 825 alloy with multiple performance characteristics. A fuzzy reasoning of the multiple performance characteristics has been performed by the fuzzy logic unit. As a result, the performance characteristics such as MRR, SR and SG can be improved through this approach. An experiment was conducted to confirm this approach. Based on the experimental results and confirmation test the conclusion can be drawn as follows.

- The experimental results for optimal settings showed that there was a considerable improvement in the performance characteristics viz., metal removal rate, surface roughness, and spark gap.
- The most important factors affecting the WEDM process robustness have been identified as pulse on time (T ON), and servo feed (SF).
- The following factor settings have been identified as to yield the best combination of process variables: A2B1C3D2E2F2G1H1
- This technique is more convenient and economical to predict the optimal machining parameters.
- The Taguchi method with fuzzy logic technique using MRPI converts the multiple performance characteristics into single performance characteristics and, therefore, simplifies the optimization procedure

- In the future, the methodology presented in this paper could be applied to different machining conditions such as different work material, electrode etc. so as to build an expert system of WEDM with the goal of automation.

References

i. P. J. Ross, *Taguchi techniques for quality engineering*, McGraw-Hill, New York (1996).

ii. G. Taguchi, *Introduction to quality engineering*, Asian productivity organization, Tokyo. (1990).

iii. J. L. Lin, K. S. Wang, B. H. Yan, and Y. S. Tarng, *J. Mater.Proc. Tech.* **102**, 48 (2000).

iv. E. A. Elsayed and A. Chen, *Int. Jl. Prod. Res.* **31**, 1117 (1993).

v. Y. S. Tarng and W. H. Yang, *Mater. Manuf. Process*. **13**,455 (1998).

vi. L. Zadeh and Fuzzy Sets, *Inform. and Control.* **8**, 338(1965).

vii. K. Raghukandan, K. Hokamoto, and P. Manikandan, *Met.Mater. -Int.* **10**, 193 (2004).

viii. T. J. Ross, *Fuzzy logic with Engineering Applications*, Mc-Graw Hill Int. Edn. (1992).

ix. Bagchi Tapan P. (1993), Taguchi methods explained, practical steps to robust design, Prentice Hall of India, India Private Limited, New Delhi.

x. Bhattacharya B, Manna A (1998), Taguchi Method based parametric study of CNC Wire-cut-EDM during machining of Al-SiC –MMC. Industrial Engineering Journal, **83,** 62-65.

xi. Klir G.J., B Yuan , Fuzzy sets and fuzzy logic, Prentice Hall of India, India Private Limited, New Delhi. (2002).

xii. Pandey P C , Shan H S , Modern Machining Processes, Tata McGraw-Hill publishing Company Limited, New Delhi, (1999).

xiii. Y. S. Tarng, S. C. Juang, and C. H. Chang, *J. Mater. Proc. Tech*. **128**, 1(2002).

xiv. E.B. Guitrau, Wire EDM--An Overview of Technology and Trends, SME Technical Paper, MR91-5191991.

xv. R.E. Williams, K.P. Rajurkar, Study of wire electrical discharge machining surface characteristics, J. Mater. Process.Technol. 127-138, 28 (1991)

xvi. T. Sone, K. Masui, Application of ion nitriding to wire-electrical-discharge-machined blanking dies, Mater. Sci. Eng. 486-493, A140(1991).

xvii. J.S. Soni, G. Chakraverti, Machining characteristics of titanium with rotary electro-discharge machining, Wear 171 51-58, (1994).

xviii. . Matsuo, E. Oshima, Investigation on the optimum carbide content and machining condition for Wire EDM of zirconia ceramics, Ann. CIRP 41 231-234, (1) (1992)

xix. K.P. Rajurkar, G.F. Royo, R.F. Effect of, Control and orbital motion on surface integrity of EDM components, J. Mech. Work. Technol. 20 341-352, (1989)

xx. K.P. Rajurkar, W.M. Wang, Thermal modeling and on-line monitoring of Wire-EDM, J. Mater. Process. Technol. 417-430. 38 (1993)

xxi. D. Scott, S. Boyina, K.P. Rajurkar, Analysis and optimizationof parameter combination in wire electrical discharge machining,Int. J. Prod. 2189-2207, Res. 29 (11) (1991)

xxii. G. Indurkhya, K.P. Rajurkar, Artificial neural network approach in modelling of EDM process, in: Proc. Artificial Neural Networks in Engineering (ANNIE' 92) Conf., St. Louis, Missouri, U.S.A., pp. 845-890, 15-18 November 1992

xxiii. J. L. Lin and Y. S. Tarng, Optimization of the multi-response process by the Taguchi method with grey relational analysis”, Journal of Grey System, 10(4), pp. 355–370,(1998).

xxiv. J. Deng, Introduction to grey system”, Journal of Grey System,1, pp. 1–24, (1989)

xxv. J. L. Lin, K. S. Wang, B. H. Yan and Y. STarng, Optimization of the electrical discharge machining process based on the Taguchi method with fuzzy logics, Journal of Materials Processing Technology,102, pp. 48–55,(2000).

xxvi. Feng, Chung ,Jeffrey, Kuo, and Su ,Te-I, Optimization of Multiple Quality Characteristics for Polyether Ether Ketone Injection Molding Process, Fibers and Polymers”, Vol.7, No.4, pp 404-413(2006)

xxvii. Tosun N, Determination of optimum parameters for multi performance characteristics in drilling by using grey relational analysis, Int J Adv Manuf Technol 28:450–455, 2006.