ISSN (Print) : 0974-6846
Indian Journal of Science and Technology, Vol 8(35), DOI: 10.17485/ijst/2015/v8i35/50946, December 2015 ISSN (Online) : 0974-5645

Application of Taguchi, Fuzzy-Grey Relational Analysis for Process Parameters Optimization of WEDM on Inconel-825

G. Rajyalakshmi[1]* and P. Venkata Ramaiah[2]

[1]School of Mechanical and Building Sciences, VIT University, Vellore - 632014, Tamil Nadu, India; rajyalakshmi@vit.ac.in
[2]Department of Mechanical Engineering, S. V. University, Tirupati - 517502, Andhra Pradesh, India

Abstract

Process parameters optimization of multiple response characteristics of WEDM on Inconel-825 super alloy using Fuzzy-Grey relational analysis is presented in this paper. Response characteristics such as MRR, surface finish and spark gap are optimized during wire EDM operation. Process parameters including pulse on time, pulse off time, corner servo voltage, flushing pressure, wire feed, wire tension, servo feed and spark gap voltage are investigated using Taguchi mixed L36 orthogonal array. These response characteristics are studied and examined using grey-fuzzy approach and optimal combination of influential input parameters are discovered. Based on the results of verification experiments it is concluded that Taguchi, Fuzzy-Grey Relational Analysis can efficaciously be used to find the optimal combination of influential input parameters of WEDM. Hence, this paper supports that the suggested approach can be a useful tool to ameliorate the performance of WEDM on Inconel-825.

Keywords: Fuzzy-Grey Relational Analysis, Inconel-825, Optimization, Taguchi Method, Wire EDM

1. Introduction

The WEDM machining plays a crucial role in fabricating sectors especially industries like aero region, ordinance, automobile and general engineering etc[1,2]. WEDM is one of the significant unconventional machining procedures, used for machining of a harder to machine materials. Figure 1 shows the schematic view of the WEDM process.

WEDM can also be used towards making of complex profiles used in prosthetics; biomedicine applications. WEDM involves alternate heating and cooling process. The spark plasma intensity level affects the crater size and this will be determined by discharge time, which in turn will determine the machining skilfulness and surface quality. With the introduction and increased use of newer and harder materials like titanium, hardened steel, high strength temperature resistant alloys, fibre-reinforced composites and ceramics in aerospace, nuclear, missile, turbine, automobile, tool and die out making industries, a different class of machining process has been emerged. Improved finishing, depressed tolerance, higher production rate, miniaturisation etc are also the present demands of the manufacturing industries.

Conventional machining is more efficient than unconventional machining like wire-cut EDM process but it is difficult to obtain intricate and complex shapes of the components[3] as it is required in the above-mentioned applications. Moreover, machine tool tables provided by the manufacturer often do not meet the requirements in machining a particular material[4]. So, to obtain various shapes of structural components the wire-cut EDM process is important in many cases, but it requires the improved machining efficiency. Hence, for improving the machining efficiency, it requires the models to predict optimum parametric combinations accurately. But wire cut EDM consists of a number of parameters, which makes it difficult to obtain optimal parametric combinations for

*Author for correspondence

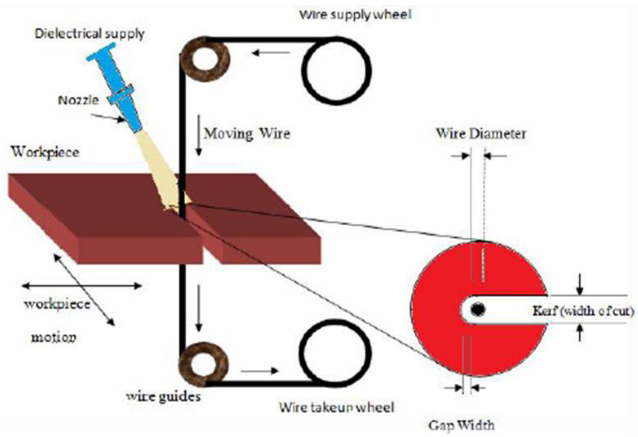

Figure 1. Schematic Diagram of WEDM Process.

machining different materials for various responses like surface roughness, material removal rate, kerf etc.

In many applications, Taguchi's robust design applied in order to obtain optimum parametric combinations[4] for selected response characteristics. In EDM, it is important to select optimal influential parameters for enhancing the machine performance[1]. Usually, the desired process parameters are determined based on experience or on handbook values. However, this does not ensure that the selected process parameters result in optimal or near optimal performance of that particular EDM machine and machining environment.

The method of optimization of WEDM operation parameters using Taguchi method was explained by S. S. Mahapatra et al[6]. It has been shown that the grey-based Taguchi method can optimize the multi-responses through the circumstances of the optimal process parameters[3]; but, in this paper, to calculate signal to noise ratios the grey relational analysis was not used. This is because grey relational analysis based on the grey system theory[4] is used for solving the complicated interrelationships among the multiple objectives. A grey relational grade is then obtained for determining the relational degree of the multiple parameters. The fuzzy-based Taguchi method can also be used for multi-objective optimization through the settings of optimal process parameters[5].

Chung-Feng et al.[7] analysed multi-response optimization of the injection molding for Polyether Ether Ketone (PEEK). This study looked into the dimensional accuracy and strength of screws produced by the injection molding. This study applied the Taguchi method to cut down on the number of experiments and combined grey relational analysis for determining the optimal process parameters with multiple responses. Tosun[8] used the grey relational analysis for the determination of optimal process parameters for drilling with the goal of achieving minimized surface roughness and burr height. Lin et al.[9] presented the grey relational analysis for optimization of the EDM parameters. Most of the applications of Taguchi method concentrate on the optimization of single response problems. The grey relational analysis based on grey system theory can be used for solving the complicated interrelationships among the multi-responses[9,10]. A gray relational grade is obtained to evaluate the multiple-responses. As a result, optimization of the multiple-responses can be converted into optimization of a single relational grade. In short, thither is a scope of applying the grey relational analysis with Taguchi method for multiple characteristics optimization.

GRA is a recommended method for optimizing the complicated inter-relationships among multiple response characteristics[11–14]. Moreover, Lin et al. showed grey relational analysis is more straightforward than the fuzzy-based Taguchi method for optimizing the EDM process for multi-objective optimization[14].

Caydas and Hascalik[15] used GRA for the optimization of laser cutting process of St-37 steel. Ko-Ta[16] employed fuzzy based grey relational analysis to find optimal process parameters of an injection-moulded thermoplastic part with a thin-shell feature.

The fuzzy logic is introduced by Zadeh, for dealing the problems with uncertain information[12]. Numerous numbers of researchers are succeeded by applying the fuzzy logic coupled with grey relational analysis is dealing the multiple response jobs with uncertain data[13-16].

This paper describes the analysis method and the experimental design and subsequently the optimization of WEDM process parameters based on the fuzzy-GRA analysis. Finally, it concludes the summary of this study.

2. Experimental Procedure

2.1 Work Material

Due to their high temperature mechanical strength and high corrosion resistance properties, super alloys are nowadays used in Marine, Space and other applications. Their ability to maintain their mechanical properties at high temperatures severely hinders the machinability of these alloys[17-18]. Its poor thermal diffusivity generates high temperature at the tool tip as well as high thermal gradients in the cutting tool, affecting the tool life adversely. Inconel-825 is very chemically responsive. Because of this propensity, during machining tool failures are observed. Owing to all these problems, it is very difficult to machine Inconel-825 by conventional machining processes and moreover, by conventionally used tool materials.

Of late, modern machining techniques such as Wire Electrical Discharge Machining (WEDM) are increasingly being used for machining such hard materials. Hence, this study focused on working of Inconel-825 using WEDM, in order to satisfy product and quality requirement.

The compositional range for Inconel-825 is provided in the Table 1 and typical properties are covered in Table2

2.2 Experimental Setup procedure

The present work was carried out on CNC WEDM machine of ULTRA CUT f2 model. In this machine, all the axes are servo controlled and can be programmed to follow a CNC codification which is fed by the control panel. All three axes have got an accuracy of 1μm. 0.25 mm diameter brass wire is utilized as wire electrode. A small gap of 0.025 mm to 0.05 mm is kept in between the wire and work-piece. The high energy density gnaws material from both the wire and work piece by local melting and vaporizing. The di-electric fluid (de-ionized water) is endlessly flashed through the gap along the wire, to the sparking area to remove the debris produced during the erosion. A collection tank is located at the bottom to collect the used wire erosions and then is discarded. The wires in one case used cannot be reused again, due to the fluctuation in dimensional accuracy. Through an NC code, machining can be programmed. WEDM of Inconel-825 alloy has been considered in the present set of research work.

Table 1. Chemical Composition of Inconel-825

Component	Content
Nickel	38–46%
Iron	22% min
Chromium Molybdenum Copper Titanium	19.5%–3.5% 2.5–3.5% 1.53% 0.6–1.2%

Table 2. Properties of Inconel-825

Property	Metric	Imperial
Density	8.14 gm/cm^3	0.294lb/in^3
Melting point	1400^{0}C	2550^{0}F
Coefficient of expansion Modulus of rigidity Modulus of elasticity	14.0 m/m.^{0}C 75.9N/mm^2 196 KN/mm^2	7.8×10^{-6}in/in.^{0}F 11009Ksi 28428ksi

The work piece is cut in to $10 \times 10 \times 15$ mm size piece during experimentation on the wire-cut EDM. According to the Taguchi method based on robust intention a L36 ($2^1 \times 3^7$) mixed orthogonal array is employed for the experimentation. Every experiment was repeated two times and mean of two readings is taken for analysis. Totally 72 work pieces are cut for this analysis.

When setting the machining parameters particularly in rough cutting operation, the object is threefold - increased MRR, lower SR and lower gap width. Generally, the machine tool builder provides machining parameter table to be utilized for determining machining parameter. This WEDM process trusts heavily on the experience of the operator. In practice, it is very unmanageable to utilize the optimal combination of parameters of a machine among many changeable machining parameters. With a view to relieve this difficulty, a simple but reliable method based on statistically designed experiments is proposed for investigating the effects of various influential parameters on MRR, SR and Gap width and determines optimal setting of input parameters. In the current research work, data have been collected from few experimental runs with randomly chosen factor combinations. A quadratic mathematical model has been suited for identification of the process to establish approximate interrelationship among various working parameters as well as quality characteristics. These mathematical models have been used to generate data based on Taguchi design. At last, Taguchi method is integrated with Fuzzy-grey relational analysis for process parameters optimization.

For experimentation eight parameters (two levels for one control factor (Pulse on time) and three levels for remaining seven control factors), are selected for optimisation analysis during WEDM machining of Inconel-825 alloy. The work piece after WED machining is shown in Figure 2.

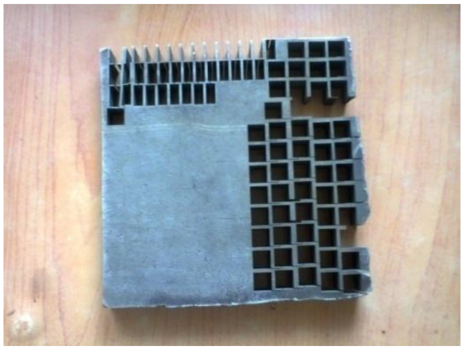

Figure 2. Machined work material after WEDM Machining.

2.3 Machining Parameter Selection and Performance Evaluation

The choice of optimum cutting parameters in WEDM is a crucial step. Improperly selected parameters may cause severe problems like short-circuiting of wire, wire breakage and damage of work surface, which is levying certain limits on the production agenda and also reducing productivity. As Material Removal Rate (MRR), Surface Roughness (Ra) and Spark gap (SG) are most important quality parameters in WEDM; several investigations have been carried out by various researchers for bettering the MRR, Surface Finish and kerf width[3-7]. However, the problem of selection of cutting conditions is not completely depending on machine controls rather material dependent. For experimental design, the selected machining parameters with different levels are presented in Table 3.

Experimental results are calculated based on the following equations and are presented in Table 4.

Material removal rate is calculated as

$$MRR = V_c^{*}\, b^{*}\, h \text{ mm}^3/\text{min}$$

Where: V= Cutting speed in mm/min

b = Width of cut in mm

h = Height of the work piece in mm

Surface roughness is measured with surfcorderSE3500 in µm.

Spark gap is measured with micrometer in mm.

Table 3. Machining parameters and their levels for WEDM process

S.No.	Factor	Parameter	Symbol	Level-1	Level-2	Level-3	Range of process parameters
1	A	Pulse On Time	T ON(µs)	105	115	-	105–115
2	B	Pulse Off Time	T OFF(µs)	50	55	60	50–60
3	C	Corner servo	CS(volts)	50	60	70	50–70
4	D	Flushing pressure Of Dielectric Fluid	WP(Kg/cm^2)	8	10	15	8–15
5	E	Wire feed rate	WF(m/min)	2	5	6	2–6
6	F	Wire tension N	WT(Kg-f)	9	10	11	9–11
7	G	Spark gap voltage	SV(volts)	20	25	30	20–30
8	H	Servo Feed	SF(mm/min)	1050	1100	1150	1050–1150

Table 4. Design of Experimentation with L36 orthogonal array and experimental results

Exp. No.	T ON	T OFF	CS	WP	WF	WT	SV	SF	MRR Mm^3/min	SR(µm)	SG(mm)
1	105	50	50	8	2	9	20	1050	120.3	1.54	0.02
2	105	55	60	10	5	10	25	1100	143.2	1.86	0.03
3	105	60	70	15	6	11	30	1150	182.2	1.41	0.03
4	105	50	50	8	2	10	25	1100	119.6	1.68	0.01
5	105	55	60	10	5	111	30	1150	139.5	1.66	0.04
6	105	60	70	15	6	9	20	1050	183.7	1.75	0.01
7	105	50	50	10	6	9	25	1150	112.8	1.47	0.04

(*Continued*)

8	105	55	60	15	2	10	30	1050	142.5	1.17	0.05
9	105	60	70	8	5	11	20	1100	195.7	1.99	0.04
10	105	50	50	15	5	9	30	1100	114.7	1.86	0.04
11	105	55	60	8	6	10	20	1150	147.7	1.54	0.04
12	105	60	70	10	2	11	25	1050	202.1	1.94	0.04
13	105	50	60	15	2	11	25	1050	115.8	1.86	0.03
14	105	55	70	8	5	9	30	1100	127.1	1.85	0.01
15	105	60	50	10	6	10	20	1150	144.3	1.61	0.04
16	105	50	60	15	5	9	20	1150	123.3	1.94	0.04
17	105	55	70	8	6	10	25	1050	131.6	1.38	0.04
18	105	60	50	10	2	11	30	1100	187.1	1.47	0.04
19	110	50	60	8	6	11	30	1050	371.2	1.91	0.05
20	110	55	70	10	2	9	20	1100	315.3	1.88	0.01
21	110	60	50	15	5	10	25	1150	325.5	2.58	0.04
22	110	50	60	10	6	11	20	1100	277.8	2.03	0.04
23	110	55	70	15	2	9	25	1150	294.3	2.30	0.01
24	110	60	50	8	5	10	30	1050	309.3	1.91	0.03
25	110	50	70	10	6	10	30	1150	267.3	1.94	0.01
26	110	55	50	15	5	11	20	1050	329.2	1.95	0.03
27	110	60	60	8	6	9	25	1100	325.8	2.25	0.03
28	110	50	70	10	5	10	20	1050	264.7	2.23	0.05
29	110	55	50	15	6	11	25	1100	247.8	2.04	0.04
30	110	60	60	8	2	9	30	1150	352.2	2.44	0.01
31	110	50	70	15	6	10	30	1100	401.2	2.05	0.01
32	110	55	50	8	2	11	20	1150	348.7	2.94	0.03
33	110	60	60	10	5	9	25	1050	360.0	2.32	0.03
34	110	50	70	8	5	11	25	1150	322.5	1.90	0.04
35	110	55	50	10	6	9	30	1050	352.5	1.82	0.03
36	110	60	60	15	2	10	20	1100	274.8	2.30	0.04

3. Identification of Optimal Parameters for WEDM on Inconel-825

Taguchi, Fuzzy-GRA is used for identifying the optimal parameter combination of wire EDM on Inconel-825.

3.1 Step 1: Calculation of S/N Ratios

For design of experiments, Taguchi method is one of the uncomplicated and effective methods[19]. Based on Taguchi technique, signal-to-noise (S/N) ratio is employed to represent a response parameters and the biggest value of S/N ratio is required. There are three types of S/N ratio—the smaller the better, the bigger the better and the nominal the better.

The material removal rate is a higher-the-better performance characteristic, since the maximization of the quality characteristic of interest is sought and can be expressed as

$$\text{S/N Ratio} = -\log_{10}\left(1/n\right)\sum_{i=1}^{n}\frac{1}{y_{ij}^{2}} \qquad (1)$$

Where

n = number of replicas and
yij = observed reaction value

Where i = 1, 2... .... n; j = 1, 2 ... k.

The surface roughness and gap width are the smaller-the-better performance characteristic and the loss function for the same can be expressed as

$$\text{S/N Ratio } = -\log_{10}\left(1/n\right)\sum_{i=1}^{n} y_{ij}^{2} \qquad (2)$$

Table 5. The Signal to Noise ratio values for the experimental results

Experiment Number	S/N Ratio MRR	S/N Ratio Surface Roughness	S/N Ratio Spark Gap
1.	41.6107	−3.75041	32.0412
2.	43.1219	−5.39026	29.1186
3.	45.2134	−2.98438	28.5194
4.	41.5564	−4.50619	36.4782
5.	42.8915	−4.40216	26.9357
6.	45.2845	−4.86076	36.4782
7.	41.052	−3.34635	26.9357
8.	43.0763	−1.36372	26.0206
9.	45.834	−5.97706	26.9357
10.	41.1951	−5.39026	27.9588
11.	43.3905	−3.75041	26.9357
12.	46.1124	−5.75603	26.9357
13.	41.2798	−5.39026	29.1186
14.	42.0846	−5.34343	36.4782
15.	43.1898	−4.13652	27.9588
16.	41.8245	−5.75603	26.9357
17.	42.3868	−2.79758	27.9588
18.	45.4426	−3.34635	27.9588
19.	51.3933	−5.62067	26.0206
20.	49.9765	−5.48316	40
21.	50.251	−8.23239	27.9588
22.	48.877	−6.14992	27.9588
23.	49.378	−7.23456	36.4782
24.	49.8097	−5.62067	29.1186
25.	48.5424	−5.75603	40
26.	50.3505	−5.80069	30.4576
27.	50.261	−7.04365	29.1186
28.	48.4567	−6.9661	26.0206
29.	47.8847	−6.1926	27.9588
30.	50.937	−7.7478	36.4782
31.	52.0683	−6.23508	40
32.	50.8503	−9.36695	30.4576
33.	51.1261	−7.30976	29.1186
34.	50.1706	−5.57507	26.9357
35.	50.9432	−5.20143	29.1186
36.	48.7827	−7.23456	26.9357

(*Continued*)

S/N ratios for the corresponding responses are calculated and presented in Table 5.

3.2 Step 2: Normalization of S/N Ratios

The beginning step in the GRA is normalization of the S/N ratio, which is performed to prepare raw data for the analysis where the original sequence is transferred to a comparable sequence. Linear normalization is usually demanded since the range and unit in one data sequence may differ from the others. A linear normalization of the S/N ratio in the range between zero and unity is also called as the grey relational generation.

3.2.1 Data Pre-Processing

Data Pre-Processing is normally required, since the range and unit in one data sequence may differ from others. It is also necessary when the sequence scatter range is too large, or when the directions of the target in the sequences are different. The formulae are

Larger the better value

$$Z_{ij} = \frac{y_{ij} - \min(y_{ij}, i = 1,\ 2, \ldots \text{n})}{\max(y_{ij},\ i = 1, 2, \ldots n) - \min(y_{ij}, i = 1, 2, \ldots n)} \qquad (3)$$

Smaller the better value

$$Z_{ij} = \frac{\max(y_{ij}, i = 1, 2, \ldots \text{n}) - \text{y}_{\text{ij}}}{\max(y_{ij},\ i = 1, 2, \ldots n) - \min(y_{ij}, i = 1, 2, \ldots n)} \qquad (4)$$

Where y_{ij} is the i^{th} performance characteristic in the j^{th} experiment. max y_{ij} and min y_{ij} are the maximum and minimum values of i^{th} performance characteristic for alternate j, respectively.

The normalized S/N ratios are presented in Table 6.

Table 6. Normalized S/N ratio values for the experimental results

Experiment Number	MRR	Surface Roughness	Spark Gap
1.	0.0507	0.2982	0.5693
2.	0.1878	0.5031	0.7783
3.	0.3777	0.2025	0.8212
4.	0.0457	0.39265	0.2519
5.	0.1669	0.3796	0.9345
6.	0.3842	0.4369	0.2519
7.	0	0.2477	0.9345
8.	0.1837	0	1
9.	0.434	0.5764	0.9345
10.	0.0129	0.5031	0.86135
11.	0.2122	0.2982	0.9345
12.	0.4593	0.5488	0.9345
13.	0.0206	0.5031	0.7783
14.	0.0937	0.4972	0.2519
15.	0.194	0.3464	0.86135
16.	0.0701	0.0685	0.9345
17.	0.1212	0.1791	0.86135
18.	0.3985	0.2477	0.86135
19.	0.9387	0.5319	1
20.	0.8101	0.5147	0
21.	0.9258	0.8582	0.86135
22.	0.7103	0.5986	0.86135
23.	0.7557	0.7335	0.2519
24.	0.7949	0.5319	0.7783
25.	0.6799	0.5488	0
26.	0.844	0.5543	0.6826
27.	0.8359	0.7097	0.7783
28.	0.6721	0.7	1
29.	0.6202	0.6033	0.86155
30.	0.897	0.7976	0.2519
31.	1	0.6086	0
32.	0.8894	1	0.6826
33.	0.9144	0.7429	0.7783
34.	0.8277	0.5262	0.9345
35.	0.8978	0.4795	0.7783
36.	0.7017	0.7335	0.9345

3.3 Step 3: Determination of Grey Relational Coefficient (GRC)

GRC for all the sequences expresses the relationship between the ideal (best) and actual normalized S/N ratio. If the two sequences agree at all points, then their grey relational coefficient is 1. $\gamma(x_0(k), x_i(k))$ Can be expressed by equation (5).

$$\gamma(x_0(k), x_i(k)) = \frac{\Delta\min + \xi\Delta\max}{\Delta_{0i}(k) + \xi\Delta\max} \tag{5}$$

Where, Δ min is the smallest value of $\Delta 0_i(k) = \min_i \min_k \left|x_0^*(k) - x_i^*(k)\right|$ and Δ max is the largest value of $\Delta 0_i(k) = \max_i \max_k \left|x_0^*(k) - x_i^*(k)\right|$, $x_0^*(k)$ is the ideal normalized S/N ratio, $x_i^*(k)$ is the normalized comparability sequence, and ζ is the distinguishing coefficient. The value of ζ can be adjusted with the systematic actual need and defined in the range between 0 and 1, $\zeta \in [0, 1]$. It will be 0.5 generally[15]. The GRC for all response parameters are presented in Table 7.

Table 7. Grey relational coefficients

Experiment Number	GRC Material Removal Rate	GRC Surface Roughness	GRC Spark gap
1.	0.9079	0.6264	0.4675
2.	0.7269	0.4984	0.3911
3.	0.5696	0.71174	0.3784
4.	0.9162	0.562	0.6649
5.	0.7497	0.5684	0.3485
6.	0.5654	0.5336	0.6649
7.	1	0.6686	0.3485
8.	0.7313	1	0.3333
9.	0.5353	0.46449	0.3485
10.	0.9748	0.4985	0.3672
11.	0.7019	0.6264	0.3485
12.	0.5212	0.4767	0.3485
13.	0.9604	0.4984	0.3911
14.	0.8421	0.5014	0.6649
15.	0.7169	0.5906	0.3672
16.	0.877	0.8795	0.3485
17.	0.8049	0.7362	0.3672
18.	0.5564	0.6686	0.3672

(Continued)

19.	0.3475	0.4845	0.3333
20.	0.3816	0.4927	1
21.	0.3506	0.3681	0.3672
22.	0.4131	0.4553	0.3672
23.	0.39818	0.4053	0.6649
24.	0.3861	0.4845	0.3911
25.	0.4237	0.4767	1
26.	0.3726	0.4742	0.4299
27.	0.3742	0.4133	0.3911
28.	0.42658	0.4166	0.3333
29.	0.4463	0.4531	0.3672
30.	0.3529	0.3853	0.6649
31.	0.3333	0.451	1
32.	0.3598	0.3333	0.42279
33.	0.3535	0.4622	0.3911
34.	0.3765	0.4872	0.3485
35.	0.3527	0.5104	0.3911
36.	0.416	0.4053	0.3485

3.4 Step 4: Determination of Fuzzy-Grey Relational Grade

A fuzzy logic unit constitutes a fuzzifier, membership functions, a fuzzy rule base, an inference engine and a defuzzifier. In the fuzzy logic analytic thinking, first, the fuzzifier uses membership functions to fuzzify the grey relational coefficient. Next, the inference engine performs a fuzzy reasoning on fuzzy rules to generate a fuzzy value. at last, the defuzzifier converts the fuzzy value into a Grey-Fuzzy grade. The structure built for this study is a three input- one-output fuzzy logic unit as shown in Figure 3.

The function of the fuzzifier is to change outside crisp sets of input data into proper linguistic fuzzy sets of information. The input variables of the fuzzy logic system in this study are the grey relational coefficients for MRR, SR, SG. They are changed into linguistic fuzzy subsets using membership functions of a triangle form, as shown in Figure 4, and are uniformly assigned into three fuzzy subsets-small (S), medium (M), and large (L) grade. The fuzzy rule base consists of a group of if-then control rules

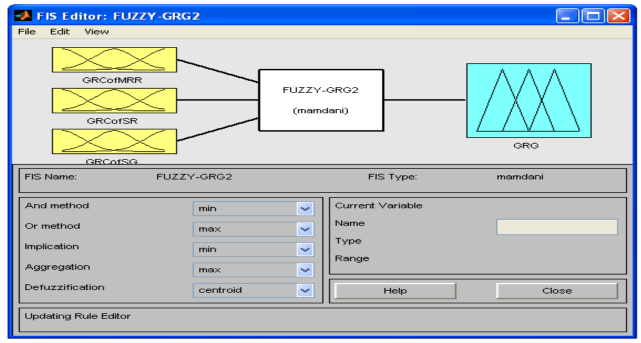

Figure 3. Input-output fuzzy logic unit

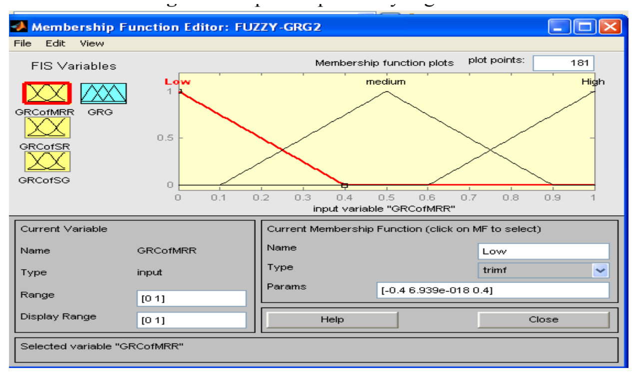

Figure 4. Membership Function for Input variables.

to express the inference relationship between input and output. A typical linguistic fuzzy rule called Mamdani is described as

Rule 1: if x1 is A1, x2 is B1, x3 is C1 and x4 is D1
then y is E1 else,

Rule 2: if x1 is A2, x2 is B2, x3 is C2 and x4 is D2
then y is E2 else,

Rule n: if x1 is An, x2 is Bn, x3 is Cn and x4 is Dn
then y is En else.

The output variable is the Grey-Fuzzy grade y_o, and also converted into linguistic fuzzy subsets using membership functions of a triangle form, as shown in Figure 5. Unlike the input variables, the output variable is assigned into relatively nine subsets i.e., very very low (VVL), very low (VL), small (S) medium low (ML), medium (M), medium high (MH) high (H), very high (VH), very very high (VVH) grade. Then, considering the conformity of three performance characteristics for input variables, fuzzy rules are defined. The fuzzy inference engine is the kernel of a fuzzy system. It can clear a problem by simulating the thinking and decision pattern of human being using approximate or fuzzy reasoning. In this paper, the

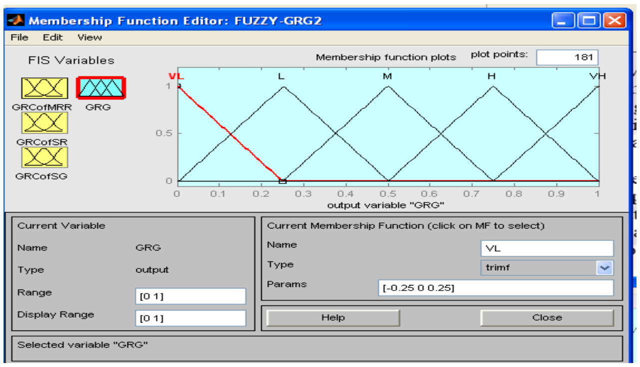

Figure 5. Membership Function for Grey-Fuzzy Grade.

max-min compositional operation of Mamdani is followed to perform calculation of fuzzy reasoning. Suppose that x1, x2, and x3 are the input variables of the fuzzy logic system, the membership function of the output of fuzzy reasoning can be expressed as

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

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 Fuzzy Grey Relational Grade. Invariably, a larger Fuzzy grey relational grade is opted, which gives a improved performance characteristic.

Table 8 shows the results of fuzzy-grey relational grade for different experiments.

4. Analysis and Discussion on Experimental Results using Fuzzy-GRG and ANOVA

The experimental strategy applied in this work is based on Taguchi, fuzzy grey relational analysis, by which it is possible to distinguish the effect of each machining parameter on the Fuzzy-GRG at different levels. The mean Fuzzy-GRG at each level for the different machining parameters is presented in Table 9, which is referred to as a response table. The influence of each machining parameter can be more clearly presented by means of the Fuzzy-GRG response graph. The Fuzzy-GRG 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

Table 8. Fuzzy-Grey Relational Grade

Experiment Number	Fuzzy-GRG	Rank
1.	0.73	4
2.	0.596	9
3.	0.5	15
4.	0.723	5
5.	0.568	10
6.	0.447	32
7.	**0.756**	**1**
8.	0.625	7
9.	0.454	28
10.	0.75	2
11.	0.535	13
12.	0.4542	27
13.	0.7148	3
14.	0.627	6
15.	0.561	12
16.	0.5625	11
17.	0.611	8
18.	0.51	14
19.	0.458	26
20.	0.32	35
21.	0.496	16
22.	0.463	24
23.	0.452	29
24.	0.494	18
25.	0.253	36
26.	0.487	21
27.	0.491	19
28.	0.441	33
29.	0.467	23
30.	0.486	22
31.	0.382	34
32.	0.461	25
33.	0.489	20
34.	0.448	31
35.	0.495	17
36.	0.449	30

Table 9. Response Table for Fuzzy-GRG

Parameter	Level-1	Level-2	Level-3
T ON	**0.595806**	0.446222	--------
T OFF	**0.556775**	0.520333	0.485933
CS	**0.577500**	0.536442	0.449100
WP	**0.543167**	0.492183	0.527692
WF	0.514833	**0.534375**	0.513833
WT	**0.550458**	0.513833	0.498750
SV	0.492542	0.558167	0.512333
SF	0.53716	0.519333	0.506542

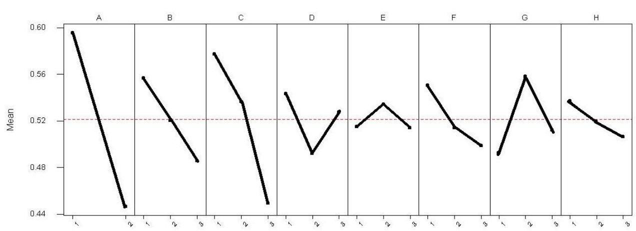

Figure 6. Response graph for Fuzzy-GRG.

on the response graph and response table, the optimal machining parameters for the Wire EDM machining process can be achieved. Basically, the larger the Fuzzy-GRG, the better the multiple performance characteristic. It was found from experimental results that the settings for experiment number 7 had the highest Fuzzy-GRG, as seen in Table 8. Therefore, experiment 7 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 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 Fuzzy-GRG, which is measured by the sum of the squared deviations from the total mean of the Fuzzy-GRG, into contributions by each machining parameter and the error.

Based on the ANOVA (Table 10.), it was found that, pulse on time and corner servo voltage were the most significant machining parameters impressing multiple performance characteristics. Referring to the average response table and average response graph, the variable settings for optimal machining parameters are the pulse

Table 10. ANOVA for Fuzzy-GRG

Parameter	Degree of Freedom	Sum of square	Mean sum of square	F-Value	% Contribution
Pulse On Time	1	0.20138	0.20138	26.51	43.81
Pulse Off Time	2	0.0301	0.0151	1.16	6.54
Corner servo	2	0.1032	0.0516	4.78	22.45
Flushing pressure Of Dielectric Fluid	2	0.0164	0.0082	0.61	3.56
Wire feed rate	2	0.0032	0.0016	0.12	0.696
Wire tension N	2	0.0170	0.0085	0.63	3.698
Spark gap voltage	2	0.0272	0.0136	1.04	5.91
Servo Feed	2	0.0057	0.0028	0.21	1.24
Error	20	0.05543	0.00277		
Total	35	0.45961			

on time at level 1, pulse of time at level 1, corner servo voltage at level 1, flushing pressure at level 1, wire feed at level 2, wire tension at level 1, spark gap voltage at level 2 and servo feed at level 1.

5. Confirmation Test

The last step of the optimization process was to forecast 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 Fuzzy-GRG, 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 Fuzzy-GRG, *Mo* is the mean Fuzzy-GRG at optimal level, and *n* is the number of main design parameters that influence the multiple responses. Table 11 shows the comparisons of predicted and actual machining performance for multiple performance characteristics using their optimal machining

Table 11. Results of Confirmation Experiment

	Initial machining parameters	Optimal machining parameters	
		Prediction	Experimental
Setting level	A1B1C1D2E3F1G2H3	A1B1C1D1E2F1G2H1	
Material removal rate	112.875	114.750	120.35
Surface roughness	1.47	1.42	1.381
Spark gap	0.0450	0.042	0.0414

parameters. Based on the confirmation experiment results, the final optimal setting for parameters are pulse on time at level 1, pulse of time at level 1, corner servo voltage at level 1, flushing pressure at level 1, wire feed at level 2, wire tension at level 1, spark gap voltage at level 2 and servo feed at level .

6. Conclusions

This paper has presented the use of Taguchi, fuzzy-Grey relational analysis for the optimization of the wire-cut electrical discharge machining process on an 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 corner servo voltage (CS).
- The following factor settings have been identified as to yield the best combination of process variables: A1B1C1D1E2F1G2H1.
- This technique is more convenient and economical to predict the optimal machining parameters.
- The Taguchi method with fuzzy logic technique using Fuzzy-GRG 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.

7. Acknowledgements

The Authors are thankful to VIT management for carrying out this work with the support of DST.

8. References

1. Sanchez A, et al. On the influence of cutting speed limitation on the accuracy of wire-EDM corner-cutting. J Mater Process Technol. 2007; 182:574–9.
2. Ramakrishnan R, Karunamoorthy L. Multi-response optimization of wire EDM operations uses robust design of experiments. 2006; 29:105–12.
3. Choi KK, Nam WJ, Lee YS. Effects of heat treatment on the surface of a die steel STD 11 machined by WEDM. J Mater Process Technol. 2008; 201:580–4.
4. Manna A, Bhattacharya B. Taghuchi and guass elimination method: a dual response approach for parametric optimization of CNC wire cut EDM. Int J Adv Manuf Technol. 2006; 28:67–75.
5. Lee HT, Yur JP. Characteristic analysis on EDMed surfaces using Taguchi method approach. Materials and Manufacturing Processes. 2000; 15(6)781–806.
6. Mahapatra SS, Patnaik A. Optimization of Wire Electrical Discharge Machining (WEDM) process parameters using Taguchi method. Int J Adv Manuf Technol. 2007; 34:911–25.
7. Kuo CFJ, Su TL. Optimization of multiple quality characteristics for polyether ether ketone injection molding process, fibers and polymers. 2006; 74:404–413.
8. Tosun N. Determination of optimum parameters for multi performance characteristics in drilling by using grey relational analysis. Int J Adv Manuf Technol. 2006; 28:450–5.
9. Lin CL, Lin JL, Ko TC. Optimization of the EDM Process based on the orthogonal array with fuzzy logic and Grey relational analysis method. Int J Adv Manuf Technol. 2002; 19:271–7.
10. Deng J. Introduction to grey system. Grey Syst. 1989; 1:1–24.
11. Kung LM, Yu SW. Prediction of index futures returns and the analysis of financial spillovers – A comparison between GARCH and the grey theorem. Eur J Oper Res. 2008; 186(3):1184–200.

12. Ng David KW. Grey system and grey relational model. ACM SIGICE Bulletin. 1994; 20(2):1–9.
13. Chang SH, Hwang JR, Doong JL. Optimization of the injection molding process of short glass fiber reinforced polycarbonate composites using grey relational analysis. J Mater Process Technol. 2000; 97:186–93.
14. Lin JL, Lin CL. The use of the orthogonal array with grey relational analysis to optimize the electrical discharge machining process with multiple performance characteristics. Inter J Mach Tools Manuf. 2002; 42(2):237–44.
15. Caydas U, Hascalik A. Use of the grey relational analysis to determine optimum laser parameters with multiperformance characteristics. Opt Laser Technol. 2008; 40(7):987–94.
16. Ko-Ta C. The optimal process conditions of an injection molded thermoplastic part with a thin shell feature using greyfuzzy logic: A case study on machining the PC/ABS cell phone shell. Mater Des. 2007; 28(6):1851–60.
17. Ezugwu EO. Key improvements in the machining of difficult-to-cut aerospace superalloys. Int J Mach Tool Manu. 2005; 45:1353–67.
18. Choudhury IA, El-Baradie MA. Machinability of nickel-base super alloys: A general review. Journal of Materials Processing Tech. 1998; 77:278–84, ISSN: 0975-54621546.
19. Lin CL. Use of the Taguchi method and grey relational analysis to optimize turning operations with multiple performance characteristics. Mater Manuf Process. 2004; 19:209–20.