Experimental Investigation and Optimization of Response Variables in WEDM of Inconel – 718

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Abstract. Effective utilisation of Wire Electrical Discharge Machining (WEDM) technology is challenge for modern manufacturing industries. Day by day new materials with high strengths and capabilities are being developed to fulfil the customers need. Inconel – 718 is similar kind of material which is extensively used in aerospace applications, such as gas turbine, rocket motors, and spacecraft as well as in nuclear reactors and pumps etc. This paper deals with the experimental investigation of optimal machining parameters in WEDM for Surface Roughness, Kerf Width and Dimensional Deviation using DoE such as Taguchi methodology, L_9 orthogonal array. By keeping peak current constant at 70 A, the effect of other process parameters on above response variables were analysed. Obtained experimental results were statistically analysed using Minitab-16 software. Analysis of Variance (ANOVA) shows pulse on time as the most influential parameter followed by wire tension whereas spark gap set voltage is observed to be non-influencing parameter. Multi-objective optimization technique, Grey Relational Analysis (GRA), shows optimal machining parameters such as pulse on time 108 Machine unit, spark gap set voltage 50 V and wire tension 12 gm for optimal response variables considered for the experimental analysis.

Keywords: WEDM, Inconel – 718, Taguchi Method, Grey Relational Analysis, Kerf Width.

1.Introduction

Wire Electrical Discharge Machining (WEDM) is one of the most important non-conventional machining process used widely in aerospace, nuclear, automotive and medical industries [1]. Selection of the optimal machining parameter combination is a challenging task in WEDM operation due to presence of large number of process variables and complicated stochastic process mechanism. The selection of appropriate machining conditions for WEDM process is based on the analysis of effect of various process parameters on performance measures. But from last many years, this was carried out by relying heavily on the operator's experience or conservative technological data provided by the WEDM equipment manufacturers, which produced inconsistent machining performance. Levy and

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Maggi [2] reported that the parameter settings given by the manufacturers are only applicable for the common steel grades. The settings for machining new materials such as alloys, advanced ceramics and MMCs have to be further optimised experimentally. Selection of machining parameters are to be carried out carefully for economical machining operation because WEDM is expensive than the conventional machining process. This paper deals with the experimental investigation of optimal machining parameters in WEDM for multi-response optimisation using Grey Relational Analysis (GRA) and DoE such as Taguchi methodology, L_9 orthogonal array.

2. Literature review

Most of the researchers have applied GRA for optimization of process parameters in various machining problems. Dabade [3] performed multi-objective process optimization using GRA to improve surface integrity on turned surface of Al/SiCp MMCs and observed surface roughness as more sensitive to a change in size than a change in volume fraction of reinforcement and depth of altered material zone (AMZ) changes with a change in size of abrasive reinforcement in MMCs. Finally author reported optimized process parameters that enhance the surface integrity on Al/SiCp composite within the scope of the experiments performed. Lin and Lin [4] carried out EDM analysis using orthogonal array with GRA for multi-objective process optimization and observed workpiece polarity as the most significant parameter affecting the response variables whereas Lin et al. [5] used Fuzzy logic and GRA to optimise EDM based on orthogonal array and observed grey relational analysis as more straightforward than the fuzzy-based Taguchi method for multi-objective process optimization.

Porwal et al. [6] developed an integrated model (ANN-GRA-PCA) of single hidden layer BPNN for prediction and GRA coupled with PCA hybrid optimization strategy with multiple performance measures of hole sinking electrical discharge micromachining (HS-EDMM) of Ti-6Al-4V and reported optimal combination as 140 V gap voltage and 100 nF capacitance within their scope of experiment. Mishra and Yadava [7] used GRA coupled with PCA for laser beam percussion drilling process utilizing the data predicted by ANN model and reported combination of optimal process variables which produces a hole with good integral quality, i.e., a reduction of hole taper by 32.1%, increase of MRR by 28.9% and reduction of extent of HAZ by 4.5%.

Gopalsamy et al. [8] optimised end milling process parameters using GRA for machinability study of hardened steel and reported that the width of cut and depth of cut as the most significant parameters in the case of rough machining and for finish machining, the cutting speed as the most significant parameter corresponding to the quality characteristics of tool life, tool wear and surface finish. The causes of tool wear were reported as chipping and adhesion.

The other applications of GRA to different machining processes include, determining tool condition in turning [9], chemical mechanical polishing [10], performance evaluation of diamond and carbide tools in dry turning [11], and optimization of drilling parameters to minimize surface roughness and burr height [12].

In this paper, parametric optimisation of WEDM on Inconel-718 with zinc coated brass wire of diameter 250 μm has been discussed. Most of the previous researchers observed current as one of the most important parameter in WEDM. Hence to analyse the effect of other process parameters on different response variables, current is kept constant at 70 A in this study. As Inconel-718 is a High Strength Temperature Resistant (HSTR) material which is extensively used in aerospace applications, such as gas turbine, rocket motors, and spacecraft as well as in nuclear reactors, pumps and tooling etc. Therefore its multi-response optimisation is essential.

3. Grey Relational Analysis (GRA)

In this paper, analysis of pulse-on time, spark gap set voltage and wire tension is performed using Taguchi L_9 orthogonal array integrated with grey relational theory. The process parameters are optimised for WEDM with respect to surface roughness, kerf width and dimensional deviation and the influencing parameters are noticed.

In GRA, the first step is data pre-processing. This avoids the problem of different scales, units and targets. The "Appendix-A" shows a worked example. Following steps were used to perform GRA:

- Experimental data are normalised in the range between zero and one.
- Grey Relational Coefficient (GRC) is calculated from the normalised experimental data to express the relationship between the ideal (best) and the actual experimental data.
- Grey Relational Grade (GRG) is then computed by averaging the weighted GRCs corresponding to each response characteristic.
- Experimental data of the multi-response characteristics is evaluated by using this GRG.
- The optimum level of the process parameters is the level with the highest GRG.

Under optimum parameters, GRG is predicted and verified by conducting experiment using the optimal parametric combination for the improvement of quality characteristics.

The performance measure with lower-the better characteristic (i.e. surface roughness, kerf width and dimensional deviation) are pre-processed as follows:

$$x_i^* (k) = \frac{\max x_i^{(o)} (k) - x_i^{(o)} (k)}{\max x_i^{(o)} (k) - \min x_i^{(o)} (k)} \tag{1}$$

where k=1 to n, i=1 to 9, n is the performance characteristic, i is the trial number, $x_i^* (k)$ is the value after grey relational generation, $\min x_i^{(o)} (k)$ is the smallest value of $x_i^{(o)}$and $\max x_i^{(o)} (k)$ is the largest value of $x_i^{(o)}$. The experimental and normalised results for different performance measures are tabulated. The higher preprocessed value shows better performance and best preprocessed result should be equal to one. The deviation sequence $\Delta 0_i$ (k) is the absolute difference between the reference sequence $x_0^*(k)$ and the comparability sequence $x_i{}^*(k)$after normalization. It is determined using Eq. 2 as:

$$\Delta 0_i (k) = |x_0^*(k) - x_i{}^*(k)| \tag{2}$$

The GRC [ξi(k)] can be calculated as follows:

$$\xi i(k) = \frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta 0_i (k) + \zeta \Delta_{\max}} \tag{3}$$

where, Δmin is the smallest value of $\Delta 0_i$ (k) = $\min_i \min_k |x_0^*(k) - x_i{}^*(k)|$ and Δmax is the largest value of $\Delta 0_i$ (k) = $\max_i \max_k |x_0^*(k) - x_i{}^*(k)|$, $x_0^*(k)$ 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; here it is considered as 0.5. After calculating GRCs, the GRG is obtained as:

$$\gamma i = \frac{1}{m} \sum_{i=1}^{m} \gamma(x_0(k), x_i(k)) \tag{4}$$

where, γi is the GRG and m is the number of performance characteristics. The GRCs and corresponding GRG for each experiment are calculated. The higher value of GRG is near to the product quality for optimum process parameters. After evaluating the optimal parameter settings, the next step is to predict and verify the improvement of quality characteristics using the optimal parametric combination. The estimated GRG by using the optimal level of the machining parameters can be calculated as

$$\hat{\gamma} = \gamma_m + \sum_{i=1}^{p} (\gamma^- - \gamma_m) \tag{5}$$

where, γ_m is the total mean GRG, γ^- is the mean GRG at the optimal level, and p is the number of the main design parameters that affect the quality characteristics. The predicted or estimated GRG (optimal) is equal to the mean GRG plus the summation of the difference between the overall mean GRG and the mean GRG for each of the factors at optimal level.

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4. Experimental Procedure and Response Variables Evaluation

In the present study, the experiments were carried out on a wire-cut EDM machine (ELEKTRA SPRINTCUT) of Electronica Machine Tools Ltd. using Inconel 718 as a work piece material with dimensions as 120 x 110 x 12.9 mm. The material compositions are shown in Table 1.

Table 1. Work piece material composition.

Element	Ni + Co	Cr	Fe	Nb + Ta	Mo	Ti	Al
Content (%)	50-55	17-21	Bal	4.75-5.5	2.8-3.3	0.65-1.15	0.2-0.8

Zinc coated brass wire of 0.25 mm diameter is used as a tool electrode with deionized water as a dielectric. The different process parameters with their levels are shown in Table 2 whereas Figure.1 shows the details of experimental setup.

Table 2. Process parameters and their levels.

Parameter	**Level**		
	I	**II**	**III**
Pulse on time, T_{ON} (Machine Unit/MU)	108	116	124
Spark gap set voltage, SV (V)	20	50	80
Wire tension, WT (gm)	4	8	12

4.1 Response Variables Evaluation

In this study, Mitutoyo surftest is used to measure the average arithmetic surface roughness (Ra) with a cut-off length of 0.8 mm. The surface roughness was measured at five different locations and the average is reported for analysis purpose. The kerf width was measured using measurement facility available on OmniTech Micro Vickers Hardness Tester. It was measured at five different points and average is reported (ref. figure.2). Dimensional deviation is calculated by using equation (6),

$$\text{Dimensional deviation } = [\frac{(\text{Observed Value} - \text{Actual Value})}{\text{Actual Value}}] * 100 \tag{6}$$

5. Results and discussion

In this work, nine experiments based on Taguchi (L_9) DoE were conducted and results were recorded for surface roughness, kerf width and dimensional deviation. For all these performance measures lower value provides better quality. Thus, the data sequences of these performance measures have "smaller-the-better" characteristics. GRA is an effective method for such analysis. It provides an efficient solution to the uncertainty in multi-input and discrete data problems to optimise the multi-response processes through the setting of process parameters. The data pre-processing is the first step in this method where data normalisation and deviation sequence for each performance measures were calculated using equation (1) and (2).

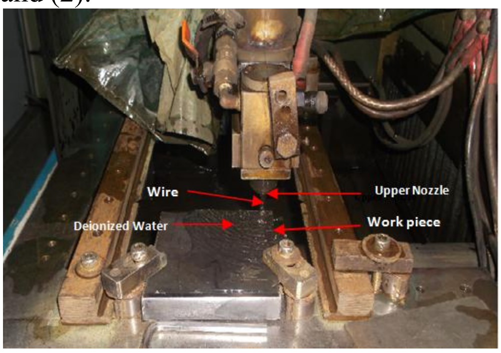

Figure 1. Experimental setup

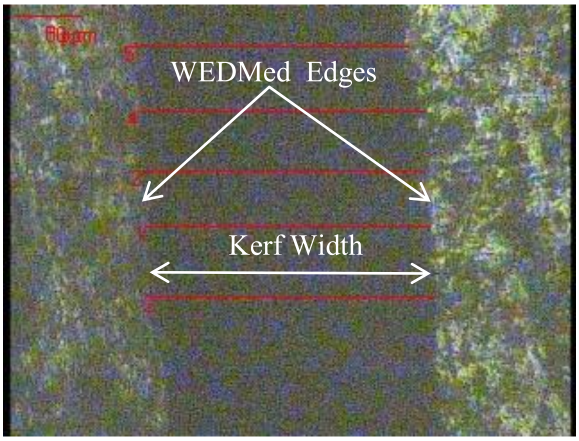

Figure 2. Kerf Width measurement

Next, the GRC was calculated from the normalised experimental data to express the relationship between the ideal (best) and the actual experimental data. Then, GRG was computed by averaging the GRCs corresponding to each performance measures. The overall evaluation of the multiple performance measures is based on the GRG. The optimum level of the process parameters is exactly the level corresponding to the highest GRG. From Table 3, it is observed that the experiment no.3 has the highest GRG. The performance measures in this experiment are surface roughness (1.207 µm), kerf width (254.086 µm) and dimensional deviation (0 %). It is close to the best machining parameters. The optimum process parameters and their effects on selected output parameters can be found out. For Pulse on time (T_{ON}), the mean of GRG at all the levels can be calculated by averaging the GRGs of the experiments (1–3), (4-6) and (7-9) respectively. Similarly, the mean of GRGs of other machining parameters, i.e. SV and WT at different levels were calculated in the same manner.

Table 3. Grey relational coefficient and corresponding grey relational grades with their ranks.

Exp. No.	Grey relational coefficient			GRG	RANK
	Surface Roughness	Kerf Width	Dimensional Deviation		
1	0.6482	0.5967	0.6024	0.6158	5
2	1.0000	1.0000	0.6012	0.8671	2
3	**0.8729**	**0.9783**	**1.0000**	**0.9504**	**1**
4	0.4240	0.6596	1.0000	0.6946	4
5	0.7453	0.5478	1.0000	0.7644	3
6	0.7655	0.3333	0.3333	0.4774	9
7	0.3333	0.4428	1.0000	0.5920	6
8	0.6543	0.4663	0.3333	0.4846	8
9	0.6697	0.5529	0.4292	0.5506	7

The mean of GRGs of all parameters at different levels and the difference between the maximum and minimum value of the GRG of the machining parameters are shown in Table 4. The maximum and minimum value of the GRG shows the importance of individual parameter in WEDM. The importance of each parameter is in the order of pulse on time (T_{ON}), wire tension (WT) and spark gap set voltage (SV). It is observed from Table 4 that the highest GRG of each parameter shows the optimal level of parameters. The optimised parameters are noticed as pulse on time $(T_{ON})_1$, Spark gap set voltage $(SV)_2$ and Wire Tension $(WT)_3$. The higher value of GRG is near to the product quality. The corresponding values for optimised parameters are T_{ON} 108 MU, SV 50 V and WT 12 gm.

Table 4. Significance of machining parameters.

Parameter	Average GRG by process parameters level			Machining Parameters Significance
	I	II	III	Max-Min
Pulse on time (MU)	**0.8111***	0.6454	0.5424	0.2687
Spark gap set voltage (SV)	0.6341	**0.7054***	0.6595	0.0459
Wire tension (gm)	0.5259	0.7041	**0.7689***	0.2430
All cell mean = 0.6663				***Optimised level of parameters**

5.1 Analysis of Variance for GRG

ANOVA is used to apply a statistical method in order to identify the effect of individual factors. It gives the impact of each process parameter on each performance measure very clearly. The effect of individual parameters on the entire process cannot be judged by Taguchi method while the percentage contribution of individual parameters can be well determined using ANOVA. Minitab 16 software is used to investigate the effect of process parameters on GRG. Results obtained from ANOVA for GRG (ref. table 5) and Main effect plot for SN ratio of GRG (ref. figure 3) indicates that the process parameters, pulse on time (T_{ON}) is the most significant parameter followed by wire tension (WT). Spark gap set voltage (SV) is found to be non-significant parameter.

Figure 3 shows that as pulse on time increases, grey relational grade decreases because discharge will last a longer time, which leads to a higher discharge energy. This affects surface roughness by increase in diameter and depth of the discharging craters which is in agreement with the findings of Han et al. [13] and Sharma et al. [14]. As pulse on time increases, kerf width increases as recorded by Shah et al. [15] and Lin et al. [16], also dimensional deviation increases in similar with Mathew et al. [17]. Thus all the three response variables result into lower value of grey relational coefficient which causes lower grey relational grade. But as wire tension increases, vibrational amplitude reduces and surface quality improves which is in agreement with the findings of Rao et al. [18]. Reduced vibrations also result into minimum kerf as observed by Dongre et al. [19] and minimised dimensional deviation as reported by Yang et al. [20]. Thus all the three response variables result into improved grey relational coefficient which causes higher grey relational grade. The order of importance obtained by ANOVA result for GRG are in the same order of importance of the WEDM parameters as, pulse on time (TON), wire tension (WT) and spark gap set voltage (SV). The Main effect plot for SN ratio of GRG (ref. figure 3) also shows similar optimum parameter settings, i.e. pulse on time 108 MU, spark gap set voltage 50 V and wire tension 12 gm. In summary, the results obtained from ANOVA are closely matching with the results of GRA.

Table 5. ANOVA results for GRG.

Source	DF	F	P
T_{ON}	2	12.91	0.072
SV	2	0.92	0.522
WT	2	11.12	0.083
Error	2		
Total	8		
S = 0.065348 R-Sq = 96.15% R-Sq(adj) = 84.58%			

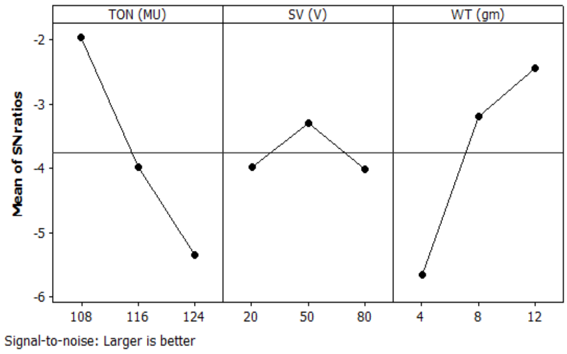

Figure 3. Effect plot for SN Ratio of GRG

5.2 Validation Experiments

The validation of optimal level of process parameters was estimated by using GRG. The estimated GRG is calculated by using equation (5). In final experiment for the validation, the improvement in machining performance with optimal process parameters is confirmed by increment in GRG. This is shown in Table 6. Optimised machining parameters shows improved surface roughness and kerf width whereas no change in dimensional deviation is observed.

Table 6. Improvements in grey relational grade with optimised machining parameters.

Setting level	Initial data	Optimal machining parameters	
		Prediction	Experimental
	$A_1B_3C_3$	$A_1B_2C_3$	$A_1B_2C_3$
Surface Roughness (μm Ra)	1.207		1.196
Kerf Width (μm)	254.086		253.043
Dimensional Deviation (%)	0		0
Grey relational grade	0.9504	0.9527	0.9557
Improvement in grey relational grade = 0.56%			

6. Conclusion

GRA is an effective and efficient method for multi response optimisation. The process parameters for WEDM of Inconel 718 are optimised with L_9 orthogonal array and GRA by keeping peak current constant at 70 A. The results were compared with ANOVA. It was found that the pulse on time is the most influencing parameter followed by wire tension whereas spark gap set voltage is observed to be non-influencing parameter. The optimal response measures were obtained as 1.1964 μm surface roughness, 253.043 μm kerf width and 0% dimensional deviation with optimal machining parameters such as pulse on time 108 Machine unit, spark gap set voltage 50 V and wire tension 12 gm.

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References

1. Guitrau E B 1997 *The EDM Handbook* (Cincinnati) Hanser Gardner Publications
2. Levy G N and Maggi F 1990 *Ann. CIRP* **39** **(1)** pp 183–85
3. Dabade U A 2013 *Procedia CIRP* **7** pp 299–304
4. Lin J L and Lin C L 2002 *Intl J Machine Tools and Manuf* **42** pp 237-44
5. Lin C L, Lin J L and Ko T C 2002 *Int J Adv Manuf Technol* **19** pp 271-77

6. Porwal R K, Yadav V and Ramkumar J 2014 *J Mech Sci and Tech* **28 (2)** pp 653-61
7. Mishra S and Yadava V 2013 *Optics and Lasers in Engg* **51** pp 681–95
8. Gopalsamy B M, Mondal B and Ghosh S 2009 *Int J Adv Manuf Technol* **45** pp 1068–86
9. Lo S P 2002 *Int J Adv Manuf Technol* **19** pp 564-72
10. Lin Z C and Ho C Y 2003 *Int J Adv Manuf Technol* **21** pp 10-14
11. Arumugam P U, Malshe A P and Batzer S A 2006 *Surface and Coatings Tech* **200** pp 3399-3403
12. Tosun N 2006 *Int J Adv Manuf Technol* **28** pp 450-55
13. Han F, Jun J and Dingwen Y 2007 *Int J Adv Manuf Technol* **34** pp 538–46
14. Sharma N, Khanna R and Gupta R 2013 *Procedia Engineering* **64** pp 710–19
15. Shah A, Nadeem A, M Rakwal D and Bamberg E 2011 *J of Mat Engg and Perfor* **20 (1)** pp 71–76
16. Lin C T, Chung I F and Huang S Y 2001 *Fuzzy Sets Syst*.**122 (3)** pp 499–511
17. Mathew B, Benkim and J Babu 2014 *Procedia Materials Science* **5** pp 1613–22
18. Rao P S, Koona R and Beela S 2014 *Procedia Materials Science*, **5** pp 2197–2206
19. Dongre G, Zaware S, Dabade U A and Joshi S S 2015 *Mat Sci in Semicondu Proc* **39** pp 793–806
20. Yang R T Chorng J T Yung K Y and Ming H H 2012 *Int J Adv Manuf Technol* **60** pp 135–47

Appendix-A

Numerical example: For Experiment No. 1

T_{ON} (MU)	SV (V)	WT (g)	SR (μm Ra)	KW (μm)	DD (%)	Normalisation (SR)	Deviation Seq= 1-Norm (SR)	GRC (SR)	GRG
108	20	4	1.513	375.766	0.249	0.7287	0.2713	0.6482	0.6158

Step 1. The normalisation value for SR (Eq. 1) ((2.6382-1.513)/ (2.6382-1.0946)) =0.7287

Step 2. The Deviation Sequence for SR (Eq.2) (1-0.7287) =0.2713

Step 3. The Grey Relational Coefficient for SR (Eq. 3) ((0+0.5*1)/ (0. 2713+0.5*1)) = 0.6482

Step 4. The Grey Relational Grade (GRG) (Eq. 5) ((0.6482+0.5967+0.6024)/3)= 0.6158