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Enhancing the Tool Die Steel Profile Cutting Performance in WEDM Process

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Abstract*: This work elaborates the experimental work on Material Removal Rate (MRR) and Surface Roughness (SR) output conditions of Wire-Electrical Discharge Machining (WEDM) and finding the optimal input conditions through Taguchi method coupled with Grey relational analysis for lower SR and higher MRR during profile cutting of high strength D3 tool steel, which is the need of the hour in industries. The machining factors considered for investigation which influences MRR and SR were: cutting speed, pulse on-time and off-time, input current, wire tension and feed and servo feed and voltage. A L_{18} orthogonal array was considered for mixed-level experimental design through Taguchi's approach and for multi-criteria optimization Grey Relational Analysis was applied. Outcome shows that SR increases with the increase of pulse on-time and decreases with increase in pulse off-time and MRR increases as the pulse on-time increases due to longer spark duration. Both SR and MRR are well within the control limits and servo voltage is the most influential parameter contributing by 48.48%, followed by wire feed rate, input current and servo feed rate with an R^2 value of 95.85%, identified through Analysis of Variance (ANOVA). With obtained optimum conditions, a validation experiment was conducted to authenticate the results, which indicates a worthy agreement with predicted output characteristics.

***Keywords* : D3 tool steel, Material Removal Rate, Taguchi's Methodology, Grey Relational Analysis.**

I. INTRODUCTION

Nontraditional machining process changed the current trend of manufacturing industries. For achieving better production rate with accuracy, conventional machining processes are replaced by nontraditional machining processes [1]. WEDM process is basically a Thermo-Electrical process which falls under the category of unconventional machining process, practiced extensively in industries to machine high hardness materials for complex geometry in electrically conductive materials [2]. In WEDM, high power spark is developed in between workpiece and wire electrode, due to which the temperature increases to about 10000°C melting away the workpiece and removed by suitable flushing arrangement [3]. WEDM process uses a moving thin wire electrode that is made up of thin wires of brass, copper or tungsten having a diameter around 0.05-0.30 mm that are capable of attaining very lesser corner radius [4]. Brass wire is used generally but it was found that the productivity and other characterization are not up to the mark. Zinc coated wires, diffused coated wires and molybdenum wire materials technologically upgraded wire materials and shows better cutting performances than plain brass wire, but are costlier than the brass wires [5]. The wire electrode is contiounsly delivered from supply spool that is clamped on to a table through wire tension rollers, as in Fig. 1. A constant gap of 0.025 mm to 0.05 mm must be maintained between workpiece and wire electrode, where no mechanical stresses are involved [6]. The dielectric fluid used in this work, is De-ionized water. A separate collection tank is used to gather the used old wire at the machine bottom and then the wire is discarded as waste. The used wire electrodes can't be reused for another machining, since it produces variation in accuracy of dimensions [7]. The dielectric fluid is uninterruptedly flushed over the gap produced by the wire electrode, towards the spark developing area to flush away the by-products that are formed during the process of erosion [8].

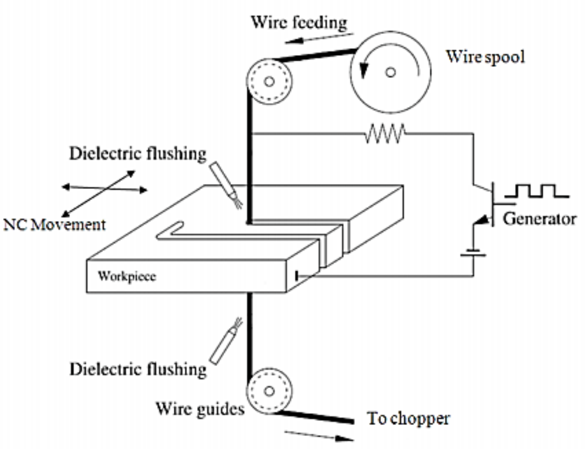

Fig. 1.WEDM process [9]

Lodhi and Agarwal [10] made an attempt to determine the optimal machining parameters for SR considering on L_9 Taguchi design for changing pulse-on-time, current, wire feed and pulse-off-time, and found that the peak current was most significant among the factors over SR. Chaubey et al. [11] performed experimental studies for optimizing WEDM parameters viz., peak current, wire feed and tension and pulse-on-time in maximizing material removal and minimizing SR using plain brass wire using Taguchi's method. Observation shows that, SR and MRR rises with higher value of current and pulse-on-time but reduces with rise in wire feed and tension.

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Priyadarshini et al. [12] studied the behaviour of P20 tool steel for MRR and kerf width in WEDM and found that, rise in current and pulse on-time increases the rate of material removal, but tends to decrease with upsurge of voltage and pulse off-time due to the change in density and spark intensity.

Shivade and Shinde [9] studied the WEDM behaviour of D3 tool steel and investigated the effect of wire speed, current and pulse on-time and off-time over machining time, dimensional accuracy, MRR and gap current using GRA. ANOVA identifies that, current is the significant parameters affecting all the responses. Abbasi et al. [13] developed a mathematical model during machining HSLA steel of 38 HRC in WEDM process considering voltage, current, pulse on-time and wire speed and found that, the effect of pulse on-time is greater for SR trailed by wire speed, power and pulse. Manjaiah et al. [14] examined the WEDM characteristics of tool steel D2 using OA design and identified that, servo voltage and pulse on-time are the utmost important parameter that affects SR and MRR through utility approach and found that, machined surface hardness value is greater than the unmachined surface because of frequent quenching effect and the surface containing different oxides due to the formation of recast layer.

In this work, profile cutting of high strength D3 tool steel was performed with plain brass as wire electrode material, considering machining factors viz., cutting speed, input current, wire tension and feed with different pulse on-time and off-time and servo voltage and feed [15]. From the performed literature, it was identified that, less limited research works were present by selecting these parameters for studying WEDM process with plain brass wire and hence the experimental investigation was planned accordingly for achieving geometrical accuracy in profile cutting. Experimental investigation was scheduled as per $L_{18}(2^1,3^7)$ orthogonal array based on Taguchi's DoE and MRR was calculated for each trial and SR was measured from each workpiece. GRA was used to simultaneously optimize the MRR (maximization) and SR (minimization) [16] and ANOVA was applied for identifying the most influential factors considered in this study.

II. MATERIALS & METHODOLOGY

A. AISI D3 Tool Steel

The workpiece material used in this study is a high chromium, high carbon D3 steel, a tool grade steel which is oil hardened and is characterized by an extremely high hardness and contains higher amount of chromium rich carbides in their microstructure. This D3 steel shows exceptional steadiness in heat treatment with the holding size of specimen similar to that of air hardening. The elemental composition of D3 steel is provided in Table I. A plain brass wire that is available commercially having a 0.25 mm diameter is chosen as material for wire electrode. A plate of 50 mm ×50 mm size and thickness 15mm of D3 Steel was used for the experimental study in this work.

Table- I: D3 steel composition

Element	C	Si	Mn	P	S	Cr	Fe
%	2.4	0.608	0.601	0.0303	0.0322	11.96	Reminder

B. Taguchi's Design of Experiments

The procedure of describing and examining all conceivable circumstances in an experimentation that involves many factors is called as Design of Experiments (DoE) [17], [18]. Taguchi thought that the ideal procedure to enhance the product quality was to build the quality into the product itself [19]. To achieve this, Taguchi designed experimental trial using specially constructed arrays called as Orthogonal Arrays (OA) [20], [21]. By using these designs in tables, DoE was made consistent and easier. Taguchi developed special OAs for his experimentation based on Latin squares which combines the inputs in a specific manner, for number of experimental states [22], [23]. Augmenting the product design implies that identification of right combination of factors or creating the appropriate modifications to the machine itself so that paramount outcomes are achieved. An OA based designed experiment may lead to a decrease in variation due to the proper controllable parameters.

In order to analyze the machinability behavior of D3 steel, a multi-level L_{18} OA was considered for performing experiments for varying combinations of factors using Minitab-18 software for one parameter varied through 2 levels and seven parameters varied through 3 levels. OA from Taguchi's design for different mixtures of input conditions is given in Table II.

C. Grey Relational Approach

Grey Relational Analysis (GRA) is adopted for identifying the best combination of input factors for obtaining better output variables [24], [25]. GRA is largely used for judging or to evaluate the dependent variable performance that has a little amount of information, but in grey analysis, the data must be initially pre-processed for conversion into some sort of indices that can quantify the data through normalizing the raw data for further analysis [26]-[28]. Pre-processing the experimental data is the procedure that converts the original values to a decimal value that lies in between 1 to 0 for assessment. If the estimated sequence of data is in "Higher-the-better" sequence, then the original data must be normalized as,

$$x_i^*(k) = \frac{x_i^0(k) - \min x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \quad (1)$$

where $x^o_i(k)$ is raw data, $x^*_i(k)$ the normalized data, max $x^o_i(k)$ is the maximum value of raw data $x^o_i(k)$, and min $x^o_i(k)$ imply the lowest value of $x^o_i(k)$. For condition of "Smaller-the-better", the raw data is normalized to a value between 1 and 0 as,

$$x_i^*(k) = \frac{\max x_i^0(k) - x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{2}$$

Subsequent to pre-processing of raw data, calculation of grey relational coefficient should be done, which determines the association between actual and ideal normalized values [29]. Therefore, grey relational coefficient is determined as,

$$\zeta_i(k) = \frac{\Delta_{\min} + \zeta.\Delta_{\max}}{\Delta_{0i}(k) + \zeta.\Delta_{\max}} \tag{3}$$

where $\Delta^o{}_i$ (k) is the deviance from the reference value of 1, given as,

$$\Delta_{0i}(k) = \left\| x_0^*(k) - x_i^*(k) \right\| \tag{4}$$

$$\Delta_{\max} = \max_{\forall j \varepsilon i} \max_{\forall k} \left\| x_0^*(k) - x_j^*(k) \right\|,$$
$$\Delta_{\min} = \min_{\forall j \varepsilon i} \min_{\forall k} \left\| x_0^*(k) - x_j^*(k) \right\| \tag{5}$$

ζ is identification coefficient which is normally [0, 1]. ζ = 0.5 [30]. After finding grey relational coefficient, its average is taken for determining grey relational grade, which can be calculated from,

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} {}_i\zeta_i(k) \tag{6}$$

D.Experimental Setup

Experimental trials were performed in an CNC Electronica ELCUT WEDM machine based on L_{18} OA mixtures and each trial were repeated thrice for obtaining reliable outputs.

Fig. 2.WEDM machine used for experimentation

After machining the workpiece, SR was measured on the cut surfaces, that were obtained through Kosaka Laboratory made Surfcorder SE1200; having vertical range of measuring 520 µm, horizontal range of 25 mm, 0.008 µm resolution, 0.8mm cut-off value with Gaussian filter. MRR was calculated through the weight loss method considering the machining time. Fig. 2 presents the experimental setup of the Wirecut EDM machine along with the workpiece and wire. The formulae used to calculate MRR is:

$$MRR = \frac{\text{Weight before machining - Weight after machining}}{\text{Machining time} \times \text{Density}} \; (mm^3/\min) \tag{7}$$

Table- II: Taguchi L_{18} OA

Trial No	Cutting Speed (%)	Pulse ON-Time (µsec)	Pulse OFF-Time (µsec)	Input Current (Amp)	Wire Feed (mm/min)	Wire Tension (gm)	Servo Volt (Voltage)	Servo Feed rate (mm/min)
1	70	126	48	190	3	7	10	2060
2	70	126	51	210	4	9	15	2080
3	70	126	54	230	5	11	20	2100
4	70	127	48	190	4	9	20	2100
5	70	127	51	210	5	11	10	2060
6	70	127	54	230	3	7	15	2080
7	70	128	48	210	3	11	15	2100
8	70	128	51	230	4	7	20	2060
9	70	128	54	190	5	9	10	2080
10	75	126	48	230	5	9	15	2060
11	75	126	51	190	3	11	20	2080
12	75	126	54	210	4	7	10	2100
13	75	127	48	210	5	7	20	2080
14	75	127	51	230	3	9	10	2100
15	75	127	54	190	4	11	15	2060
16	75	128	48	230	4	11	10	2080
17	75	128	51	190	5	7	15	2100
18	75	128	54	210	3	9	20	2060

III. RESULTS AND DISCUSSIONS

As per designed experiments, experimental trials were performed and for each experiment SR and MRR were determined, which are recorded as in Table III. Impact of input factors on SR and MRR shows that, higher SR was observed with higher values of pulse on-time but gets lowered with higher pulse off-time. With low pulse off-time decreases, increased spark discharges between the wire electrode and workpiece increases producing rough surface. When the current density was changed from 190A to 230A, SR values were higher due to higher energy discharge for each spark, making uneven rough surfaces [31].

But with eventual increase in current lowers the SR, i.e., when the supplied current exceeds a threshold value, widening of average discharge gap occurs which results in good surface. The influence of wire tension and feed rate were less significant towards the SR values [32]. When input current was varied from 10A to 20A, SR gets reduced, proving that higher current produces lower SR values. The rate of material removal upsurges with higher pulse on-time [33]. For MRR, the most significant parameter is pulse on-time [34]. In the process of WEDM, high temperature was produced due to the spark produces between the electrode and workpiece surface, discharging higher energy level, which effects melting of workpiece at selected areas causing vaporization. Longer duration of spark was due to the higher pulse on-time, which means higher energy reaches the surface per spark, melting more metal. With increase in input current the average discharge gap widens which results in reduced MRR. The influence of wire tension and feed rate on MRR are least significant. It is obvious that MRR was minimum at lower values of pulse on-time and maximum at lower values of pulse off-time.

Table- III: Output response and Normalizing procedure of GRG

Trial No	Output Responses		Normalizing Sequence	
	Material Removal Rate (mm^3/min)	*Surface Roughness (microns)*	*Material Removal Rate*	*Surface Roughness*
1	10.190	3.553	0.318	0.000
2	9.974	2.663	0.289	0.732
3	10.597	2.655	0.373	0.738
4	12.550	2.769	0.638	0.645
5	8.381	3.170	0.073	0.315
6	10.524	3.089	0.363	0.382
7	9.429	3.079	0.215	0.390
8	12.364	2.337	0.613	1.000
9	9.143	3.045	0.176	0.418
10	15.221	3.158	1.000	0.325
11	11.325	2.869	0.472	0.563
12	9.558	3.074	0.232	0.394
13	11.688	2.779	0.521	0.637
14	9.619	3.120	0.241	0.356
15	7.844	2.638	0.000	0.752
16	11.844	3.493	0.542	0.049
17	9.091	2.734	0.169	0.674
18	10.560	2.607	0.368	0.778

$\bar{X}$ chart is the customary chart for data with variables, which benefits in identifying whether a process is steady and are foreseeable, which shows how the mean or average changes over time [35]. This chart is further used for assessing the process stability and process control statistically [36]. $\bar{X}$ chart for MRR is shown in Fig. 3, where the lower control limit (LCL) is 3.93 mm^3/min and upper control limit (UCL) is 17.17 mm^3/min. All the data points for 18 experimental trial is within the lower and upper control limits, proving the stability of the experiments. Similarly, for SR the $\bar{X}$ chart as given in Fig. 4 has an LCL of 1.931 microns and UCL of 3.939 microns and all the data points obtained from experiments lies in between the LCL and UCL.

Optimization is a procedure for determining better results from the resources available before us, which can be a single or multiple objective that is purely based on the output response selection. Bearing in mind all responses at a period leads to multi-criteria optimization. GRA was used for optimization and for further analysis of data [37], [38]. Normally, low values of SR and high values of MRR are the desired target values [39]. Hence, for data normalizing, lower-the-better condition for SR and higher-the-better condition for MRR was considered. The distinguish coefficient ξ value was substituted as 0.5 in the equation of grey relation coefficient as in Equ. (3). For further evaluation, the grey relational grade determined from the grey relational coefficient is considered. Table III shows the first step in GRA calculation, where normalizing sequence is generated followed by deviation sequence and grey relational coefficient as in Table IV. By taking the average values of grey relational coefficient values corresponding to each input parameter level, grey relation grades (GRG) are obtained [40]. It was noticeably perceived from Table IV that, the combination of input factors pertaining to the experimental trial 8 has the largest value of GRG of 0.782, identified by giving ranking.

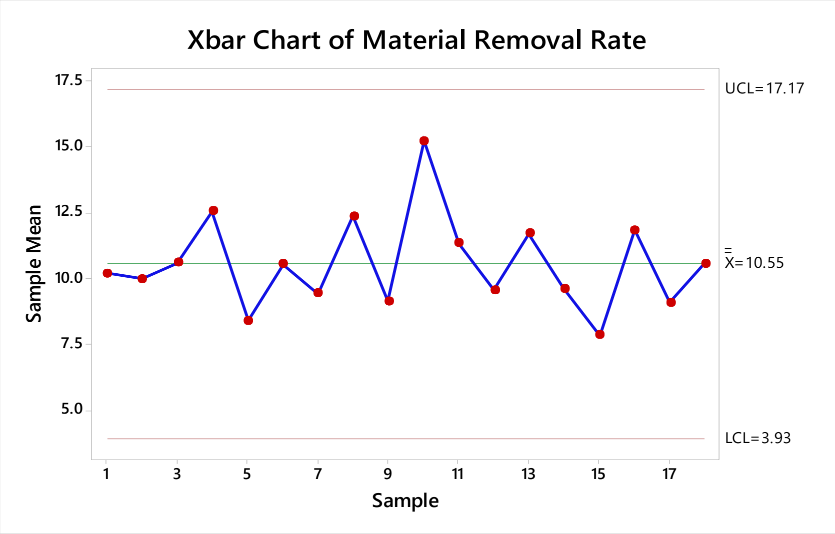

Fig. 3. $\overline{X}$ chart for Material Removal Rate

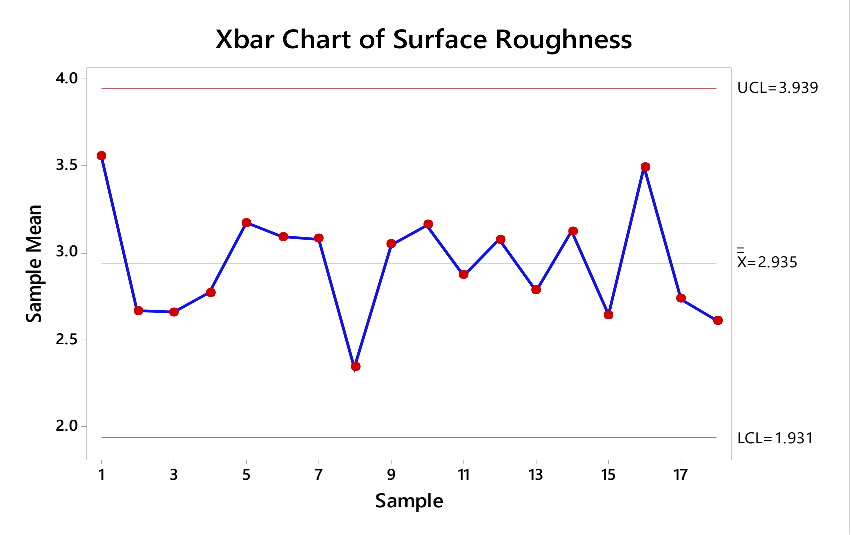

Fig. 4. $\overline{X}$ chart for Surface roughness

Table- IV: Grey relational coefficient and grade in GRA

Trial No	Deviation Sequence		Grey Relational Coefficient		Grey Relational Grade
	Material Removal Rate	*Surface Roughness*	*Material Removal Rate*	*Surface Roughness*	
1	0.682	1.000	0.423	0.333	0.378
2	0.711	0.268	0.413	0.651	0.532
3	0.627	0.262	0.444	0.657	0.550
4	0.362	0.355	0.580	0.585	0.582
5	0.927	0.685	0.350	0.422	0.386
6	0.637	0.618	0.440	0.447	0.443
7	0.785	0.610	0.389	0.450	0.420
8	0.387	0.000	0.564	1.000	0.782
9	0.824	0.582	0.378	0.462	0.420
10	0.000	0.675	1.000	0.425	0.713
11	0.528	0.438	0.486	0.533	0.510
12	0.768	0.606	0.394	0.452	0.423
13	0.479	0.363	0.511	0.579	0.545
14	0.759	0.644	0.397	0.437	0.417
15	1.000	0.248	0.333	0.669	0.501
16	0.458	0.951	0.522	0.345	0.433
17	0.831	0.326	0.376	0.605	0.490
18	0.632	0.222	0.442	0.692	0.567

The plot of half normal probability is a graphical representation used to compare two distributions of probability by plotting values of individual against the other. Points on the plot correspond to ordered absolute values of model diagnostic (i.e. standardized residuals) plotted against theoretical order statistics from a half-normal distribution. In half probability plot, the effects of absolute values were plotted, the negative or positive effects were provided in detail by means of color coding. The half probability plot for GRG is shown in Fig. 5, where all the input parameters were placed adjacent to the straight line fit.

The normal probability plot specifies whether a normal distribution is followed by the residuals, following a straight line, definite patterns such as S-shaped curve, indicates the need for data transformation for superior analysis. The normal probability plot of GRG in Fig. 6 shows the residuals fitting in a straight line with normal distribution. Predicted vs. actual response value plot identifies a data value or group of data, that cannot be predicted easily by the developed model. It is observed that, all the points were scattered on either side of 45° line, intimating that it is easily possible for prediction.

The average value of each parameter level was considered for the purpose of plotting the main effects plot of GRG as presented in Fig. 7. Optimum conditions were evolved from this through a choice of the values of selected levels that has higher grey grade. The optimal values of input factors that were determined from the main effects plot is cutting speed of 75%, pulse ON-time of 128 µsec, pulse OFF-time of 51µsec, input current of 230A, wire feed rate of 4 mm/min, wire tension of 9 gm, servo voltage of 20V and servo feed of 2060 mm/min. Influences of independent factors can be identified with the curve having higher steepness which shows the significant of that factor. If the significance is more, the slope will be higher.

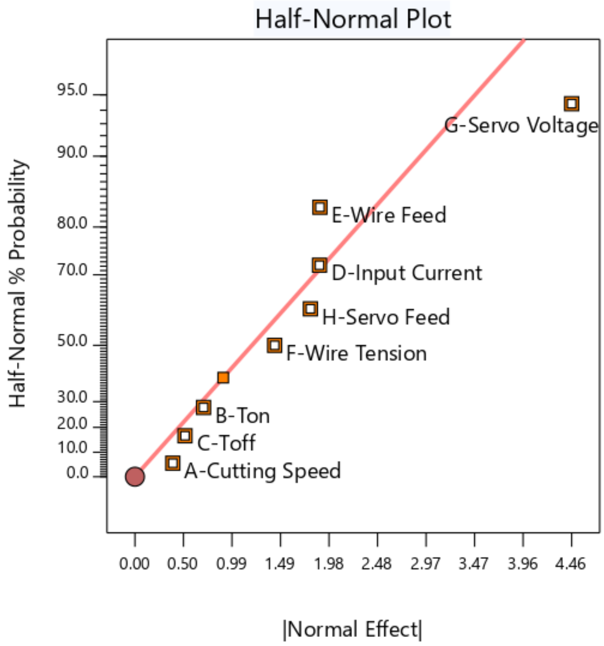

Fig. 5.Half Normal probability plot of GRG

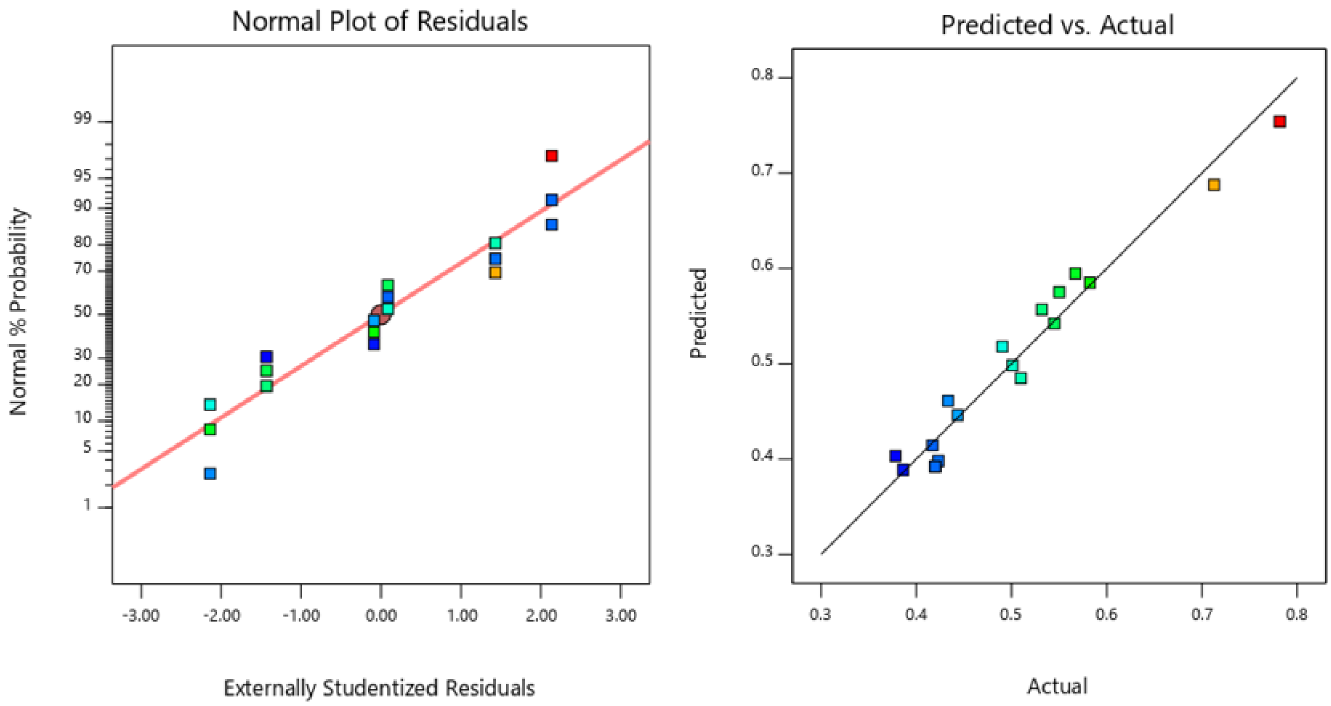

Fig. 6.Normal probability and predicted vs. actual plot of GRG

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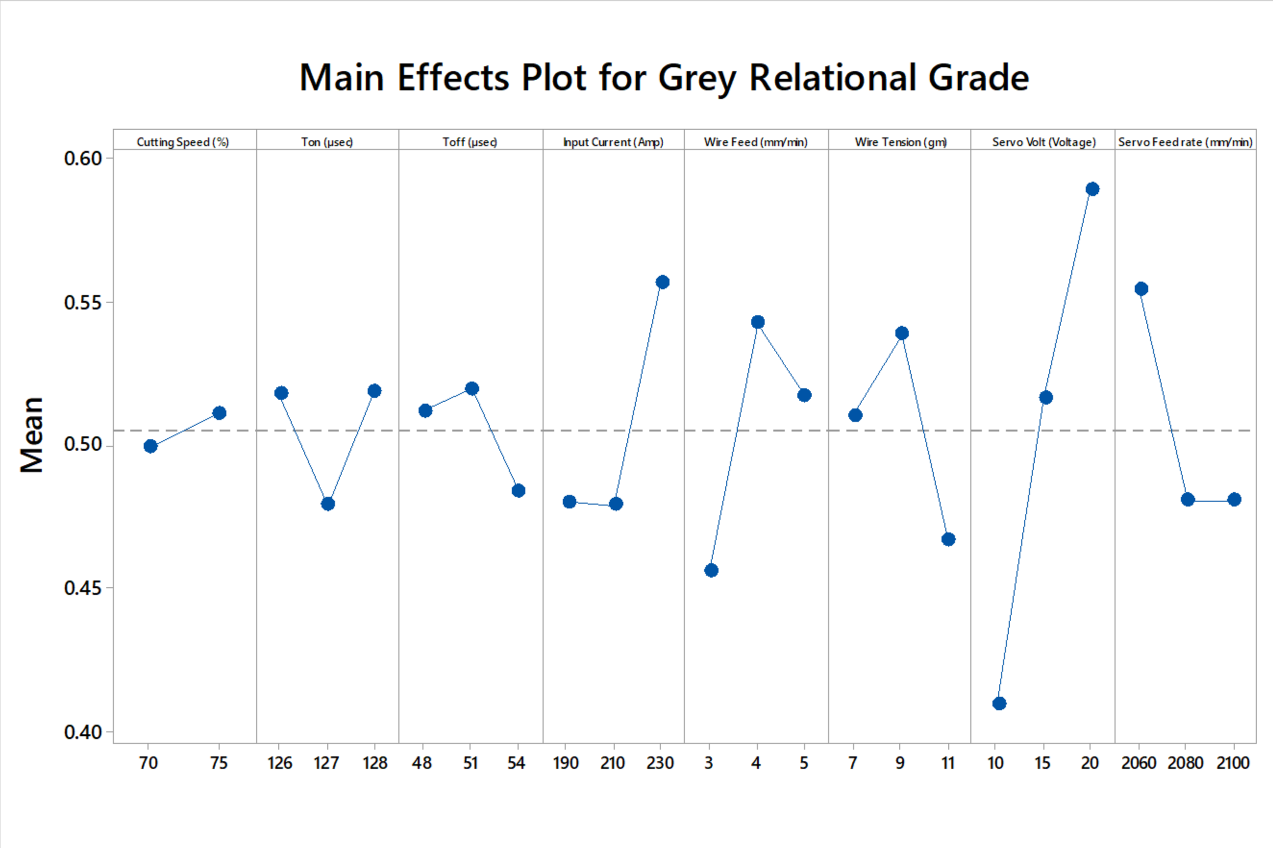

Fig. 7.Main effect plot for GRA Grade

Linear graph or Interaction graph was drawn to analyze the effect of chosen parameters on the measured outputs. The influence of various selected inputs towards the GRG is provided in Fig. 8. In linear graph, if relationship between selected input parameters towards the output is shown as matching lines, it is obvious that no relationship or interaction is present in between the two inputs [41]. If the correlation between two input factors is characterized by dissimilar lines, it may be decided that a considerable association is found to exist amid the considered inputs.

Observation proves that, a considerable relationship is present with 75% cutting speed with other chosen parameters. Interaction exists between pulse on-time and pulse off-time, wire feed, wire tension, servo voltage and servo feed, represented by non-parallel lines. Similar effect is sensed between pulse off-time and feeding of wire and with the tension of wire. Wire feed has significant relationship with servo voltage for a 4mm/min of wire feed and wire tension has an interaction effect with 10V of servo voltage. In between input current and other selected parameters, no interaction effect is observed.

Table- V: ANOVA for Grey relational grade

Source	DoF	Adj. SS	Adj. MS	F Value	P Value	% Contribution
Cutting Speed	1	0.000627	0.000627	0.15	0.736	0.31%
Pulse ON-Time	2	0.006092	0.003046	0.73	0.579	3.01%
Pulse OFF-Time	2	0.004151	0.002075	0.49	0.669	2.05%
Input Current	2	0.023645	0.011823	2.82	0.262	11.69%
Wire Feed rate	2	0.023719	0.011859	2.83	0.261	11.73%
Wire Tension	2	0.015692	0.007846	1.87	0.348	7.76%
Servo Voltage	2	0.098054	0.049027	11.69	0.079	48.48%
Servo Feed rate	2	0.021903	0.010952	2.61	0.277	10.83%
Error	2	0.008389	0.004194			4.15%
Total	17	0.202272				100.00%

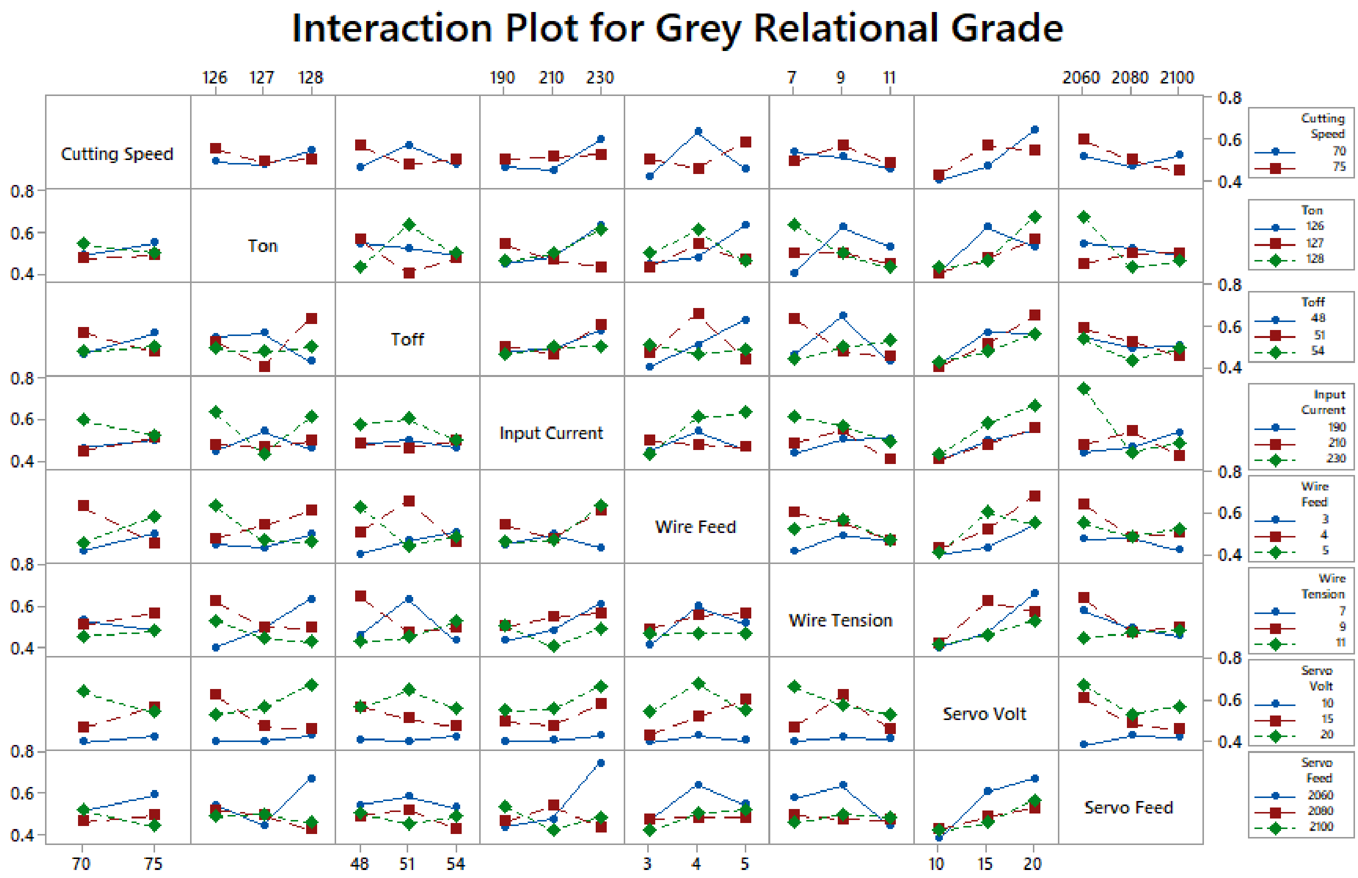

Fig. 8. Interaction plot for GRG

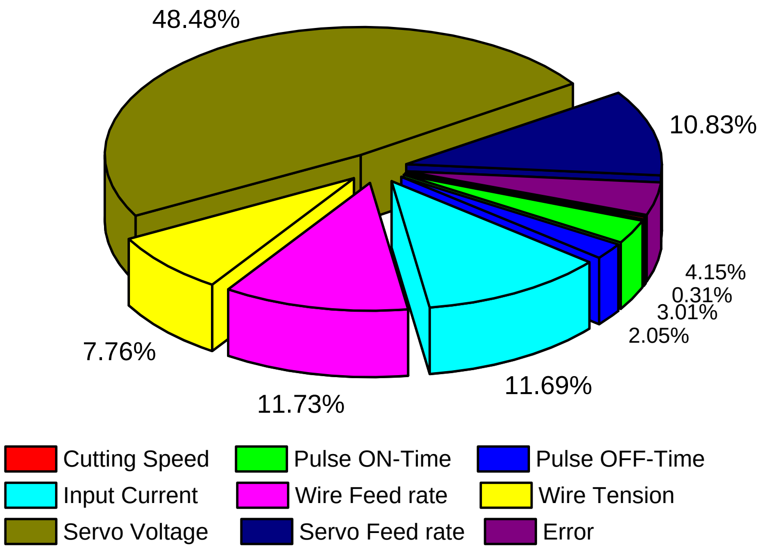

Fig. 9.Percentile contribution of input parameters over GRG

From ANOVA, a statistical procedure for examining investigational data's, researchers have recognized the factors that were selected as dependent and independent variables, which were closely connected to one another [42], [43]. Based on the examination category, it is important to detect which parameters produces a remarkable result on the dependent parameter, and quantifying the variation in responses attributed towards individual factors. ANOVA executed on GRG identifies that, servo voltage is the most influential parameter contributing by 48.48%, followed by wire feed rate, input current and servo feed rate by 11.73%, 11.69% and 10.83%, as given in Table V. As ANOVA is implemented in 95% confidence interval, R^2 value obtained as 95.85% is good for the results obtained. The contribution of individual independent factors on the determined GRG is shown in Fig. 9.

A. Prediction of GRG value

For predicting the optimum value of grey relational grade, as a guide in machining feature, the grey relational grade (η_{opt}) is predicted [44], [45] using Equ. (8). The noteworthy factors and their best settings were selected from the linear graph (Fig. 7), that is, cutting speed of 75%, pulse ON-time of 128 µsec, pulse OFF-time of 51µsec, input current of 230A, wire feed rate of 4 mm/min, wire tension of 9 gm, servo voltage of 20V and servo feed of 2060 mm/min.

$$\mu_{predicted} = V_{2m} + Ton_{3m} + Toff_{2m} + I_{3m} + WF_{2m} + WT_{2m} + SV_{3m} + SF_{1m} - 7\mu_{mean} \tag{8}$$

where, V_{2m}, Ton_{3m}, $Toff_{2m}$, I_{3m}, WF_{2m}, WT_{2m}, SV_{3m} and SF_{1m} and are the average GRG value of input parameters at optimal levels and μ_{mean} is the total average of GRG. At optimum setting, the mean predicted ($\mu_{predicted}$) value is determined as 0.794.

B. Confirmation Experiment

Confirmation experiment was performed at the best setting of input factors to confirm the sturdiness of best combination of optimal machining parameters with the same experimental procedure. The output responses obtained is presented in Table VI along with the predicted and experimental GRGs, a deviation of 7.44% was obtained between the experimental and predicted GRGs, which is acceptable in real time prediction. From this, it was prominent that multi-criteria dependent parameters of WEDM process can be much improved by adopting this approach.

Table- VI: Predicted and Experimental values of GRG

Responses	Observed	Experimental GRG	Predicted GRG	Error (%)
MRR (mm^3/min)	12.728	0.739	0.794	-7.44%
SR (microns)	2.419			

IV. CONCLUSIONS

Optimization of performance measures during machining D3 tool steel by WEDM towards MRR and SR considering $L_{18}(2^1,3^7)$ OA based on Taguchi-Grey analysis was performed. From the experimental investigation, the following conclusions were made.

- SR gets intensified with higher pulse on-time and were lower for higher pulse off-time. When peak current exceeds a certain threshold value, the average discharge gap gets widened resulting into better surface finish. When input current is increased from 10A to 20A, surface roughness decreases but further increase of gap set voltage reduces surface roughness. The MRR increases as the pulse on-time increases due to longer spark duration.
- A control chart, $\overline{X}$ chart drawn for MRR and SR shows that the obtained values were well within the control limits, showing the better control of input parameters over the experimental condition.
- The optimum parameters attained through multi-criteria optimization were: cutting speed of 75%, pulse ON-time of 128 µsec, pulse OFF-time of 51µsec, input current of 230A, wire feed rate of 4 mm/min, wire tension of 9 gm, servo voltage of 20V and servo feed of 2060 mm/min.
- Interaction plot shows that, significant relationship exists between 75% cutting speed with other chosen parameters, and interaction exists between pulse on-time and pulse off-time, wire feed, wire tension, servo voltage and servo feed. Similar effect is sensed between pulse off-time and wire feed and with wire tension. In between input current and other selected parameters, no interaction effect is observed.
- ANOVA performed on the GRG identifies that, servo voltage was the significant factor that contributes by 48.48%, trailed by wire feed rate, input current and servo feed rate with an R^2 value of 95.85%.
- Prediction of GRG is carried out for the optimum input conditions and a confirmation experiment was also performed and the comparison between these two shows a deviation of 7.44% between the experimental and predicted GRGs, which is acceptable.

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