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Multi-parametric Optimization of Wired Electrical Discharge Machining Process to Minimize Damage Cause in Steel - A Soft Computing-Based Taguchi-Grey Relation Analysis Approach

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Abstract

The automotive industry makes crucial components from a wide array of materials. Euro Norm (EN) 31 steel is a highly regarded engineering functional material that meets the industry's requirements. However, conventional machining is not cost effective due to EN 31's high hardness and strength. Thus, the current research focuses on the effect of wired electrical discharge machining (WEDM) process parameters on the material removal rate (MRR) and average arithmatic mean of surface roughness (Ra) of EN 31 steel, as WEDM is a highly sustainable and cost-effective alternative to the conventional machining processes. Experiments are conducted utilizing a Taguchi L27 orthogonal array with the following input parameters: servo voltage, pulse width, pulse interval, and cutting speed. Grey relational analysis (GRA) has been used to optimize the multiple responses. The analysis of variance (ANOVA) of the grey relational grade (GRG) demonstrated that the most influential element in simultaneously improving performance measures is the speed, S (rpm) as it contributes 62.39 % to the variance in the response.

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1. Introduction

The automobile industry utilises a vast variety of materials, including casting tools, dies, studs, nuts & bolts, bearings, and punches. These require a high degree of hardenability, toughness, increased strength, and resistance to thermal shock. Among the numerous steel grades, the Euro Norm (EN) 31 effectively satisfies all of these requirements. However, because to EN 31's high hardness and strength, traditional machining is not cost effective.[1] Traditional machining is primarily a material removal process that involves the creation of chips, resulting in a deterioration in surface smoothness and precision. Non-traditional machining procedures remove material by utilising other energy sources such as electrical, chemical, and optical, avoiding contact between the tool and the workpiece and lowering friction. The development of innovative materials with significantly superior chemical, physical, and thermal properties has rendered standard machining procedures undesirable and economically unfeasible for these modern materials. This has necessitated the development of non-traditional machining methods. Wire electrical discharge machining (WEDM) is a highly sustainable and cost-effective alternative to conventional machining technologies for producing high-quality machining.[2,3] Only a few studies have recently focused on enhancing the machining performance parameters when cutting EN 31 steel with an electrical discharge machining (EDM). Vates *et al*. (2014) used a single variable at a time concept to optimise the influence of gap voltage, dielectric flush rate, pulse on time, and pulse off time on the surface roughness and material removal rate (MRR) of EN 31 alloy steel.[4] Thomas *et al*. (2015) used the response surface approach to optimise the influence of current, pulse on time, pulse off time, and wire tension on the MRR and surface

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roughness of EN 31 alloy steel.[5,6] Patel and Maniya (2015) optimised the effect of machining parameters on the MRR, kerf width, and surface roughness of EN 31 alloy steel. The authors optimised the multi-objective problem using an analytical hierarchy approach in conjunction with the Taguchi method.[7] Diyaley *et al*. (2017) optimised the influence of pulse on and off time, servo voltage, and wire tension on the MRR and surface roughness of EN 31 alloy steel. The authors optimised the multi-objective problem using the Preferential Selection Index (PSI) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS).[8] Das *et al*. (2019) optimised the influence of servo voltage, wire tension, pulse on/off time, and pulse on/off time on the MRR and surface roughness of EN 31 alloy steel. The authors optimised the multi-objective problem using fuzzy logic and Grey Relation Analysis (GRA).[9] Chopra *et al*. (2019) used a response surface technique to optimise the effect of pulse on-time, servo voltage, wire feed, and wire tension on edge roughness, kerf width, and cutting rate of EN 31 alloy steel.[3] Payla *et al*. (2017) used a statistical technique to optimise the effect of servo voltage, pulse on-time, wire feed, and wire tension on the MRR and power consumption of EN 31 alloy steel.[10] Sankar *et al*. (2020) used Simulated Annealing (SA) to optimise the influence of pulse on time, pulse off time, table feed rate, flushing pressure, wire tension, and wire velocity on the MRR of EN 31 alloy steel.[11]

According to the literature, only a few studies have been conducted on WEDM machining of EN 31 alloy steel. Additionally, in most cases, the researchers concentrated on servo voltage, pulse on time, pulse off time, table feed rate, flushing pressure, wire tension, and wire velocity. The effect of cutting speed, pulse interval, and pulse width on WED machining of steels has received scant attention. Thus, the purpose of this work is to add to the literature by examining the effect of speed, pulse width, pulse interval, and servo voltage on the MRR and surface roughness of EN 31 alloy steel when machined using WEDM.

2. Materials and Methods

2.1 Experimental setup

The steel machining experiments are carried out with the Concord WEDM-DK7732, a computer numerically controlled wire electro discharge machine. The nozzle moves in the x- and y-direction to cut the workpiece. The EN 31 steel workpiece material is mounted on the WEDM machine bed, and specimens measuring 30 mm × 30 mm × 30 mm (length, width, and thickness) are cut in WEDM. With the use of a Taylor Hobson Surtronic 3+ surface roughness tester, the average surface roughness, Ra, is determined. For this study, the EN 31 material was chosen as the workpiece material. Table 1 shows the chemical composition of EN 31. Table 2 shows the process parameters and their levels in terms of real value. The current investigation employs a 0.16 mm molybdenum wire as an electrode. The weight lost by the work material after machining is used to calculate MRR. The workpiece's weight (Wt.) is determined using a computerised weighing equipment with a minimum count of 0.001 gm.

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2.2 Experimental design

Taguchi's L27 orthogonal array experimental design approach is used to conduct twenty-seven experiments. Table 3 shows the value of each variable's response characteristics at various levels, as computed from the experimental data. For parameter optimization of a single response problem, the conventional Taguchi approach is extensively utilised.

However, when performance is assessed in various units for different attributes, the significance of some attributes may be overlooked. This may also occur if some performance characteristics have a very wide range. Additionally, if the objectives and directions of these attributes contradict, the analysis will produce inaccurate results.[12] Grey Theory is a system science theory first proposed by Deng Julong in 1982. It is a significant contribution to the field of uncertainty system research.[13] Grey relational analysis is a multi-criteria decision-making approach that is based on Grey theory.[14] The primary technique of GRA is to convert the performance of all alternatives into a sequence of comparability. This process is referred to as grey relational generation. A target sequence is defined in terms of these sequences. The grey relational coefficient is then determined between all comparability sequences and the ideal target sequence. Finally, the grey relational degree between the ideal target sequence and each comparability sequence is determined using these grey relational coefficients. If a comparability sequence translated from an alternative has the largest grey relational degree between the ideal target sequence and itself, it is the best choice.[15] Grey relation analysis involves the following steps:[16,17]

The measured values are normalised to account for output responses such as MRR and arithmetic average roughness (Ra) values ranging from 0 to 1. Grey Relational Normalization is the term used to describe this process. MRR values are normalized using ‘larger-is-better’ approach and Ra values are normalized using ‘smaller-is-better’ approach. Both approaches are mathematically represented by Equations (1) and (2).

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

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

Grey relational co-efficient can be determined using the relevant attributes from the grey relational normalisation

Table 1. Chemical composition of EN 31 steel.

Elements	C%	Mn%	P%	S%	Si%	Ni%	Cr%	Cu%	Mo%
Contents	0.96	0.44	0.025	0.015	0.17	0.25	1.43	0.30	0.10

Table 2. Experimental parameters and their levels.

S. No	Process Parameter	Unit	Level 1	Level 2	Level 3
1	Servo Voltage	V	70	80	90
2	Pulse width	µs	3	4	5
3	Pulse interval	µs	20	25	30
4	Speed	rpm	180	350	700

values. The Grey Relational Coefficient is used to characterise the relationship between desired and actual data. Mathematically it is represented by Equation (3). Given that all of the process parameters are equally weighted, the distinguishing coefficient is set at 0.5 in Equation (3) and $\delta_{01}(k)$ is determined using Equation (4).

$$\varepsilon_i(k) = \frac{\delta min+\zeta\delta \max}{\delta_{01}(k)+\zeta\delta \max} \tag{3}$$

$$\delta_{01}(k) = |x_0^*(k) - x_1^*(k)| \tag{4}$$

Grey Relational grade is calculated as the average value of the Grey Relational coefficients for the MRR and Ra. Mathematically, it is represented by Equation (5).

$$GRG = \frac{1}{n}\sum_{i=1}^{n} \varepsilon_i(k) \tag{5}$$

A Microsoft excel sheet was well formulated to facilitate the data management. The worksheet was completely formulated to achieve error free values of all the required terms of grey relation analysis.

3. Results and Discussion

Statistical analysis was performed using the statistical software Minitab 21 on the experimental data gathered using the Taguchi experimental design. Analysis of variance (ANOVA) was used to examine the effect of input factors on the response variables at the output. Due to the study's primary focus on grey relational analysis, the results of Taguchi trials

Table 3. Experimental results using Taguchi L27 Orthogonal Array (OA).

	Process parameters				Responses	
Exp No.	Servo voltage [V]	Pulse width [µs]	Pulse interval [µs]	Speed [rpm]	Material removal rate [mm^3/min]	Average surface roughness [µm]
1	70	3	20	180	2.579	3.279
2	70	3	25	350	2.571	3.236
3	70	3	30	700	3.175	3.164
4	80	4	20	350	5.118	3.425
5	80	4	25	700	5.622	3.353
6	80	4	30	180	3.168	3.421
7	90	5	20	700	8.269	3.541
8	90	5	25	180	5.715	3.609
9	90	5	30	350	5.607	3.554
10	80	5	20	350	6.302	3.543
11	80	5	25	700	6.806	3.471
12	80	5	30	180	4.352	3.526
13	90	3	20	700	5.801	3.305
14	90	3	25	180	3.347	3.373
15	90	3	30	350	3.239	3.330
16	70	4	20	180	3.863	3.397
17	70	4	25	350	3.755	3.354
18	70	4	30	700	4.159	3.282
19	90	4	20	700	6.785	3.423
20	90	4	25	180	4.531	3.501
21	90	4	30	350	4.423	3.448
22	70	5	20	180	5.047	3.515
23	70	5	25	350	4.939	3.467
24	70	5	30	700	5.443	3.401
25	80	3	20	700	5.124	3.250
26	80	3	25	350	3.248	3.301
27	80	3	30	180	2.184	3.303

have been omitted. As a result, this section is divided into two subsections. The first subsection briefly summarises the Taguchi technique experiments' outcomes. The second subsection on outcomes delves deeply into the application of grey relational analysis.

3.1 Results based on Taguchi Analysis

Individual performance characteristics were analysed statistically to identify the effect of control variables on response variables. The orthogonal arrays with levels and responses for all 27 experiments are listed in Table 3. The ANOVA results for the response variables: material removal rate and average surface roughness are shown in Table 4 and Table 5, respectively.

The problem in the presented case includes two performance characteristics: the MRR must be enhanced while the average surface roughness must be minimized. In such circumstances, grey relational analysis is used to convert the problem to a single objective problem. The values for the grey relational normalisation, grey relational coefficients, and grey relation grade determined using grey relation analysis is given in Table 6.

A greater grey relational grade suggests that the corresponding grey relational grade (GRG) mean value is closer to the ideal normalised mean value. The highest grey relational grade is found in trial number three with a GRG

Table 4. Anova results for MRR.

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Regression	4	57.0866	99.81%	57.0866	14.2716	2880.47	0.000
V	1	8.2499	14.42%	8.2499	8.2499	1665.10	0.000
PW	1	24.9972	43.70%	24.9972	24.9972	5045.22	0.000
PI	1	9.5893	16.77%	7.9044	7.9044	1595.36	0.000
S	1	14.2502	24.91%	14.2502	14.2502	2876.14	0.000
Error	22	0.1090	0.19%	0.1090	0.0050		
Total	26	57.1956	100.00%				

Table 5. Anova results for Ra.

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Regression	4	0.331866	99.87%	0.331866	0.082967	4358.71	0.000
V	1	0.054340	16.35%	0.054340	0.054340	2854.79	0.000
PW	1	0.241744	72.75%	0.241744	0.241744	12700.20	0.000
PI	1	0.003445	1.04%	0.005144	0.005144	270.23	0.000
S	1	0.032337	9.73%	0.032337	0.032337	1698.87	0.000
Error	22	0.000419	0.13%	0.000419	0.000019		
Total	26	0.332285	100.00%				

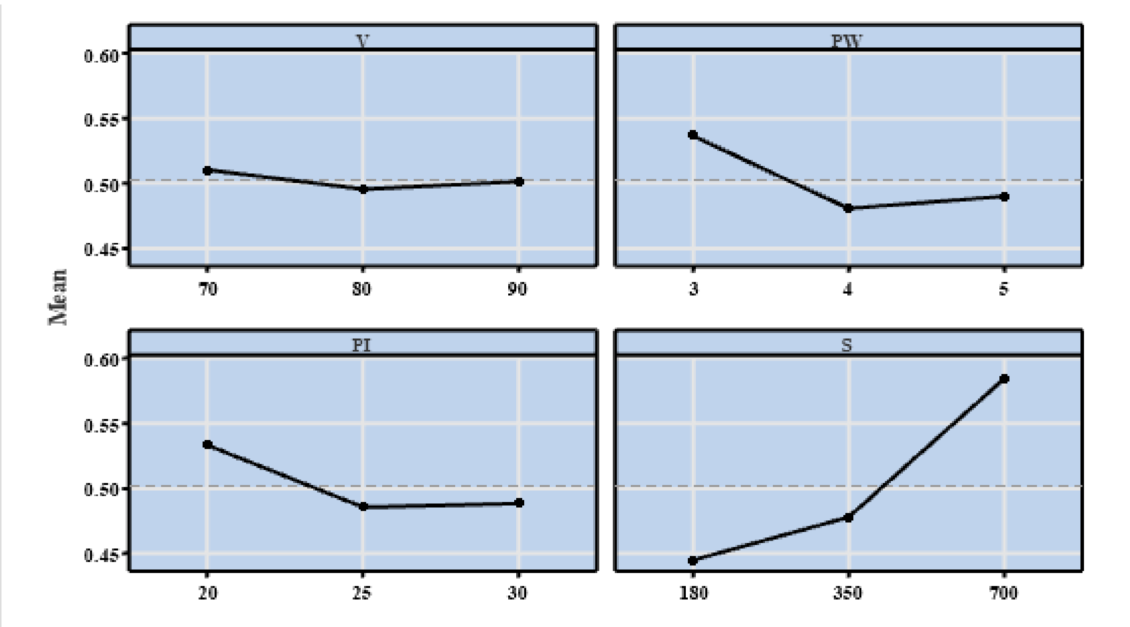

Fig. 1 Main effect plots for GRG mean.

Table 6. Values obtained using grey relation analysis for response variables.

Experimental Values			Grey relational normalization		Deviation Sequence		Grey relational coefficient		Grey relational grade
Exp No.	MRR	Ra	MRR	Ra	MRR	Ra	MRR	Ra	GRG
1	2.68	3.28	0.112	0.742	0.888	0.258	0.360	0.660	0.504
2	2.57	3.24	0.095	0.839	0.905	0.161	0.356	0.756	0.552
3	3.08	3.16	0.176	1.000	0.824	0.000	0.378	1.000	0.687
4	5.12	3.43	0.507	0.415	0.493	0.585	0.503	0.461	0.476
5	5.62	3.35	0.588	0.577	0.412	0.423	0.548	0.541	0.538
6	3.17	3.42	0.191	0.423	0.809	0.577	0.382	0.464	0.419
7	8.17	3.54	1.000	0.153	0.000	0.847	1.000	0.371	0.686
8	5.72	3.61	0.603	0.000	0.397	1.000	0.558	0.333	0.438
9	5.61	3.57	0.586	0.096	0.414	0.904	0.547	0.356	0.448
10	6.30	3.54	0.698	0.150	0.302	0.850	0.624	0.370	0.489
11	6.81	3.47	0.780	0.311	0.220	0.689	0.694	0.421	0.548
12	4.35	3.54	0.383	0.158	0.617	0.842	0.448	0.373	0.409
13	5.80	3.31	0.617	0.684	0.383	0.316	0.566	0.613	0.582
14	3.35	3.37	0.220	0.531	0.780	0.469	0.391	0.516	0.449
15	3.24	3.33	0.203	0.627	0.797	0.373	0.385	0.573	0.475
16	3.86	3.40	0.304	0.477	0.696	0.523	0.418	0.489	0.448
17	3.76	3.35	0.286	0.573	0.714	0.427	0.412	0.539	0.471
18	4.26	3.28	0.368	0.734	0.632	0.266	0.442	0.653	0.539
19	6.99	3.42	0.809	0.419	0.191	0.581	0.723	0.462	0.567
20	4.53	3.49	0.412	0.266	0.588	0.734	0.459	0.405	0.423
21	4.42	3.45	0.394	0.362	0.606	0.638	0.452	0.439	0.440
22	5.05	3.52	0.495	0.211	0.505	0.789	0.498	0.388	0.437
23	4.94	3.47	0.478	0.307	0.522	0.693	0.489	0.419	0.450
24	5.44	3.40	0.559	0.469	0.441	0.531	0.531	0.485	0.501
25	5.12	3.25	0.508	0.807	0.492	0.193	0.504	0.722	0.606
26	3.25	3.29	0.204	0.716	0.796	0.284	0.386	0.637	0.498
27	1.98	3.30	0.000	0.689	1.000	0.311	0.333	0.617	0.474

Table 7. Response table for means.

Level	V	PW	PI	S
1	0.510	0.536	0.533	0.445
2	0.495	0.480	0.485	0.478
3	0.501	0.490	0.488	0.584
Delta	0.015	0.056	0.048	0.139
Rank	4	2	3	1

value of 0.687. As a result, it might be deemed the best experimental sequence for the given instance. Furthermore, the Taguchi method is employed to examine the resulting grey relational grades. In the Taguchi approach, the estimated grey relational grade was used as the response value. Table 7 shows the mean response table for the overall grey relational grade, which is graphically displayed in Fig. 1. The ordinate of the figure represents the means of grey relational grade derived using the Taguchi method's larger-is-better criteria. The steep slope of the grey relational grade graph suggests that machining factors have a considerable influence on performance attributes. In general, the higher the grey relationship grade, the better the various performance features. The ideal parametric combination was found from the grey relational grade graph as V1 (70 V), PW1 (3 µs), PI1 (20 µs), and S3 (700 rpm).

Others obtained similar results when machining this alloy at greater cutting speeds.[18–23] Because of the increased heat influence in the machining region, surface defects and discontinuities are wiped out at higher cutting speeds. As a result, there is a considerable reduction in surface roughness.[22,23] Furthermore, because of the lower dynamic shear strength of alloy steel in the presence of higher heat effect in the machining region, it promotes easy removal of the work material. As a result, fewer forces are generated during machining.[22,23] As a result, overall machining performance is improved, which is reflected in the greater value of the grey-

Table 8. Anova results for GRG.

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Regression	4	0.109735	75.59%	0.109735	0.027434	17.03	0.000
V	1	0.000366	0.25%	0.000366	0.000366	0.23	0.638
PW	1	0.009852	6.79%	0.009852	0.009852	6.12	0.022
PI	1	0.008947	6.16%	0.005222	0.005222	3.24	0.086
S	1	0.090571	62.39%	0.090571	0.090571	56.22	0.000
Error	22	0.035445	24.41%	0.035445	0.001611		
Total	26	0.145180	100.00%				

related grade. Combining the classic response surface method (RSM) or Taguchi approach with machine learning algorithms for the WEDM process[24–28] can further improve the optimization. Nonetheless, it is beyond the scope of the current work and should be regarded as a possible extension.

The integration of machine learning and manufacturing understanding demands the perfect synthesis of computer science and manufacturing knowledge, allowing interdisciplinary engineers to collaborate in the future to deliver a significantly superior solution.

3.2 Anova for GRG and Mathematical Modelling

The experiment data were evaluated using analysis of variance to determine the impact of each input component on the grey relation grade. Table 8 shows the ANOVA results. According to the ANOVA results, speed is the most influential component, accounting for 62.39% of the variance in GRG. The other linear terms and a few interative terms do indicate an influence over GRG but can be neglected as the contribution to variance for each of them is less than 10%.

4. Conclusion

This study attempted to identify the critical machining parameters for performance indicators such as MRR and average surface roughness in the WEDM process. EN 31 alloy steel was chosen as the material for the work. The critical elements: servo voltage, pulse width, pulse interval, and speed were used for prediction. Taguchi's experimental design method was utilised to find the best parameter combination for maximising MRR while minimising surface roughness. Surprisingly, the optimal levels of the parameters for all of the objectives vary greatly. Grey relational analysis was offered as an optimization strategy to achieve both aims. As a result, this method substantially simplified the optimization of complex multiple performance characteristics, and because it does not require complex mathematical computations, it was simply implemented in the work. The following are the key findings of the experimental investigation.

- The optimum "process variables" for the wire cut EDM of EN 31 alloy steel based on the Taguchi-grey relational analysis are servo voltage of 70 V, pulse width of 3 μs, pulse interval of 20 μs, and cutting speed of 700 rpm.
- When using the Taguchi-GRA method, the best material removal rate is 3.075 mm^3/min, with a surface roughness value of 3.164 μm.
- The analysis of variance (ANOVA) of the grey relational grade (GRG) demonstrated that the most influential element in simultaneously improving performance measures is the speed, S (rpm) as it contributes 62.39 % to the variance in the response.

Conflict of Interest

The authors declare no conflict of interest.

Supporting information

Not applicable.

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