Int J Adv Manuf Technol (2013) 67:2051–2062
DOI 10.1007/s00170-012-4630-1

ORIGINAL ARTICLE

Estimating the effect of process parameters on surface integrity of *EDM*ed AISI D2 tool steel by response surface methodology coupled with grey relational analysis

M. K. Pradhan

Received: 9 October 2011 / Accepted: 5 November 2012 / Published online: 4 December 2012

Abstract In this investigation, a hybrid optimization approach is used for the estimation of minimal surface integrity of surface created in electrical discharge machining (*EDM*). A new combination, response surface methodology coupled with the grey relational analysis method has been proposed and used to optimize the machining parameters of EDM. The significant input parameters such as pulse current (*Ip*), pulse duration (*Ton*), duty cycle (*Tau*) and discharge voltage (*V*) are considered, and white layer thickness, surface roughness, and surface crack density have been considered as responses for this study. Thirty experiments were conducted on American Iron and Steel Institute (AISI) D2 steel work piece materials based on central composite design. The optimum conditions of the machining parameters were obtained from the grey relational grade. Analysis of variance is used to find the percentage contribution of the input parameters and found that Tau was the most influencing parameter followed by Ton and Ip in EDM of D2 steel. The R^2 value for the grey relational grade model was 0.918. These results provide useful information about how to control the responses and ensure the high-quality surfaces-quality surfaces. This method is simple with easy operability. The assessment outcome provides a scientific reference to obtain the minimal condition of surface integrity, and they were found to be a pulse current of 1 A, a pulse duration of 50 μs, a duty cycle of 80 %, and discharge voltage 40 V.

M. K. Pradhan (✉)
Department of Mechanical Engineering,
Maulana Azad National Institute of Technology,
Bhopal, India
e-mail: mohanrkl@gmail.com; mohankpradhan@manit.ac.in

Keywords Electrical discharge machining · White layer thickness · Surface roughness · Surface crack density · Response surface methodology · Central composite design · Grey relational analysis

1 Introduction

There is an increasing tendency to use lightweight, slim, and compact mechanical component in recent years; hence, there has been an increased interest in the advance materials. These advanced materials having attractive properties such as high strength, high bending stiffness, good damping capacity, low thermal expansion, and better fatigue characteristics, which make them possible material for the modern day industrial application used in mold and die making industries, aerospace component, medical appliance, and automotive industries. The modern manufacturing industries are facing challenges from these advanced materials viz. super alloys, ceramics, and composites, that are hard and difficult to machine, requiring high precision and surface quality, which increases machining cost [1]. To meet these challenges, the development of appropriate machining systems to support this growth is essential because the traditional processes are unable to cope with those challenges and thus results in poor material removal rate, excessive tool wear, and poor surface finish. Electrical discharge machining (*EDM*) is a thermal process, has firmly established its use for more than 60 years, providing unique capability to machine “difficult-to-machine” materials in the production of forming tools, dies, and molds and effective machining of advanced materials. The material removal in EDM is carried out by a series of discrete electrical discharges in the presence of a dielectric medium, generates extreme localized heating in the vicinity of the discharge, high enough to melt and even vaporize the work piece material. Since, there is no direct contact between the tool and the workpiece, the material removal is not carried out by the mechanical action of a cutting or abrasive tool. Therefore, machining in EDM is not dependent on the mechanical properties of the workpiece material, rather, it depends on the thermal properties, and thus machining can be carried out no matter how high the hardness is. In consequence, EDM has become very popular in the tool and die making industry, in which complex geometries with tight tolerances can be produced on difficult-to-machine materials. However, EDM is a very demanding process and the mechanism of the process is complex and not entirely understood yet. Therefore, it is difficult to establish an analytical model and its optimal setting that can exactly predict the performance and optimal response by correlating the process parameters.

The state and characteristics of any machined surface that affect performance are designated by the term "surface integrity." If the surface integrity is worst, the operational performance will be poor, and if it is good, the functional performance will be better. The surface integrity produced by EDMed surfaces is extremely significant. Normally, surface integrity is characterized by the surface roughness and the presence of a white layer, surface cracks, and residual stress in it. The surface integrity of EDMed surface is becoming more and more significant to satisfy the increasing demands of sophisticated component performance. The combination of stresses, and high temperatures engendered during EDM lead to defects and/or alterations of the microstructure, cause surface cracking, craters, folds, inclusions, plastic deformation, and residual stresses in the finished component. The extreme heat generated during EDM and when allied with each discharge result in local temperature gradients in the surface, and after subsequent quenching the residual stresses develops, which is certainly responsible for the formation of multiple fatigue cracks in the EDMed surfaces [2] Therefore, it is critical for industries, like automobile, tool and mold making, aerospace, etc., to know and understand the consequences of these defects by fine-tuning the operating parameters. The layer, produced due to the EDM spark called heat-affected layer, is normally different in character from the parent material, consists of microcracks, voids, impurities, stress and several other defects and is responsible for the deterioration the mechanical properties of the machined components [3]. The recast layer also called the white layer is produced by the solidified molten material, during the electric discharge, since it is very difficult to etch and as its appearance is white when observed through an optical microscope. It contains many pock marks, globules, cracks, and microcracks. Its thickness and density depend on the process conditions [4]. Surface crack is a vital defect, which certainly affects the fatigue life of the components [5], and these are generally formed when the induced stress exceeds the ultimate stress [6]. The surface roughness of the EDMed surface is also associated to the distribution of the craters formed due to the electric discharge.

To enhance the life of the EDMed product, the recast layer is normally removed, as this layer plays a critical role particularly for applications in which the part is subjected to cyclical stress or fluctuating loads. The component having a good surface improves the fatigue strength, wear resistance, and corrosion resistance of the surface [7]. Moreover, the surface cracks in EDMed surfaces are limited up to the white layers only; therefore, removing white layers also eradicates the surface cracks on the surface [8]. Consequently, white layer must be removed either by hand polishing, etching, or by heat treatment to improve the properties and make the component functional. The polishing must be done appropriately to just remove the white layer which causes damage to the component. Excessive polishing may lead to remove excess material and lose the tolerance. Moreover, such processes are supplementary and may increase cost of the component and time. Therefore, it is necessary to get the appropriate optimal set of machining parameters, which minimizes the white layer thickness *WLT* and also determines/predicts it appropriately to minimize the cost and time. Ultimately, by removing that exact thickness, the required tolerance and dimension can be achieved, else the component may be rejected as a defective item. Meanwhile, there are several factors that affect the EDM process—subsequently, the formation of surface integrity—and it is a traditionally difficult topic to understand. Selection of optimal set of process parameters is always a vital factor in any machining process, since the process and materials are normally costly, and suboptimal production leads to increase the end cost of the component. Numerous researches have been carried out to investigate and improve the process performance. Niwa and Furuya [9] proposed the optimization of the rate of material removed at a certain stage to the surface finish at the previous stage. Being a complex and stochastic process, it is very difficult in EDM to determine optimal setting for best machining parameters, which could minimize the WLT, surface roughness *Ra*, and surface crack density *SCD*. These responses are the vital factors which decide the quality of the end product and parameter such as *Ip* that has two distinct effects on these responses, i.e., decreasing Ip decreases WLT and increases the SCD. Therefore, one cannot decrease Ip to any extent to minimize the thickness of white layer as it certainly increases the SCD. Furthermore, it is hard to locate a single optimal combination of process parameters for the responses, as the process parameters influence them differently as stated earlier. Hence, there is a need for a multi-objective optimization method to arrive at the solutions to this problem [10]. Liao et al. [11] optimized the number of stages, the volume of material removed, and the electrode wear at each stage, and proposed an explicit relationship to relate material removal rate (MRR), Ra, and electrode wear. Pradhan and Biswas [12] applied composite desirability function method to optimize the parameters to obtain MRR and Ra with a reduced number of experiments that needed to provide sufficient information for statistically acceptable results. Bhattacharyya et al. [13] found in their experimental study that Ip and *Ton* are the vital factors which influence the crack, WLT, and Ra. Lin et al. [14] employed grey relational analysis for solving the complicated interrelationships between process parameters and the multiple performance measures of the EDM process. Pradhan et al. [15] applied response surface methodology *RSM* to model and estimate Ra and establish that Ip and Ton are the most influencing parameters with their interactions, as later conformed by the scanning electron microscopy (SEM) results. Lin and Lin [16] studied the effect of current, polarity, voltage, and spark on-time on the EDM process by using the Taguchi method. Singh et al. [17] used grey relational analysis *GRA* for multi-response optimization for optimizing, metal removal rate, tool wear rate, taper, radial overcut, and surface roughness on EDM of Al-10 %SiCp as cast metal matrix composites using the orthogonal array. The optimal setting helps in considerable improvement in the process since this technique converts the multi-response variable to a single-response grey relational grade and, therefore, simplifies the optimization procedure. Improving the performance of machining operation and setting the appropriate machining parameters are solved by many traditional and non-traditional optimization algorithms. Recent advancements in optimization techniques introduced new prospects to accomplish better solutions for the aforesaid problems. To solve these issues, numerous novel optimization techniques and its hybridization have been established and applied successfully on manufacturing optimization problems [18–27]. And more such attempts are still going on since, in optimization, no one can be said to be the best solution technique that can be the finest one to handle difficulties and to select the optimal machining variables. Hence, there is a need to introduce new approaches to overcome disadvantages, if any and to an upsurge, the existing optimization techniques to manufacturing the products economically. Moreover, the complexity of some optimization techniques necessitates paying great attention on hybrid approaches of optimization.

Though several attempts have been made to study surface integrity and many hybridization techniques have also been successfully attempted, an attempt of integration of RSM and GRA for finding out optimal setting to obtain surface integrity on EDMed American Iron and Steel Institute (AISI) D2 tool steel are very rare. In addition, AISI D2 tool steel has been abundant in growing ranges of applications in manufacturing tools in mold industries. Moreover, the advancement of an automatic processing system that contains a technology repository will permit operators to ascertain in a simple way optimum processing conditions meeting different processing prerequisites. Therefore, the multiple objective optimization problems have been of increasing interest to the researchers to minimize this complexity. A trouble-free and trustworthy technique based on statistically designed experiments and RSM approach has been adopted with a face-center cube experimental design, as a special case of central composite designs *CCD*. Later, it synergies with GRA for optimizing the machining parameters in order to minimize the surface integrity to produce intricate precise components. Grey analysis delivers exceptional solution to uncertain, multi-input, and discrete data problems. As the EDM process is of similar nature, thus, the technique is extremely suitable in parameter optimization of such experimental work.

2 RSM-based experimentation

Experiments were independently conducted to acknowledge the significance of machining parameters, i.e., Ip, Ton, *Tau*, and *V* on WLT, Ra, and SCD of the AISI D2 tool steel work piece on die sinking electro discharge machine (make, Electronica Elektra plus PS 50 ZNC). An electrolytic pure copper with a diameter of 30 mm was used as a tool electrode (positive polarity), and the workpiece material used was steel square plates of dimensions 35 × 35 mm^2 and of a thickness of 4 mm. Commercial grade EDM oil (specific gravity = 0.763, freezing point = 94 °C) was used as dielectric fluid. Lateral flushing with a pressure of 0.4 kgf/cm^2 was used. The arrangement to conduct the experiments use a face-centered CCD with four variables, having a total of 30 runs in three blocks [28]. The different levels of a factor considered for this study are depicted in Table 1. Machining was carried out to remove nearly 1 mm from the top surface, and the different responses are measured and tabulated in Table 2.

Table 1 Input variables used in the experiment with their levels

Variable	Unit	Levels		
		1	2	3
Discharge current (Ip)	A	1	5	9
Pulse on time (Ton)	μs	50	75	100
Duty cycle (Tau)	%	80	85	90
Discharge voltage (*V*)	volt	40	50	60

Table 2 CCD and experimental results for four variables in uncoded units

Run order	Blocks	Ip A	Ton µs	Tau %	*V* volt	WLT µm	Ra µm	SCD µm/µm^2
1	1	9	100	90	40	39.21	8.03	0.0176
2	1	9	50	90	60	31.23	6.24	0.0162
3	1	1	100	90	60	25.68	2.15	0.0612
4	1	1	100	80	40	16.81	1.65	0.0547
5	1	5	75	85	50	26.00	5.41	0.0210
6	1	9	100	80	60	37.02	7.64	0.0177
7	1	9	50	80	40	19.43	6.11	0.0146
8	1	5	75	85	50	25.51	5.22	0.0218
9	1	1	50	80	60	9.43	2.11	0.0516
10	1	1	50	90	40	19.50	2.39	0.0468
11	2	9	50	90	40	32.85	6.01	0.0152
12	2	9	100	80	40	31.59	7.43	0.0173
13	2	1	50	90	60	18.89	2.45	0.0550
14	2	1	100	90	40	23.18	2.09	0.0578
15	2	9	100	90	60	46.60	7.58	0.0182
16	2	5	75	85	50	31.59	5.29	0.0212
17	2	9	50	80	60	25.64	5.83	0.0152
18	2	1	100	80	60	17.18	1.74	0.0625
19	2	5	75	85	50	27.65	5.36	0.0210
20	2	1	50	80	40	6.19	2.15	0.0482
21	3	5	75	85	40	30.07	5.57	0.0219
22	3	5	50	85	50	21.04	4.77	0.0188
23	3	5	100	85	50	29.60	5.81	0.0234
24	3	9	75	85	50	40.59	6.48	0.0165
25	3	5	75	80	50	27.30	5.54	0.0202
26	3	5	75	85	50	32.87	5.60	0.0218
27	3	1	75	85	50	22.87	1.98	0.0547
28	3	5	75	90	50	31.66	5.77	0.0201
29	3	5	75	85	60	27.49	5.52	0.0214
30	3	5	75	85	50	25.74	5.53	0.0210

3 Measurement of responses

3.1 White layer thickness

In order to measure the thickness of the white layer after EDM operations, the cross section of each specimen was cut off and polished on silicon carbide paper with grit sizes 120, 220, 320, 400, and 800, successively. Finally, the specimen was polished with diamond paste of 1-µm size. The surface was subsequently electropolished with slurry of Trinity diamond compound and HIFIN Fluid-"OS" type. This was necessary in order to expose the white layer structure and the boundary line. The micrograph of white layer was then seen under SEM (Model, Joel JSM-6480LV, Japan) with a magnification of ×500 for the analysis, as shown in Fig. 1. The area of white layer was measured on

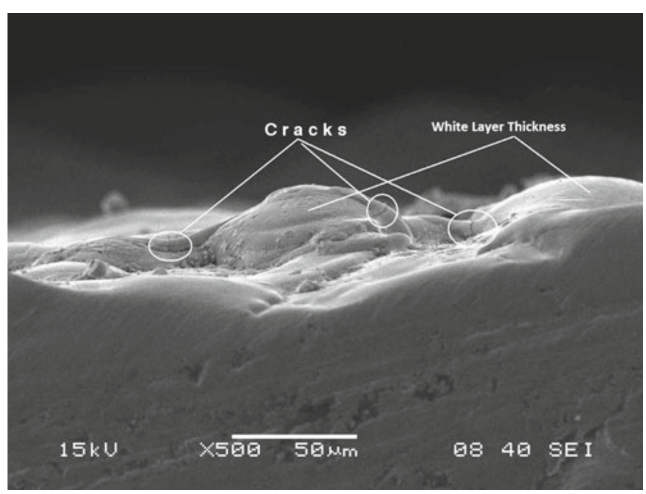


Fig. 1 SEM image of EDMed AISI D2 tool steel (transverse section)

each micrograph, and the mean deposition of white layer was obtained by dividing the measured area with the length of the micrograph, i.e., 258 μm.

3.2 Surface roughness

Surface roughness is another very significant response of interest when investigating EDM process since it influences the fatigue strength of the machined component. Roughness measurement was carried out using a portable Stylus-type Profilometer, Talysurf (Taylor Hobson, Surtronic 3+). The profilometer was set to a cutoff length of 0.8 mm, filter 2CR, traverse speed of 1 mm/s, and 4-mm evaluation length. Roughness measurements, in the transverse direction, on the workpieces were repeated four times, and the average of four measurements of Ra parameter values was recorded. The measured profile was digitized and processed through the dedicated surface finish analysis software Talyprofile and tabulated in Table 2. Surface roughness is a measure of the technological quality of a product, which mostly influence the manufacturing cost of the product. It is defined as the arithmetic value of the profile from the centerline along the length. This can be express as follows:

$$Ra = \frac{1}{L}\int_0^L |y(x)|dx \tag{1}$$

where L is the sampling length, y is the profile curve, and x is the profile direction. The average Ra is measured within $L = 0.8$ mm. Center-line average Ra measurements of electrodischarge machined surfaces were taken to provide quantitative evaluation of the effect of EDM parameters on surface finish.

3.3 Surface crack density

Surface crack is also one of the possible sources of failure of machined component. Since, it is difficult to quantify the cracks in terms of an approximation of the width, length, or depth of the crack or even by the amount of cracks, a term Surface Crack Density, is defined as the total length of cracks (μm) in a unit area (μm^2) to assess the severity of cracking [3]. In this study, the EDMed surfaces were viewed under the SEM at ×1,000 magnification (Fig. 2). The measurement of surface cracks was carried out by measuring the length of cracks on randomly selected six-sample micrographs on each specimen and subsequently dividing this total length of the cracks by the number of samples taken. The average crack lengths are then divided by the average area (12,400 μm^2) of the sample micrographs to obtain the SCD.

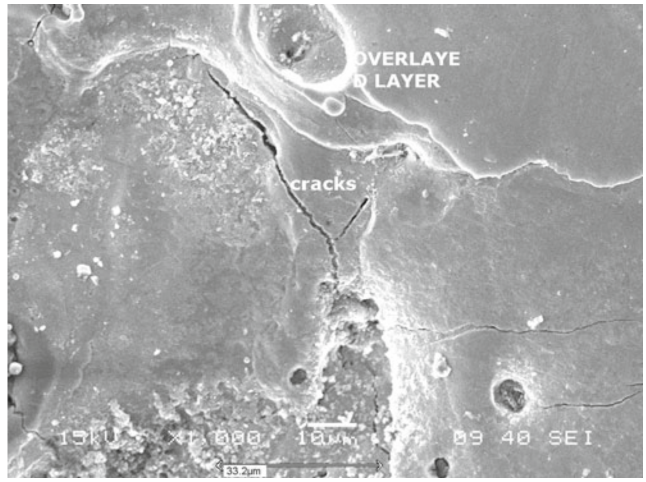


Fig. 2 SEM image of EDMed AISI D2 tool steel (top surface showing the cracks)

4 Grey relational analysis

GRA is a decision-making technique based on grey system theory originally developed by Deng [29]. In grey theory, black represents a system with deficient information, while a white system stands for complete information. However, the grey relation is the relation with incomplete information and is used to characterize the grade of association between two sequences so that the distance of two factors can be measured discretely. When experiments are unclear or if the experimental method cannot be carried out accurately, grey analysis assists to reimburse for the deficiency in statistical regression. Grey relation analysis is an effective means of analyzing the relationship between sequences with less data and can analyze many factors that can overcome the disadvantages of statistical method [30].

4.1 Data preprocessing

When the range of sequences is large or the standard value is large, the function of factors is neglected. However, if the factor measured unit, goals, and directions are different, the grey relational analysis might produce incorrect results. Therefore, original experimental data must be pre-processed to avoid such effects. The data pre-processing is the process of transforming the original sequence to a comparable sequence. For which, the experimental data are normalized in the range of 0 and 1—the process is called grey relational generating. There are three different kinds of data normalizations that are generally carried out, rendering whether the lower is better (*LB*), the higher is better (*HB*), or the nominal the better (NB). If the target value of original sequence is as small as possible, then it has a characteristic of "the lower, the better." The normalization is taken by the following equations. LB and the original sequence should be normalized as follows:

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

If the expectancy is the as-high-as-possible, then the original sequence should be normalized by the following equations for HB:

$$X_i^*(k) = \frac{X_i(k) - \min X_i(k)}{\max X_i(k) - \min X_i(k)}. \tag{3}$$

Conversely, if there is a specific target value to be achieved, then the original sequence will be normalized by the following equation of NB:

$$X_i^*(k) = 1 - \frac{|X_i(k) - X_{ob}(k)|}{\max X_i(k) - X_{\mathrm{ob}}(k)} \tag{4}$$

where $i = 1, \ldots n$; $k = 1, 2, \ldots, p$; $X_i^*(k)$ is normalized value of the kth element in the ith sequence, $X_{\mathrm{ob}}(k)$ is desired value of the kth quality characteristic, max $X_i^*(k)$ is the largest value of $X_i(k)$, and min $X_i^*(k)$ is the smallest value of $X_i(k)$, n is the number of experiments, and p is the number of quality characteristics.

4.2 Grey relational coefficient and grey relational grade

A grey relational coefficient is calculated to display the relationship between the optimal and actual normalized experimental results. The grey relational coefficient can be expressed as

$$\zeta_i^*(k) = \frac{\Delta \min + \zeta \Delta \max}{\Delta_{0,i}(k) + \zeta \Delta \max} \tag{5}$$

where $\Delta_{0,i}(k) = |X_0(k) - X_i(k)|$ is the difference of the absolute value $X_0(k) - X_i(k)$; and ζ is the distinguishing coefficient or identification coefficient. In general, it is set to 0.5. Δ min is the smallest value and Δ max is the largest value of $\Delta_{0,i}$, respectively.

Finally, the grey relational grade $0 \leq \zeta \leq 1$ was obtained by calculating the average values of all the grey relational coefficients. The grey relational grade γ_i can be compounded as

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

where n is the number of process responses. The higher value of GRG corresponds to the intense relational degree between the reference sequence $X_0(k)$ and the given sequence $x_i(k)$. The reference sequence $X_0(k)$ represents the best process sequence; therefore, higher GRG means that the corresponding parameter combination is closer to the optimal. The mean response for the GRG with its grand mean and the main effect plot of GRGs are very important because optimal process condition can be evaluated from this plot. With the values above, the influential degree of the factors on the system could be identified.

4.3 Analysis and discussion of experimental results

In this work, the effect of different processing parameters on surface integrity such as WLT, SCD, and Ra of the EDMed component has been investigated. Table 2 lists experimental results obtained by the various parametric conditions. Usually, a lower value of the surface integrity is desirable; therefore, the data sequences have a the-lower-the-better characteristic. In normalized experimental results for each performance characteristic, the original sequence in the experiment must be normalized in the range of 0–1 due to different measurement units; this data preprocessing step is termed as "grey relational generating." For this purpose, the WLT, SCD, and Ra "the-lower-the-better" characteristics

Table 3 Normalized values for WLT, Ra, and SCD

Run order	WLT	Ra	SCD
1	0.183	0.000	0.937
2	0.380	0.281	0.967
3	0.518	0.925	0.027
4	0.737	1.003	0.163
5	0.510	0.412	0.866
6	0.237	0.061	0.935
7	0.672	0.302	1.000
8	0.522	0.442	0.850
9	0.920	0.931	0.228
10	0.671	0.887	0.328
11	0.340	0.318	0.987
12	0.371	0.094	0.944
13	0.686	0.877	0.157
14	0.580	0.934	0.098
15	0.000	0.071	0.925
16	0.371	0.431	0.862
17	0.519	0.346	0.987
18	0.728	0.989	0.000
19	0.469	0.420	0.866
20	1.000	0.925	0.299
21	0.409	0.387	0.848
22	0.633	0.513	0.912
23	0.421	0.349	0.816
24	0.149	0.244	0.960
25	0.478	0.392	0.883
26	0.340	0.382	0.850
27	0.587	0.951	0.163
28	0.370	0.355	0.885
29	0.473	0.395	0.858
30	0.516	0.393	0.866

have been adopted. Table 3 lists normalized experimental results for these responses using Eq. 4. Also, the deviation sequences Δ_{0i} in the range are calculated as follows:

$$\Delta_{0,1}(k) = |x_0(1) - x_1(1)| = |1.00 - 0.187| = 0.817$$
$$\Delta_{0,2}(k) = |x_0(2) - x_2(2)| = |1.00 - 0.000| = 1.000$$
$$\Delta_{0,3}(k) = |x_0(3) - x_3(3)| = |1.00 - 0.937| = 0.063$$

So $\Delta_{0,1} = (0.817 \quad 1.00 \quad 0.063)$ and the result of all Δ_{0i} are presented in Table 4. The deviation sequence Δ_{max} and Δ_{min} are derived and given as follows:

$$\Delta_{max} = \Delta_{15}(1) = \Delta_1(2) = \Delta_{18}(3) = 1.00$$
$$\Delta_{min} = \Delta_{20}(1) = \Delta_4(2) = \Delta_7(3) = 0.00$$

The grey relational coefficients, given in Table 5, for each response have been accumulated by using Eq. 6 to evaluate GRG, which is the overall representative of all the features of the surface integrity. The GRG is the mean of three grey

Table 4 Deviation sequences for WLT, Ra, and SCD

Run order	WLT	Ra	SCD
1	0.817	1.000	0.063
2	0.620	0.719	0.033
3	0.482	0.078	0.973
4	0.263	0.000	0.837
5	0.490	0.589	0.134
6	0.763	0.939	0.065
7	0.328	0.699	0.000
8	0.478	0.560	0.150
9	0.080	0.072	0.772
10	0.329	0.116	0.672
11	0.660	0.683	0.013
12	0.629	0.906	0.056
13	0.314	0.125	0.843
14	0.420	0.069	0.902
15	1.000	0.929	0.075
16	0.629	0.571	0.138
17	0.481	0.655	0.013
18	0.272	0.014	1.000
19	0.531	0.582	0.134
20	0.000	0.078	0.701
21	0.591	0.614	0.152
22	0.367	0.489	0.088
23	0.579	0.652	0.184
24	0.851	0.757	0.040
25	0.522	0.610	0.117
26	0.660	0.619	0.150
27	0.413	0.052	0.837
28	0.630	0.646	0.115
29	0.527	0.607	0.142
30	0.484	0.608	0.134

Table 5 Grey relational coefficient, grey relational grade, and rank

Run order	Grey relational coefficient			Grey relational grade	Rank
	WLT	Ra	SCD		
1	0.380	0.333	0.889	0.534	29
2	0.447	0.410	0.937	0.598	11
3	0.509	0.864	0.339	0.571	20
4	0.655	1.000	0.374	0.676	3
5	0.505	0.459	0.789	0.584	14
6	0.396	0.347	0.885	0.543	27
7	0.604	0.417	1.000	0.674	4
8	0.511	0.472	0.769	0.584	15
9	0.862	0.874	0.393	0.710	2
10	0.603	0.812	0.427	0.614	8
11	0.431	0.423	0.976	0.610	9
12	0.443	0.356	0.899	0.566	21
13	0.614	0.799	0.372	0.595	12
14	0.543	0.879	0.357	0.593	13
15	0.333	0.350	0.869	0.517	30
16	0.443	0.467	0.784	0.565	23
17	0.510	0.433	0.976	0.639	7
18	0.648	0.973	0.333	0.651	5
19	0.485	0.462	0.789	0.579	18
20	1.000	0.864	0.416	0.760	1
21	0.458	0.449	0.766	0.558	25
22	0.576	0.506	0.851	0.644	6
23	0.463	0.434	0.731	0.543	28
24	0.370	0.398	0.926	0.565	22
25	0.489	0.451	0.810	0.583	16
26	0.431	0.447	0.769	0.549	26
27	0.548	0.906	0.374	0.609	10
28	0.442	0.436	0.813	0.564	24
29	0.487	0.452	0.779	0.573	19
30	0.508	0.451	0.789	0.583	17

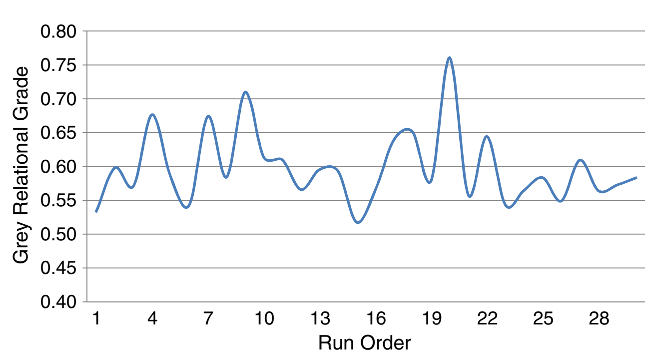


Fig. 3 Response graph for grey relational grade

Table 6 Estimated regression coefficients for GRG (before elimination)

Term	Coef	SE coef	t	p
Constant	0.574807	0.006428	89.428	0.000
Block1	0.003317	0.004781	0.694	0.500[a]
Block2	0.002093	0.004781	0.438	0.669[a]
Ip	−0.029668	0.004014	−7.391	0.000
Ton	−0.036069	0.004014	−8.985	0.000
Tau	−0.033703	0.004014	−8.395	0.000
V	−0.010387	0.004014	−2.587	0.023
Ip × Ip	0.016757	0.010690	1.568	0.141[a]
Ton × Ton	0.023267	0.010690	2.177	0.049
Tau × Tau	0.003401	0.010690	0.318	0.755[a]
$V \times V$	−0.005133	0.010690	−0.480	0.639[a]
Ip × Ton	−0.010842	0.004258	−2.546	0.024
Ip × Tau	0.016374	0.004258	3.846	0.002
Ip × V	0.001930	0.004258	0.453	0.658[a]
Ton × Tau	0.009062	0.004258	2.128	0.053[a]
Ton × V	0.001802	0.004258	0.423	0.679[a]
Tau × V	0.004042	0.004258	0.949	0.360[a]
$R^2 = 95.6\ \%$			$R^2_{(adj)} = 90.2\ \%$	

T value was obtained from the t-test, which indicates the significance of the regression coefficients

[a]Nonsignificant

relational coefficients obtained using Eq. 6. Experiment number 20 generated the highest GRG. Thus, the multi-criteria optimization problem has been transformed into a single equivalent objective function optimization problem using the combination of RSM and GRA. Higher is the value of GRG; the corresponding factor combination is said to be close to the optimal. The GRGs were analyzed in the main effect analysis, and then the optimization processing parameters of multiple quality characteristics were obtained from the response table and response graph for grey relational analysis, as shown in Table 5 and Fig. 3, respectively. Therefore, the optimal combination of processing parameters for surface integrity was obtained when they are at their minimal setting.

5 Results and discussion

Statistical analysis was carried out on the experimental data obtained through face-centered central composite design using statistical software MINITAB 14. This section, therefore, discusses the results of RSM analysis of experimental analysis in detail.

5.1 Modeling of responses and statistical analysis

The responses obtained from the aforesaid experimental conditions are given in Table 2, and the regression coefficient values, standard deviations, t-values, and probability (p) values are given in Table 6. Regression analysis is performed to find out the relationship between the input factors

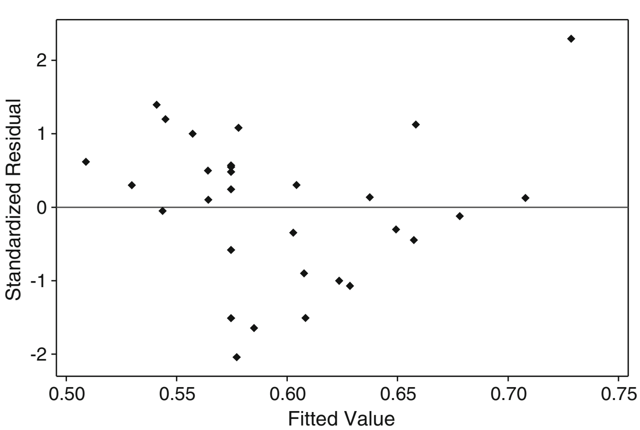


Fig. 4 Plot of standardized residuals vs. fitted grey relational grade value

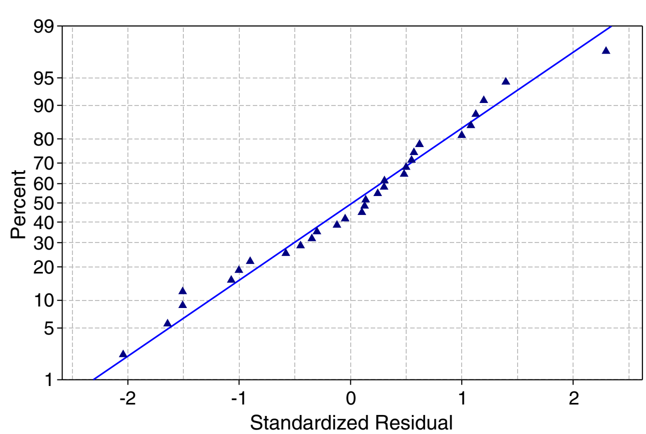


Fig. 5 Normal probability plot of standardized residuals

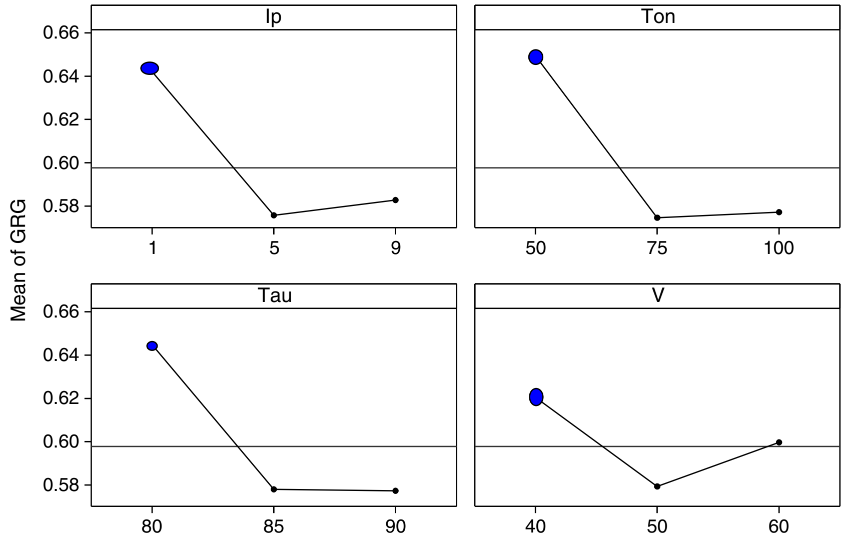


Fig. 6 Influence of process parameters on grey relational grade

and the responses. ANOVA is used to check the sufficiency of the second-order model, which includes test for significance to the regression model, model coefficients, and test for lack of fit. To test the adequacy of the model, ANOVA is used for testing the null hypothesis (H_0) of the experimental data at a confidence level of 95 %. The p value for the F-statistic is expressing the probability of observing a value of F at least as large, if H_0 is true, then treatments have no effect. If the p value ≤ 0.05, it is concluded that H_α is true, and the treatments have a statistically significant effect. Responses obtained from the experiments are compared with the predicted value calculated from the model.

Table 6 is the ANOVA summary that depicts the terms in the model, corresponding coefficients (Coef.), t-statistic and p value to decide whether to reject or fail to reject the null hypothesis. The terms marked "^{a}" in the table, are exceeding the α value. Thus, these terms are eliminated for the further analysis. The blocking does not have any significant effect on the response, which reveals that the uncontrollable factors of the experiment conducted were held constant. The backward elimination process discards the insignificant terms (p value greater than 0.05) to adjust the fitted quadratic model. The model, with the rest of the terms are eliminated and presented in Eq. 7. After the ANOVA of the model, it can be observed in this table that the p value of the regression model is less than 0.05; hence, the responses' fitting the regression model with the linear, square, and interaction terms are significant at the level of 95 % after elimination. It also displays that the test of lack of fit is insignificant with the associated p value of 0.289, which is greater than 0.05, as desired for the model adequacy. This way, the simplified truncated model having the highest value of R^2 is 0.918, indicating a high significance of the model because of the value of F-statistic. The truncated model has lower R^2 than that of the full quadratic model (96.6 %), and R^2_{adj} value is 89.2 %, exhibiting significance of relationship between the response and the variables and the terms of the adequate model after the elimination are Ip, Ton, Tau, V, Ton^2, Ip$\times$Ton, and Ip$\times$Tau. Nevertheless, the p value of the regression model is 0.000, therefore the model is statistically significant at 95 % confidence and consequently, the model adequately represents the experimental data.

$$\begin{aligned} \text{GRG} = {} & 1.9997 - 0.0689\, Ip - 0.0102\, Ton \\ & - 0.0108\, Tau - 0.0010\, V + 0.0001\, Ton^2 \\ & - 0.0001\, Ip \times Ton + 0.0008\, Ip \times Tau \end{aligned} \tag{7}$$

In the Fig. 4, plotted between the standardized residuals, and the fitted value a random distribution was observed for the residual plots for the models, indicating that the residual

Table 7 ANOVA analysis

Source	DF	Seq SS	Adj MS	F	p
Regression	7	0.078562	0.011223	35.31	0.000[a]
Residual error	22	0.006992	0.000318		
Lack-of-Fit	17	0.005966	0.000351	1.71	0.289[b]
Total	29	0.085554			

$R^2 = 0.918$
[a]Indicates highly significant
[b]Indicates insignificant

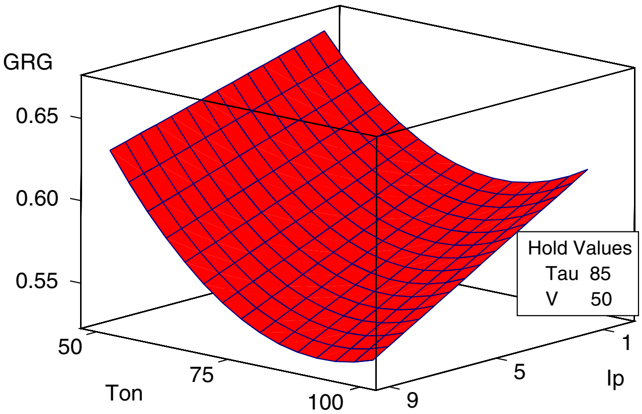


Fig. 7 Surface plot of Ip and Ton for grey relational grade

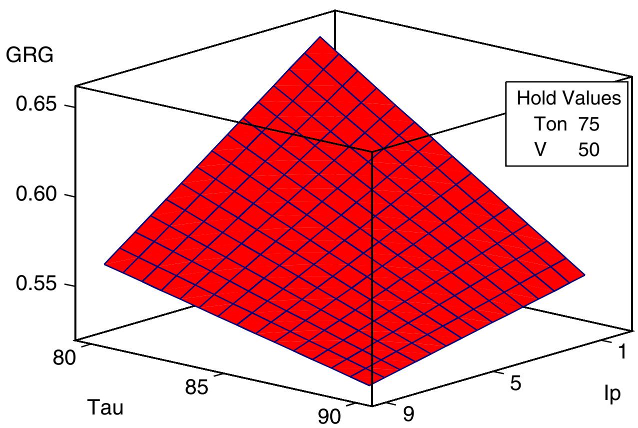
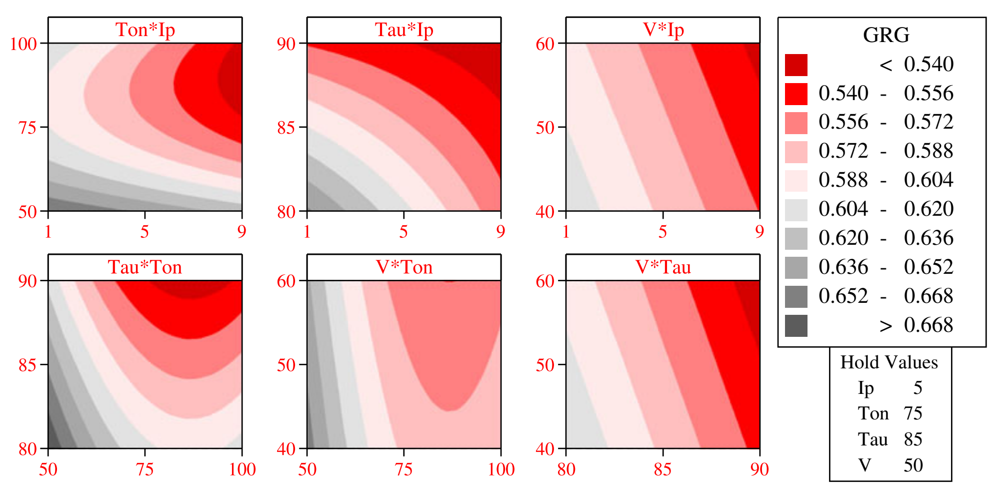


Fig. 8 Surface plot of Ip and Tau for grey relational grade

distribution of the regression equation follows normal and independent patterns [31]. This suggests the high adequacy of the quadratic models for evaluating the surface integrity. The normal probability plot is presented in Fig. 5, it can be seen that the points lie close to the straight line, indicating that the data follow a normal distribution, except one outlier. Figure 6 depicts the plots of the main effects on surface integrity and can be used to graphically assess the effects of the factors on the response. It indicates that Ip, Ton, and Tau have significant effect on surface integrity, which is supported by the results in Table 7.

The GRG graph showing the different factors at different level contributing to the mean grey relational grade is shown in Fig. 3. The higher the value of the GRG, the better is the multiple characteristics. It can be clearly seen that all the parameters at their lower level produce higher GRG. With GRG as the response, the surface plot of the quadratic model with other two significant variables kept at their central levels and the other two varying within the experimental ranges are, respectively, shown in Figs. 7 and 8. Figure 7 represents response surface for GRG in relation to the machining parameters of Ip and Ton, and Fig. 8 represents response surface for GRG in relation to the machining parameters of Ip and Tau, respectively. It can be seen that the highest GRG and thereby low surface integrity can be achieved when the parameters Ip, Ton, and Tau are kept at their minimum level. The contour plots of the quadratic model with two variables kept at their central levels and the other two varying within the experimental ranges are, respectively, shown in Fig. 9. Figure 9a represents the contour plot for surface integrity in relation to the machining parameters of Ip and Ton. The surface integrity decreases significantly with the decrease of Ip. Ton also has similar impact on surface integrity. As a result, therefore, the minimum surface integrity can be seen when Ip and Ton at their low level. Similar counter plots were also observed in Fig. 9b–f. The corresponding two-dimensional contours show a considerable curvature, implying that these

Fig. 9 Two-dimensional contour plots for grey relational grade: effect of **a** Ip and Ton, **b** Ip and Tau, **c** Ip and *V*, **d** Ton and Tau, **e** Ton and *V* and **f** Tau and *V*



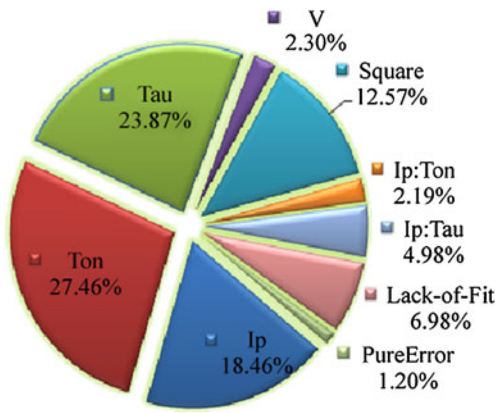


Fig. 10 Percentage contributions of factors on the grey relational grade

three factors were interdependent. In other words, there were significant interactive effects on surface integrity.

ANOVA is used to get the percentage of contribution of different input variables and their interactions that produces the optimal response. The percentage of contribution is computed as the ratio of total sum of squared deviation and the individual sum of square of each parameter and their interactions that are significant [12, 32]. Percentage contribution of each factor and their interactions on the grey relational grade has been depicted in Fig. 10 with the EDM parameter levels on the GRG. From the figure of the GRG for various levels (Table 5), significance of each parameter can be visually understood. The Ip contributes to 18.46 %, Ton contributes to 27.46 %, and Tau contributes 23.87 % of variation of GRG in the range of experiment conducted. Further, discharge voltage contributes very little to the GRG with 2.30 %, along with integration Ip × Ton and Ip × Tau with 2.19 and 4.98, respectively. The squire terms contribute to 12.57 %. Finally, the residual error contribution is 8.17 % split into two divisions' lack of fit and pure error with a contribution of 6.98 and 1.2 %, respectively.

6 Conclusion

In this investigation using response surface methodology coupled with grey relational analysis to optimize the machining parameters having a significant effect upon the surface integrity (WLT, SCD, and Ra) of EDMed surfaces are recognized and mathematical model is developed. It was found that the pulse duration was the most dominant factor for surface integrity followed by duty factor, pulse current, and discharge voltage. The optimal operational conditions established by grey analysis approach are as follows: a pulse current 1 A, pulse duration 50 μs, duty cycle = 80 % and discharge voltage 40 V. By applying these process parameter values, minimum output responses such as white layer thickness, surface roughness, and surface crack density have been predicted. This may provide the experimenter and practitioner an effectual guideline to pick optimum parameter settings for attaining desired WLT, SCD, and Ra during EDM die sinking of AISI D2 tool steel.

Acknowledgements The author is extremely thankful to his guide Dr. C. K. Biswas and the anonymous reviewers for their valuable comments and suggestions, which contributed significantly to improve the quality of the paper.

References

1. Kozak J, Rajurkar K (2001) Hybrid machining processes, evaluation and development. In: Proceedings of 2nd international conference on machining and measurement of sculptured surfaces, vol 1, pp 501–536
2. Abu-Zeid O (1996) The role of voltage pulse off-time in the electrodischarge machined AISI T1 high-speed steel. J Mater Process Technol 61(3):287–291
3. Lee HT, Tai TY (2003) Relationship between EDM parameters and surface crack formation. J Mater Process Technol 142:676–683
4. Ramasawmy H, Blunt L, Rajurkar K (2005) Investigation of the relationship between the white layer thickness and 3D surface texture parameters in the die sinking EDM process. Precis Eng 29(4):479–490
5. Lee LC, Lim LC, Narayanan V, Venkatesh VC (1988) Quantification of surface damage of tool steels after EDM. Int J Mach Tools Manuf 28(44):359–372
6. Lee HT, Hsu FC, Tai TY (2004) Study of surface integrity using the small area EDM process with a copper-tungsten electrode. Mater Sci Eng 364:346–356
7. Tai T, Lu S (2009) Improving the fatigue life of electro-discharge-machined SDK11 tool steel via the suppression of surface cracks. Int J Fatigue 31(3):433–438
8. Pradhan MK (2010) Experimental investigation and modelling of surface integrity, accuracy and productivity aspect in EDM of AISI D2 steel. PhD thesis, National Institute of Technology, Rourkela
9. Niwa S, Furuya M (1995) A study on optimum machining conditions in EDM process for making mould and dies. ISEM XI:325–332
10. El-Taweel T (2008) Multi-response optimization of EDM with Al–Cu–Si–TiC P/M composite electrode. Int J Adv Manuf Technol 44(1–2):100–113
11. Liao Y, Chen Y (2001) A computer-aided process planning system for the finishing operations of EDM. ISEM XIII:171–185
12. Pradhan MK, Biswas CK (2011) Multi-response optimisation of EDM AISI D2 tool steel using response surface methodology. IJMMM 9:66–85
13. Bhattacharyya B, Gangopadhyay S, Sarkar BR (2007) Modelling and analysis of EDMed job surface integrity. J Mater Process Technol 189:169–177
14. Lin C, Lin J, Ko T (2002) Optimisation of the EDM process based on the orthogonal array with fuzzy logic and grey relational analysis method. Int J Adv Manuf Technol 19(4):271–277
15. Pradhan MK, Biswas CK (2011) Investigation in to the effect of process parameters on surface roughness in EDM of AISI D2 steel by response surface methodology. Int J Precis Technol 2:64–80
16. Lin J, Lin C (2002) The use of the orthogonal array with grey relational analysis to optimize the electrical discharge machining process with multiple performance characteristics. Int J Mach Tools Manuf 42:237–244

17. Singh S, Maheshwari S, Pandey P (2004) Some investigations into the electric-discharge machining of hardened tool steel using different electrode materials. J Mater Process Technol 149(1–3):272–277
18. Yildiz AR (2008) Optimal structural design of vehicle components using topology design and optimization. Mater Test 50(4):224–228
19. Yildiz AR, Saitou K (2011) Topology synthesis of multicomponent structural assemblies in continuum domains. J Mech Des 133(1):011008
20. Yildiz AR (2009) A novel hybrid immune algorithm for global optimization in design and manufacturing. Robot Comput-Integr Manuf 25(2):261–270
21. Yildiz AR (2009) A new design optimization framework based on immune algorithm and Taguchi's method. Comput Ind 60(8):613–620
22. Yildiz AR (2009) A novel particle swarm optimization approach for product design and manufacturing. Int J Adv Manuf Technol 40(5–6):617–628
23. Yildiz AR, Ozturk N, Kaya N, Ozturk F (2006) Integrated optimal topology design and shape optimization using neural networks. Struct Multidisc Optim 25(4):251–260
24. Yildiz AR (2009) An effective hybrid immune-hill climbing optimization approach for solving design and manufacturing optimization problems in industry. J Mater Process Technol 50(4):224–228
25. Yildiz AR (2009) Hybrid immune-simulated annealing algorithm for optimal design and manufacturing. Int J Mater Prod Technol 34(3):217–226
26. Yildiz AR, Ozturk N, Kaya N, Ozturk F (2007) Hybrid multi-objective shape design optimization using Taguchi's method and genetic algorithm. Struct Multidisc Optim 34(7):277–365
27. Yildiz AR, Kaya N, Alankus O, Ozturk F (2004) Optimal design of vehicle components using topology design and optimization. Int J Veh Des 34(4):387–398
28. Minitab14 (2003) Minitab user manual release 14. State College, PA, USA
29. Deng JL (1989) Introduction to grey system theory. J Grey Syst 1:1–24
30. Chang C, Tsai C, Chen L (2003) Applying grey relational analysis to the decathlon evaluation model. Int J Comput Internet Manage 11(3):54–62
31. Hwang S, Lee Y, Yang K (2001) Maximization of acetic acid production in partial acidogenesis of swine wastewater. Biotechnol Bioeng 75(5):521–529
32. Krishnamoorthy A, Boopathy SR, Palanikumar K, Davim JP (2012) Application of grey fuzzy logic for the optimization of drilling parameters for CFRP composites with multiple performance characteristics. Measurement 45(5):1286–1296