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PARAMETRIC OPTIMIZATION OF NON-TRADITIONAL MACHINING PROCESSES USING TAGUCHI METHOD AND SUPER RANKING CONCEPT

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Abstract: In order to achieve higher dimensional accuracy along with better surface quality, the conventional machining processes have now-a-days being replaced by non-traditional machining (NTM) processes, because of their ability to generate intricate shape geometries on various advanced engineering materials. In order to exploit their fullest machining potential, it is often recommended to operate those NTM processes at their optimal parametric settings. Several optimization tools and techniques are now available which can be effectively applied to obtain the optimal parametric conditions of those processes. In this paper, Taguchi method and super ranking concept are integrated together to present an efficient optimization technique for simultaneous optimization of three NTM processes, i.e. electro-discharge machining process, wire electro-discharge machining process and electro-chemical discharge drilling process. The derived results are validated with the help of developed regression equations, which show that the proposed approach outperforms the other popular multi-response optimization techniques. Analysis of variance is also performed to identify the most influencing control parameters for the considered NTM processes. The developed response surface plots further help the process engineers in identifying the effects of various NTM process parameters on the calculated sum of squared rank values.

Keywords: Taguchi Method, Super Ranking Concept, Non-Traditional Machining Process, Optimization; Process Parameter, Response.

MSC: 90C29, 90C31.

1. INTRODUCTION

In conventional machining processes, material is removed in the form of chips while applying cutting forces on the workpiece with the help of a wedge-shaped tool. These machining processes have many disadvantages, like incapability of machining harder and tougher materials, unwanted distortion of the work material, higher energy requirement, formation of burrs, excessive tool wear, and inability to generate complex shape geometries and achieve higher dimensional accuracy with lower surface roughness. To overcome these problems, the conventional machining processes have gradually being replaced by the non-traditional machining (NTM) processes. These NTM processes use energy in the form of mechanical, thermal, electrical, chemical or a combination of them to remove material from the workpiece. Unlike the conventional machining processes, in these NTM processes, there may be even no contact between the tool and the workpiece or the tool needs not to be harder than the workpiece material.

In these processes, material is removed from the workpiece even without formation of any chip. Like in electro-discharge machining (EDM) process, material is removed from the workpiece by a series of rapidly recurring current discharges between the two electrodes, separated by a dielectric medium, or in electrochemical machining (ECM) process, material is eroded from the workpiece due to electrochemical dissolution at atomic level. These processes are now being extensively used in machining of various difficult-to-machine and high-strength-temperature-resistant materials, like stainless steel, ceramics, nimonics, tungsten carbide, metal matrix composites etc., which have found wide application in automobile, aerospace, nuclear plant, wafer fabrication, and tool and die making industries [10, 18].

In order to explore the fullest machining potential from these NTM processes, careful selection of their various input (control) parameters is needed redundant to achieve the desired values of the corresponding responses (outputs). Selection of these NTM process parameters mainly depends on the technical knowledge and experience of the operators. Often the manufacturers' booklets are referred to for identifying the most appropriate combination of NTM process parameters for a specific work material and shape feature combination. But, it is often noticed that the parametric combination provided by the manufacturers does not meet the requirements of the operators/process engineers. For a particular NTM process, the best parametric combination may not be derived from the given information booklet and even sometimes, this may be far from the optimal combination, redundant constraining the NTM process to perform machining at its fullest capability. Thus, selection of the optimal combination of NTM process parameters is often judged to be a challenging task with the increasing number of the considered process parameters and responses. Various optimization tools, like Taguchi methodology, grey relational analysis (GRA), technique for order of preference by similarity to ideal solution (TOPSIS), principal component analysis (PCA), desirability function approach etc., are already available and can be effectively deployed to overcome this problem.

2. LITERATURE REVIEW

Optimization of various NTM process parameters while employing different mathematical approaches has been the topic of immense research interest since the last few years. While considering pulse-on time, wire tension, delay time, wire feed speed and ignition current intensity as the controllable process parameters, and material removal rate (MRR), surface roughness (Ra) and wire wear ratio (WWR) as the responses, Ramakrishnan and Karunamoorthy [21] applied Taguchi methodology as an optimization tool for determining the optimal parametric mix for a wire electro-discharge machining (WEDM) process. Rao and Yadava [22] proposed a hybrid approach combining Taguchi method with GRA technique for optimization of Nd:YAG laser cutting process parameters in order to minimize kerf width, kerf taper and kerf deviation. While selecting current, pulse-on time and pulse-off time as the control parameters in an EDM process, Nayak and Routara [16] applied GRA technique to optimize the values of three responses, i.e. MRR, electrode wear rate (EWR) and Ra. Senthil et al. [26] considered discharge current, pulse-on time and pulse-off time as the control parameters of an EDM process, and applied TOPSIS method for optimization of three responses, i.e. MRR, tool wear rate (TWR) and Ra. Khanna et al. [12] presented the application of Taguchi method along with GRA technique in an electro-discharge drilling process while considering pulse-on time, pulse-off time and flushing pressure as the important input parameters in order to maximize MRR and minimize TWR in drilling of aluminium Al-7075 alloy.

Reddy et al. [24] investigated the performance of an EDM process while machining PH17-4 stainless steel material using graphite powder-mixed and surfactant-mixed dielectric fluids. An integrated Taguchi-data envelopment analysis-based multi-response optimization technique was applied while choosing peak current, surfactant concentration and graphite powder concentration as the three important process parameters, and MRR, Ra and TWR as the responses. Considering pulse-on time, pulse-off time, pulse current and wire drum speed as the input parameters, Lal et al. [13] adopted Taguchi method-based GRA technique to improve two quality characteristics, i.e. Ra and kerf width in a WEDM process. Bose [5] presented the application of Taguchi methodology aided with fuzzy logic as a multi-criteria decision making (MCDM) tool to obtain the optimal parametric combination of an electrochemical grinding process. Rao and Padmanabhan [23] optimized the input parameters of an ECM process while integrating Taguchi method with utility concept. Applied voltage, electrolyte concentration, electrode feed rate and percentage of reinforcement were considered as the important process parameters, and MRR, Ra and radial overcut were the responses.

Marichamy et al. [15] fabricated a duplex (-) brass plate and investigated its machinability behavior during EDM operation. While taking current, pulse-on time and voltage into consideration as the process parameters, Taguchi method was later employed to improve MRR, EWR and Ra during the machining operation. Ekici et al. [9] studied the effects of wire tension, reinforcement percentage, wire speed, pulse-on time and pulse-off time on Ra and MRR during WED cutting operation of high-density Al/B4C metal matrix composites. Taguchi method was subsequently applied so as to obtain the optimal combination of the considered process parameters. Long et at. [14] applied Taguchi method for maximizing MRR in a powder-mixed EDM process while taking titanium powder-mixed HD-1 as the dielectric fluid. Workpiece material, electrode material, electrode polarity, pulse-on time, current, pulse-off time and powder concentration were the process parameters. Considering machining time, temperature and concentration as the input parameters in a photochemical machining process, Bhasme and Kadam [3] applied GRA technique to optimize MRR, Ra and undercut.

Bhuyan and Routara [4] selected pulse-on time, peak current and flushing pressure as the three important EDM process parameters, and applied VIKOR (Vlse Kriterijumska Optimizacija Kompromisno Resenje) aided with entropy method to optimize four responses, i.e. MRR, TWR, radial overcut and Ra. While selecting compact load, current and pulse-on time as the three process parameters, Rahang and Patowari [19] applied Taguchi method to optimize the performance measures, such as TWR, MRR, Ra and edge deviation of an EDM process.Dhuria et al. [8] proposed the application of a hybrid Taguchi-entropy weight-based GRA method to optimize MRR and TWR in an ultrasonic machining (USM) process while considering slurry type, tool type, power rating, grit size, tool treatment and workpiece treatment as some of the significant input parameters. Antil et al. [1] selected voltage, electrolyte concentration, inter-electrode gap and duty factor as the control parameters in electrochemical discharge drilling of SiC reinforced polymer matrix composite, and later applied Taguchi method along with GRA technique to derive the optimal parametric mix.

Huang et al. [11] considered pulse duration, pulse-off time, discharge current and working period as the process parameters in a micro-EDM milling process, and adopted grey-based Taguchi method to optimize three responses, i.e. EWR, MRR and overcut. Sonawane and Kulkarni [29] integrated PCA technique with Taguchi method to optimize a WEDM process. Pulse-on time, servo voltage, pulse-off time, peak current, wire feed rate and cable tension were considered as the process parameters, and Ra, overcut and MRR were the responses. Chakraborty et al. [6] adopted GRA technique along with fuzzy logic approach to solve three multi-objective optimization problems for determining the optimal parametric settings of abrasive water-jet machining, ECM and USM processes. Also, Chakraborty et al. [7] introduced a multivariate quality loss function approach in parametric optimization of three NTM process and showed that the proposed approach outperforms other multi-response optimization techniques, like desirability function, distance function and mean squared error methods. Considering pulse discharge-on time, pulse discharge-off time, wire feed rate and material characteristics of varying boron nitride volume fractions as the input parameters, Thankachan et al. [32] integrated Taguchi method with GRA technique to solve a multi-objective optimization problem for a WEDM process while optimizing two responses, i.e. MRR and Ra. Taking dielectric fluid, pulse-on time, discharge current, duty cycle, gap voltage, tool electrode material and tool electrode lift time as the important parameters of an EDM process, Payal et al. [17] applied Taguchi-fuzzy logic approach to obtain the optimal parametric combination in order to increase MRR and decrease Ra. Shrivastava and Pandey [28] adopted Taguchi-based regression analysis and particle swarm optimization technique in a laser cutting process of Inconel-718 sheet. Gas pressure, stand-off distance, cutting speed and laser power were considered as the input parameters while optimizing three responses, i.e. bottom kerf deviation, bottom kerf width and kerf taper as the responses.

From the extensive review of the above-cited literature, it can be fully justified that parametric optimization of various NTM processes is very much essential, and it has been the research interest of many researchers. It can also be noticed that various optimization tools, like Taguchi method, TOPSIS, GRA, PCA, VIKOR etc. have already been extensively deployed in solving a wide range of problems related to parametric optimization of numerous NTM processes. But, the application of these optimization techniques is found to be often conservative leading to near or sub-optimal solutions. Thus, this paper presents a simple methodology integrating Taguchi method and super ranking concept in solving multi-response optimization problems for three NTM processes. The distinct feature of this combined approach is to transform each response into a single rank variable by subsequent addition of the squared ranks for each of the responses resulting in a single master rank, also referred to as the super rank response, thus changing all independent values into a single non-dimensional value.

3. TAGUCHI METHOD AND SUPER RANKING CONCEPT

Taguchi method, developed by Genichi Taguchi [30, 31], is a very effective tool that deals with responses influenced by multiple variables. Besseris [2] later proposed a simple and easy approach of Taguchi methodology to solve difficult multi-response optimization problems without considering the theoretical base of the data. The application of Taguchi method and super ranking concept starts with identification of the control (process parameters) and noise factors (responses) along with their working ranges. An appropriate orthogonal array is then selected which requires minimum effort while considering all the control and noise factors, and executes the trial runs accordingly. The recorded responses are transformed into the corresponding signal-to-noise (S/N) ratios based on three generic classes, i.e. larger-the-better (LTB), smaller-the-better (STB) and nominal-the-best (NTB). The following equations are usually employed for this transformation depending on the type of the considered quality characteristic, i.e. Eq. (1) for LTB, where higher values are preferred; Eq. (2) for STB, where lower values are desired; and Eq. (3) for NTB, where target values are desired.

$$\mathrm{S/N} = -10log_{10}\left[\frac{1}{n}\sum\frac{1}{x_i(k)^2}\right] \tag{1}$$

$$\text{S/N} = -10log_{10}\left[\frac{1}{n}\sum x_i(k)^2\right] \tag{2}$$

$$\text{S/N} = 10log_{10}\frac{\mu^2}{\sigma^2} \tag{3}$$

where $x_i(k)$ is the observed data (response) for i^{th} alternative (experimental run) and k^{th} criterion, n is the total number of responses, and μ and σ are the mean and standard deviation of the responses for a given criterion, respectively.

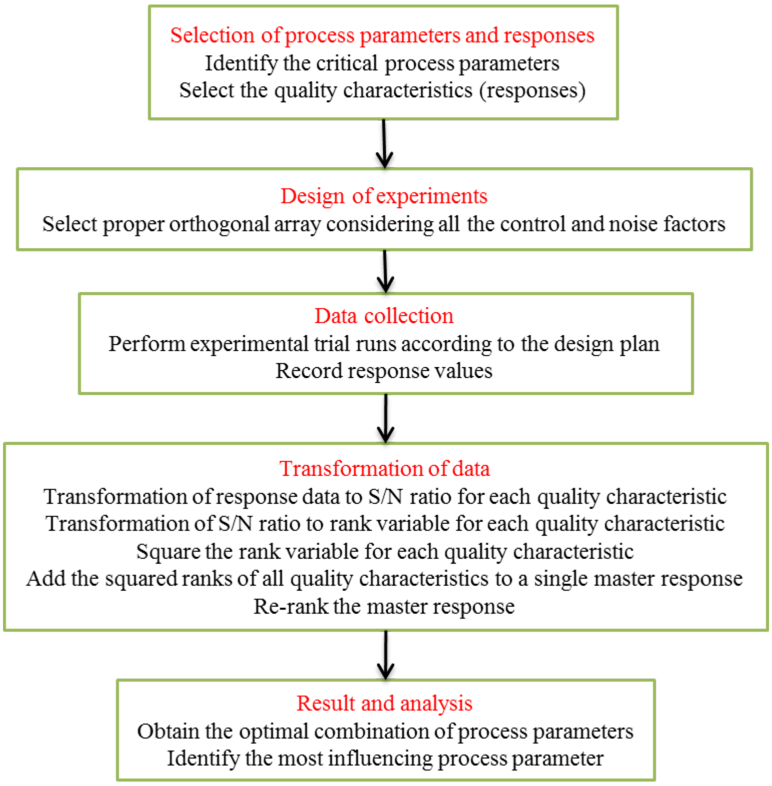


Figure 1: Flowchart for Taguchi method and super ranking concept leading to parametric optimization of NTM processes

After calculation of the S/N ratios, ranks are assigned to all these S/N ratios for each of the responses separately. This ranking is performed in descending order based on the calculated S/N ratio values, i.e. the largest S/N ratio is assigned rank 1, the second largest rank 2, and so on. If there is a tie between two or more S/N ratios, their average rank is then assigned to each of them. After proper ranking of all the responses, the next step involves squaring up of all those ranks. The squared ranks are added together to generate a single response, which is called as sum of squared ranks (SSR). The calculated SSR values further receive one more ranking, starting from the lowest value as rank 1, second lowest as rank 2 and so forth, thus converting the multi-response data into a single rank column, conveniently called as super rank (SR) response. A smaller value of SSR for a particular experimental run indicates its superiority over the others for a said machining application. The corresponding flowchart representing the application of Taguchi method along with super ranking concept for parametric optimization of NTM processes is exhibited in Figure 1.

Each NTM process has several control parameters and the optimal parametric combination of those parameters is mostly desired so as to explore the fullest machining potential with respect to the considered responses. This becomes a challenging task with the increased number of process parameters and responses, which are also conflicting in nature, thus forming a multi-objective optimization problem where all the responses need to be optimized simultaneously. Usually, in manufacturing industries, selection of those process parameters mainly depends on the operators' knowledge or manufacturer's handbook that does not often ensure achieving a global optimal parametric mix for a considered NTM process. In this paper, a combined Taguchi method and a super ranking concept are applied to three NTM processes, i.e., EDM, WEDM, and electrochemical discharge drilling (ECDD) processes for identifying the optimal parametric mixes resulting in achievement of better quality characteristics. It can also be noticed that this proposed approach would excel over the other popular optimization techniques, which proves its application potentiality and solution accuracy as an efficient multi-objective optimization tool.

4. PARAMETRIC OPTIMIZATION OF NTM PROCESSES

4.1. EDM process

Rahul et al. [20] applied satisfaction function and distance-based approach as a multi-response optimization technique during EDM operation of superalloy Inconel 718 while using a pure copper rod of 20 mm diameter as an electrode. Gap voltage, peak current, pulse-on time, duty cycle and flushing pressure, each with five different levels, were chosen as the input parameters for the considered EDM process. All these EDM process parameters are independent and controllable factors. On the other hand, MRR (in mm^3/min), EWR (in mm^3/min), Ra (in μm), surface crack density (SCD) (in μm/μm^2), white layer thickness (WLT) (in μm) and micro hardness (MH) (in $HV_{0.05}$) were treated as the responses. The considered process parameters along with their levels are presented in Table 1. Taguchi's L_{25} orthogonal array was employed for conducting the experiments. This experimental design plan and the measured response values are shown in Table 2. Amongst the six responses, MRR is the only LTB quality characteristic (beneficial criterion), whereas, the remaining five responses are of STB type (non-beneficial criteria). The values of correlation coefficient (r) between these six EDM responses, as shown in Table 3, identify them to be almost uncorrelated. Depending on the type of each response, Eqs. (1)-(2) are now utilized to convert the measured response values into the corresponding S/N ratios, as presented in Table 4. These S/N ratios are then ranked in descending order for the considered 25 experimental trial runs. As explained earlier, the assigned ranks are now squared for all the responses for a particular experimental trial run and further added together to obtain a single SSR value, as shown in Table 5. Finally, these calculated SSR values are again ranked in ascending order to provide the values of SR, as provided in Table 5. Among the 25 experimental runs, it is observed that the experiment trial number 22 with the parametric combination of $A_5B_2C_1D_5E_4$ has the smallest SSR value, signifying it to be the most preferred experimental run for the considered EDM process for simultaneous optimization of all the six responses.

Process parameters	Symbol	unit	Level				
			1	2	3	4	5
Gap voltage	A	V	50	60	70	80	90
Peak current	B	A	3	5	7	9	11
Pulse-on time	C	μs	100	200	300	400	500
Duty factor	D	%	65	70	75	80	85
Flushing pressure	E	bar	0.2	0.3	0.4	0.5	0.6

Table 1: Process parameters with levels for the EDM process [20]

Run	A	B	C	D	E	MRR	EWR	Ra	SCD	WLT	MH
1	50	3	100	65	0.2	8.926014	0.111982	3.800	0.0158	19.261	439.3333
2	50	5	200	70	0.3	14.10501	0.022396	6.333	0.0166	19.577	387.7000
3	50	7	300	75	0.4	38.40095	0.022396	9.133	0.0151	16.954	441.1333
4	50	9	400	80	0.5	48.49642	0.078387	9.867	0.0136	18.596	463.7000
5	50	11	500	85	0.6	88.21002	0.111982	7.600	0.0141	17.667	389.5667
6	60	3	200	75	0.5	4.892601	0.156775	3.733	0.0154	19.074	391.4333
7	60	5	300	80	0.6	15.179	0.134378	4.400	0.0152	17.065	518.0667
8	60	7	400	85	0.2	26.92124	0.044793	8.067	0.0152	17.523	388.9667
9	60	9	500	65	0.3	38.78282	0.055991	7.667	0.0156	20.308	373.8667
10	60	11	100	70	0.4	89.16468	0.145577	9.600	0.0056	17.742	392.4333
11	70	3	300	85	0.3	5.298329	0.011198	2.967	0.0189	19.861	394.5000
12	70	5	400	65	0.4	10.04773	0.011198	5.533	0.0163	20.090	390.0000
13	70	7	500	70	0.5	18.30549	0.011198	7.267	0.0168	20.100	406.4333
14	70	9	100	75	0.6	49.21241	0.022396	8.533	0.0093	19.445	405.9667
15	70	11	200	80	0.2	79.57041	0.067189	9.733	0.0125	19.086	390.3000
16	80	3	400	70	0.6	2.362768	0.011198	4.267	0.0172	18.310	384.1333
17	80	5	500	75	0.2	4.868735	0.022396	5.267	0.0157	18.067	352.6000
18	80	7	100	80	0.3	22.52983	0.022396	7.200	0.0108	18.137	385.6333
19	80	9	200	85	0.4	44.8926	0.022396	5.667	0.0084	18.673	390.6333
20	80	11	300	65	0.5	49.06921	0.011198	9.867	0.0110	18.835	410.7333
21	90	3	500	80	0.4	1.312649	0.011198	2.133	0.0156	17.602	378.2000
22	90	5	100	85	0.5	7.207637	0.011198	5.667	0.0117	16.646	372.9000
23	90	7	200	65	0.6	18.61575	0.033595	7.333	0.0136	17.707	375.8000
24	90	9	300	70	0.2	25.1074	0.044793	9.200	0.0116	19.752	399.1000
25	90	11	400	75	0.3	48.01909	0.022396	10.333	0.0100	19.077	431.8667

Table 2: Experimental details for the EDM process [20]

EDM process parameter	MRR	EWR	Ra	SCD	WLT	MH
MRR	1.000	0.333	0.734	-0.631	-0.060	0.086
EWR	0.333	1.000	-0.012	-0.138	-0.155	0.381
Ra	0.734	-0.012	1.000	-0.574	0.043	0.127
SCD	-0.631	-0.138	-0.574	1.000	0.192	0.006
WLT	-0.060	-0.155	0.043	0.192	1.000	-0.136
MH	0.086	0.381	0.127	0.006	-0.136	1.000

Table 3: Correlation coefficients between the EDM responses

	S/N ratio					
Run	MRR	EWR	Ra	SCD	WLT	MH
1	19.0132	19.017	-11.5957	36.0269	-25.6936	-52.8559
2	22.9875	32.9966	-16.0322	35.5978	-25.8349	-51.7699
3	31.6868	32.9966	-19.2123	36.4205	-24.5854	-52.8914
4	33.7142	22.1151	-19.8837	37.3292	-25.3884	-53.3247
5	38.9104	19.017	-17.6163	37.0156	-24.9433	-51.8116
6	13.7908	16.0945	-11.4412	36.2496	-25.6088	-51.8532
7	23.6249	17.4334	-12.8691	36.3631	-24.6421	-54.2877
8	28.6019	26.9758	-18.1342	36.3631	-24.8722	-51.7982
9	31.7728	25.0376	-17.6925	36.1375	-26.1533	-51.4543
10	39.0039	16.7381	-19.6454	45.0362	-24.9801	-51.8753
11	14.4828	39.0172	-9.44640	34.4708	-25.9600	-51.9209
12	20.0414	39.0172	-14.8592	35.7562	-26.0596	-51.8213
13	25.2516	39.0172	-17.2271	35.4938	-26.0639	-52.1798
14	33.8415	32.9966	-18.6220	40.6303	-25.7762	-52.1698
15	38.015	23.454	-19.7649	38.0618	-25.6143	-51.828
16	7.4684	39.0172	-12.6025	35.2894	-25.2538	-51.6896
17	13.7483	32.9966	-14.4313	36.0820	-25.1377	-50.9456
18	27.0552	32.9966	-17.1466	39.3315	-25.1713	-51.7235
19	33.0435	32.9966	-15.0671	41.5144	-25.4243	-51.8354
20	33.8162	39.0172	-19.8837	39.1721	-25.4993	-52.2712
21	2.3630	39.0172	-6.57980	36.1375	-24.9112	-51.5544
22	17.1559	39.0172	-15.0671	38.6363	-24.4262	-51.4318
23	25.3976	29.4745	-17.3056	37.3292	-24.9629	-51.4991
24	27.996	26.9758	-19.2758	38.7108	-25.9122	-52.0216
25	33.6283	32.9966	-20.2845	40.0000	-25.6102	-52.707

Table 4: Calculated S/N ratios for the EDM process

Now, the arithmetic means of the calculated SSR values at different operating levels of the EDM process parameters are computed as the response variables and are shown in Table 6. Based on these mean values, the best operating levels of the EDM process parameters (shown in bold faced) are identified. Thus, in order to achieve the most preferred machining performance of the considered EDM process, the optimal parametric combination is to be set as gap voltage = 80 V, peak current

= 7 A, pulse-on time = 100 μs, duty factor = 85% and flushing pressure = 0.4 bar, which can also be represented as $A_4B_3C_1D_5E_3$. The max-min column in Table 5 identifies gap voltage as the most influencing EDM process parameter. Figure 2 depicts the corresponding response graph, which also validates $A_4B_3C_1D_5E_3$ as the optimal combination of input parameters for the considered EDM process. As observed from this figure, a steep slope for gap voltage also confirms it to be the most important EDM process parameter. The analysis of variance (ANOVA) results based on the estimated SSR values are provided in Table 7, which show that gap voltage has the highest contribution of 32.85% in determining the SSR values, thus validating the above-obtained conclusion.

	Rank						Squared rank							
Run	MRR	EWR	Ra	SCD	WLT	MH	MRR	EWR	Ra	SCD	WLT	MH	SSR	SR
1	19	21.5	4	20	18	22	361	462.25	16	400	324	484	2047.25	25
2	17	11	11	22	20	8	289	121	121	484	400	64	1479	15
3	10	11	19	13	2	23	100	121	361	169	4	529	1284	11
4	6	20	23.5	10.5	12	24	36	400	552.25	110.25	144	576	1818.5	22
5	2	21.5	15	12	6	10	4	462.25	225	144	36	100	971.25	5
6	22	25	3	16	15	14	484	625	9	256	225	196	1795	21
7	16	23	6	14.5	3	25	256	529	36	210.25	9	625	1665.25	20
8	11	16.5	17	14.5	4	9	121	272.25	289	210.25	16	81	989.5	6
9	9	18	16	17.5	25	3	81	324	256	306.25	625	9	1601.25	19
10	1	24	21	1	8	15	1	576	441	1	64	225	1308	12
11	21	4	2	25	22	16	441	16	4	625	484	256	1826	23
12	18	4	8	21	23	11	324	16	64	441	529	121	1495	16
13	15	4	13	23	24	19	225	16	169	529	576	361	1876	24
14	4	11	18	3	19	18	16	121	324	9	361	324	1155	9
15	3	19	22	9	17	12	9	361	484	81	289	144	1368	14
16	24	4	5	24	11	6	576	16	25	576	121	36	1350	13
17	23	11	7	19	9	1	529	121	49	361	81	1	1142	8
18	13	11	12	5	10	7	169	121	144	25	100	49	608	2
19	8	11	9.5	2	13	13	64	121	90.25	4	169	169	617.25	3
20	5	4	23.5	6	14	20	25	16	552.25	36	196	400	1225.25	10
21	25	4	1	17.5	5	5	625	16	1	306.25	25	25	998.25	7
22	20	4	9.5	8	1	2	400	16	90.25	64	1	4	575.25	1
23	14	15	14	10.5	7	4	196	225	196	110.25	49	16	792.25	4
24	12	16.5	20	7	21	17	144	272.25	400	49	441	289	1595.25	18
25	7	11	25	4	16	21	49	121	625	16	256	441	1508	17

Table 5: Rank, squared rank, SSR and SR for the considered EDM process

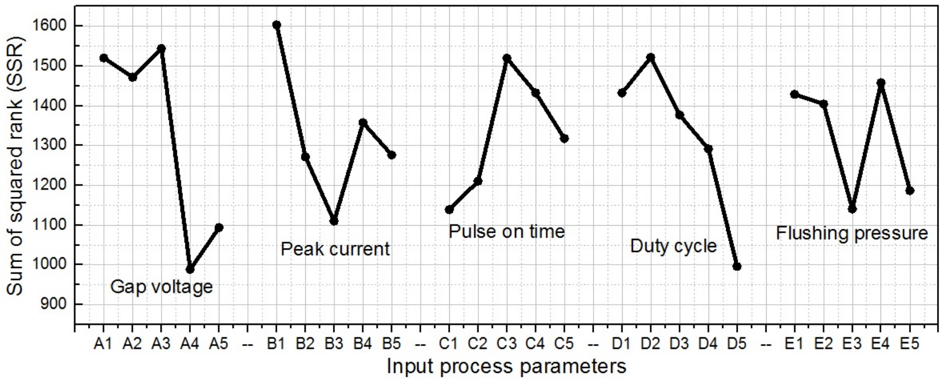


Figure 2: Response graph for SSR values for the EDM process

Process parameters	Level					Max-Min	Rank
	1	2	3	4	5		
Gap voltage	1520	1471.8	1544	988.5	1093.8	555.5	1
Peak current	1603.3	1271.3	1109.95	1357.45	1276.1	493.35	3
Pulse-on time	1138.7	1210.3	1519.15	1432.2	1317.75	380.45	4
Duty factor	1432.2	1521.65	1376.8	1291.6	995.85	525.8	2
Flushing pressure	1428.4	1404.45	1140.5	1458	1186.75	317.5	5

Table 6: Response table for SSR values for the EDM process

Source	DoF	Adj SS	Adj MS	f-value	% contribution
Gap voltage	4	1371062	342766	3.29	32.85
Peak current	4	650079	162520	1.56	15.57
Pulse-on time	4	485464	121366	1.16	11.63
Duty factor	4	811460	202865	1.95	19.44
Flushing pressure	4	439183	109796	1.05	10.52
Error	4	416812	104203		9.99
Total	24	4174061			100

Table 7: ANOVA results for the EDM process

From the above analysis, it can thus be observed that the experiment trial number 22, i.e. $A_5B_2C_1D_5E_4$ with the lowest SSR value of 575.25 is the most preferred combination of input parameters for the considered EDM process. But, the response graph of Figure 2, which is developed based on the arithmetic means of SSR values, provides another parametric combination of $A_4B_3C_1D_5E_3$ for the same EDM process. This parametric mix derived from the response graph differs from that of the experimental trial number 22. As the chance of obtaining lower SSR value is more at setting $A_4B_3C_1D_5E_3$ than at combination $A_5B_2C_1D_5E_4$, it is thus preferred to operate the considered EDM process at an optimal parametric setting of $A_4B_3C_1D_5E_3$. On the other hand, Rahul et al. [20] identified the best parametric setting of the same EDM process as $A_4B_5C_1D_5E_3$, which slightly varies from the setting $A_4B_3C_1D_5E_3$ with respect to peak current. In the setting of $A_4B_3C_1D_5E_3$, the peak current is required to be set at level 3 (7 A), whereas, Rahul et al. [20] advised to set peak current at level 5 (11 A). Now, in order to show the effectiveness of this approach as an effective multi-response optimization tool, the two different parametric combinations are compared with respect to the SSR values, which can be predicted using Eq. (4).

$$S_p = S_m \sum_{i=1}^{n} (\bar{S}_i - S_m) \tag{4}$$

where, S_p is the predicted SSR value, S_m is the mean SSR value for all the 25 experiments, $\bar{S}_i$ is the mean SSR value for i^{th} level of the process parameters, and n is the total number of process parameters.

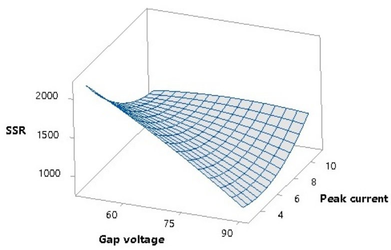
The SSR value for setting $A_4B_3C_1D_5E_3$ is predicted as 79.02, whereas, for setting $A_4B_5C_1D_5E_3$, it is estimated to be 245.17. Thus, it can be noticed that for setting $A_4B_3C_1D_5E_3$, there is a decrement of 166.15 in the predicted SSR value, which justifies the selection of $A_4B_3C_1D_5E_3$ as the optimal parametric combination for the considered EDM process. In order to fully justify the superiority of this combination over that as obtained by Rahul et al. [20], the following regression equations are also developed while considering only the main effects of various EDM process parameters.

$$MRR = -25.7 - 0.0494\times A + 8.176\times B - 0.0155\times C + 0.449\times D + 11.1\times E \tag{5}$$
$$EWR = 0.161 - 0.001792\times A + 0.00134\times B - 0.000067\times C + 0.00013\times D + 0.0358\times E \tag{6}$$
$$Ra = 6.68 - 0.0107\times A + 0.7420\times B - 0.00089\times C - 0.0472\times D - 8.19\times E \tag{7}$$
$$SCD = 0.02274 - 0.000059\times A - 0.000764\times B + 0.000011\times C - 0.000032\times D - 0.00184\times E \tag{8}$$
$$WLT = 24.37 - 0.045\times A + 0.0193\times B + 0.00090\times C - 0.0666\times D - 25.14\times E \tag{9}$$
$$MH = 427.0 - 1.96\times A + 0.67\times B - 0.0137\times C + 0.239\times D + 55.6\times E \tag{10}$$

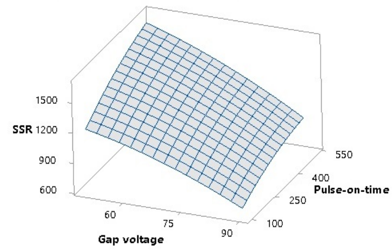
Based on these regression equations, a comparison of the response values at the derived optimal parametric combination and that of Rahul et al. [20] is shown in Table 8. It is interesting to observe from the table that at this optimal parametric mix, the value of MRR (being an LTB quality characteristic) is substantially increased by 25.53%, i.e. from 54.6764 mm^3/min to 68.635 mm^3/min. Similarly, for the remaining five responses, i.e. EWR, Ra, SCD, WLT, and MH (all being STB quality characteristics), there are decrements in their values by 70.87%, 6.64%, 9.33%, 2.47%, and 1.093%, respectively at this optimal parametric combination. Finally, the corresponding response plots are developed, as shown in Figure 3. These plots, basically, demonstrate the effects of different EDM process parameters in estimating the SSR values. It would further help the concerned process engineers in determining the corresponding SSR value for any given combination of the EDM process parameters.

Optimization method	MRR	EWR	Ra	SCD	WLT	MH
Taguchi method and super ranking concept ($A_4B_3C_1D_5E_3$)	68.635	0.0457	3.641	0.00369	5.2781	316.075
Satisfaction function and distance-based approach ($A_4B_5C_1D_5E_3$)[20]	54.6764	0.1569	3.9	0.00407	5.4120	319.5667
Improvement (%)	25.53	70.87	6.64	9.33	2.47	1.093

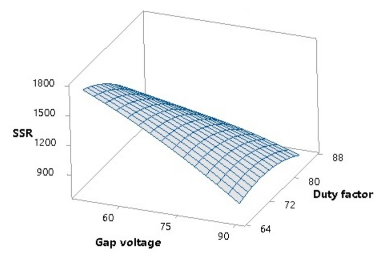
Table 8: Predicted response values for the EDM process



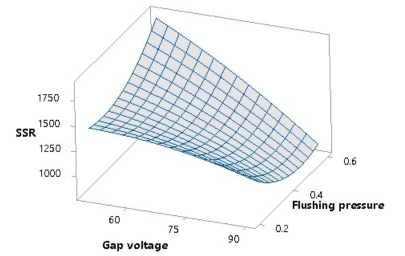
(a) SSR vs. gap voltage, peak current



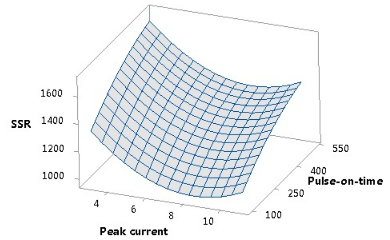
(b) SSR vs. gap voltage, pulse-on time



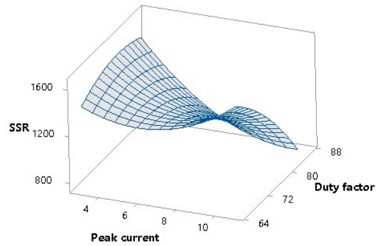
(c) SSR vs. gap voltage, duty factor



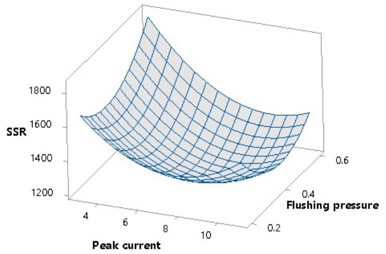
(d) SSR vs. gap voltage, flushing pressure



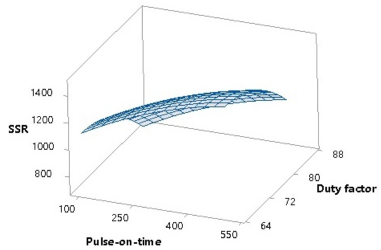
(e) SSR vs. peak current, pulse-on time



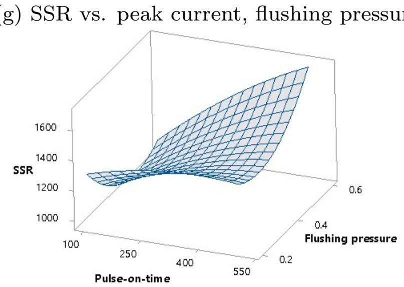
(f) SSR vs. peak current, duty factor



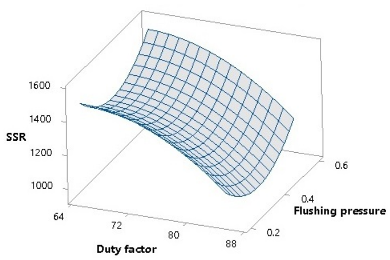
(g) SSR vs. peak current, flushing pressure



(h) SSR vs. pulse-on time, duty factor



(i) SSR vs. pulse-on time, flushing pressure



(j) SSR vs. duty factor, flushing pressure

Figure 3: Surface plots showing the effects of different EDM process parameters on SSR value

4.2. WEDM process

Santhanakumar et al. [25] studied the effects of four important WEDM process parameters, i.e. gap voltage, capacitance, feed rate, and wire tension on three responses, i.e. Ra (in μm), kerf width (KW) (in μm) and MRR (in μg/s). The correlation coefficients between Ra and kerf width, Ra and MRR, and kerf width and MRR are estimated as -0.112, -0.027 and -0.014 respectively, which prove the independency between the considered WEDM responses. Four different levels were chosen for each of those process parameters, as shown in Table 9. The work material was considered as Ti 6-4 sheet and based on L_{16} orthogonal array, 16 experiments were conducted. The experimental design plan and the measured response values are exhibited in Table 10. An integrated TOPSIS and RSM-based approach was later adopted to identify the best parametric combination as $A_3B_1C_3D_4$ for the considered WEDM process. Now, following the same computational procedures, adopted in the first example, the combined Taguchi method and super ranking concept are again adopted here for parametric optimization of the said WEDM process. The S/N ratio values for the three responses, their ranks and squared ranks along with the SSR and SR values are estimated in Table 10. It can be observed from the table that the experimental trial number 9 has the lowest SSR value, which identifies it to be the most preferred experimental run among the 16 parametric combinations for the WEDM process.

Process parameters	Symbol	unit	Level			
			1	2	3	4
Gap voltage	A	V	80	90	100	110
Capacitance	B	μF	0.1	1	10	40
Feed rate	C	μm/s	3	6	9	12
Wire tension	D	gm	9	12	15	18

Table 9: WEDM process parameters and their corresponding levels [25]

Run	A	B	C	D	Ra	KW	MRR
1	80	0.1	3	9	0.484	100	1.755
2	80	1	6	12	0.586	110	3.861
3	80	10	9	15	1.32	120	6.318
4	80	40	12	18	2.464	90	6.318
5	90	0.1	6	15	0.531	110	3.861
6	90	1	3	18	0.596	110	1.93
7	90	10	12	9	1.514	100	7.02
8	90	40	9	12	2.977	80	4.212
9	100	0.1	9	18	0.272	80	4.212
10	100	1	12	15	0.674	70	4.914
11	100	10	3	12	1.692	90	1.579
12	100	40	6	9	2.498	110	3.861
13	110	0.1	12	12	0.958	90	6.318
14	110	1	9	9	0.683	100	5.265
15	110	10	6	18	1.831	80	2.808
16	110	40	3	15	2.928	100	1.755

Table 10: Experimental design plan and response values for the WEDM process [25]

The corresponding response table and response graph are subsequently developed based on the calculated SSR values, and are presented in Table 12 and Figure 4, respectively. It can be revealed that gap voltage = 100 V, capacitance = 0.1 μF, feed rate = 12 μm/s and wire tension = 18 gm, i.e. $A_3B_1C_4D_4$ is the optimal combination of input parameters for the considered WEDM process so as for achieving the desired machining performance. This optimal parametric mix, obtained based on Taguchi method and super ranking concept, slightly differs from the setting $A_3B_1C_3D_4$ [25] only with respect to feed rate. The max-min column of Table 12 and a steep slope in the response graph identify feed rate as the most influencing control parameter for the said WEDM process. This finding can also be well validated from the ANOVA results of Table 13, where feed rate has a maximum contribution of 59.56% in determination of the SSR value.

	S/N ratio			Rank			Squared rank				
Run	Ra	KW	MRR	Ra	KW	MRR	Ra	KW	MRR	SSR	SR
1	6.3031	-40	4.8855	2	9.5	14.5	4	90.25	210.25	304.5	11
2	4.642	-40.8279	11.734	4	13.5	10	16	182.25	100	298.25	10
3	-2.4115	-41.5836	16.0116	9	16	3	81	256	9	346	12
4	-7.8328	-39.0849	16.0116	13	6	3	169	36	9	214	6
5	5.4981	-40.8279	11.734	3	13.5	10	9	182.25	100	291.25	8
6	4.4951	-40.8279	5.7111	5	13.5	13	25	182.25	169	376.25	13
7	-3.6025	-40	16.9267	10	9.5	1	100	90.25	1	191.25	5
8	-9.4756	-38.0618	12.4898	15	3	7.5	225	9	56.25	290.25	7
9	11.3086	-38.0618	12.4898	1	3	7.5	1	9	56.25	66.25	1
10	3.4268	-36.902	13.8287	6	1	6	36	1	36	73	2
11	-4.568	-39.0849	3.9676	11	6	16	121	36	256	413	14
12	-7.9518	-40.8279	11.734	14	13.5	10	196	182.25	100	478.25	15
13	0.3727	-39.0849	16.0116	8	6	3	64	36	9	109	3
14	3.3116	-40	14.428	7	9.5	5	49	90.25	25	164.25	4
15	-5.2538	-38.0618	8.9679	12	3	12	144	9	144	297	9
16	-9.3314	-40	4.8855	15	9.5	14.5	225	90.25	210.25	525.5	16

Table 11: S/N ratio and rank calculations for the WEDM process

	Level					
Process parameters	1	2	3	4	Max-Min	Rank
Gap voltage	290.6875	287.25	257.625	273.9375	33.0625	4
Capacitance	192.75	227.9375	311.8125	377	184.25	2
Feed rate	404.8125	341.1875	216.6875	146.8125	258	1
Wire tension	284.5625	277.625	308.9375	238.375	70.5625	3

Table 12: Response table for SSR values for the WEDM process

Source	DoF	Adj SS	Adj MS	f-value	% contribution
Gap voltage	3	2706	902.2	0.17	0.98
Capacitance	3	82866	27622.1	5.31	30.06
Feed rate	3	164168	54722.5	10.51	59.56
Wire tension	3	10276	3425.2	0.66	3.73
Error	3	15620	5206.6		5.67
Total	15	275636			100

Table 13: ANOVA results for the WEDM process

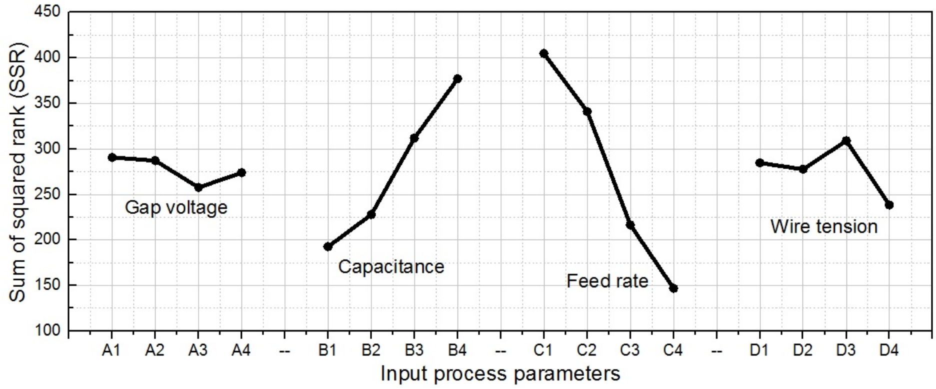
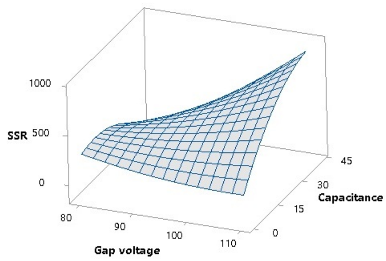
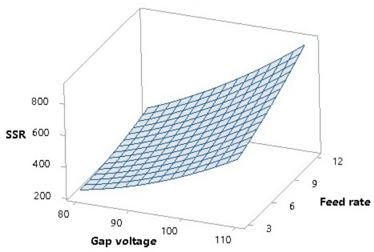


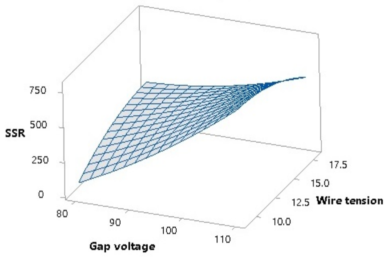
Figure 4: Response graph for SSR values for the WEDM process



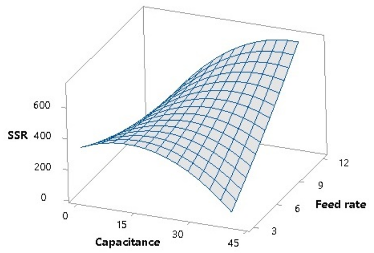
(a) SSR vs. gap voltage, capacitance



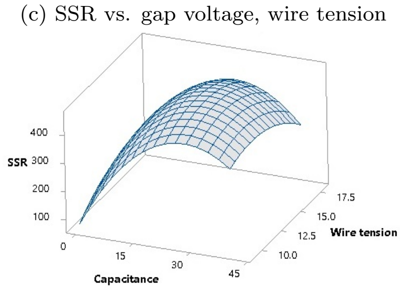
(b) SSR vs. gap voltage, feed rate



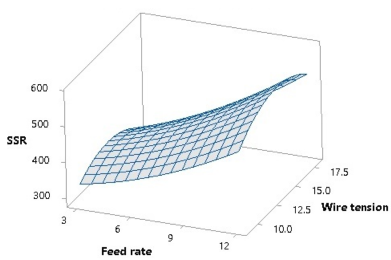
(c) SSR vs. gap voltage, wire tension



(d) SSR vs. capacitance, feed rate



(e) SSR vs. capacitance, wire tension



(f) SSR vs. feed rate, wire tension

Figure 5: Surface plots showing the effects of different WEDM process parameters on SSR value

Based on the computational procedure as adopted in the first example, the SSR value is predicted to be 3.4375 at the parametric setting $A_3B_1C_4D_4$, whereas, it is estimated as 73.3125 at the parametric mix $A_3B_1C_3D_4$, thus showing a decrement of 69.875 in the estimated value of SSR for the proposed parametric combination. The corresponding regression equations are also developed depicting the relationships between the responses and input parameters of the considered WEDM process. Using these equations, the response values, as predicted at the two different parametric settings, are compared in Table 14, which shows a marginal improvement of 5.88% and 0.89% in Ra and KW values respectively, whereas, there is a remarkable improvement of 41.12% in the MRR value. Finally, the corresponding response surface plots showing the influences of various WEDM process parameters on the SSR value are developed, as exhibited in Figure 5.

$$Ra = -0.62+0.01039\times A+0.05244\times B-0.0039\times C-0.0067\times D \quad (11)$$
$$KW = 168.9-0.500\times A-0.035\times B-1.500\times C-1.200\times D \quad (12)$$
$$MRR = 3.36-0.0219\times A-0.0006\times B+0.4856\times C-0.0585\times D \quad (13)$$

Optimization method	Ra	KW	MRR
Taguchi method and super ranking concept ($A_3B_1C_4D_4$)	0.256	79.29	5.944
TOPSIS-based RSM approach ($A_3B_1C_3D_4$) [25]	0.272	80	4.212
Improvement (%)	5.88	0.89	41.12

Table 14: Predicted responses for the WEDM process

4.3. ECDD process

While taking SiC reinforced polymer matrix composite as the work material, Antil et al. [1] investigated the effects of four ECDD process parameters, i.e. voltage, electrolyte concentration, inter-electrode gap, and duty factor on three responses, i.e. MRR (in mg/min), overcut (in mm), and taper (in mm). The correlation coefficients between MRR and overcut, MRR and taper, and overcut and taper are determined as 0.546, 0.070 and 0.083, respectively. An L_9 orthogonal array was adopted as the experimental design plan. Those four ECDD process parameters along with their three levels are shown in Table 15. Table 16 exhibits the detailed observations of the considered responses obtained from the nine experimental trials. Using Taguchi method-based GRA technique as an optimization tool, Antil et al. [1] determined the most preferred combination of input parameters for the considered ECDD process as $A_2B_3C_2D_2$ (i.e. voltage = 60V, electrolyte concentration = 110 g/l, inter-electrode gap = 120 mm, and duty factor = 0.66). This problem is now solved while employing the proposed Taguchi method and super ranking concept to determine the optimal combination of different process parameters. From the derived results, as provided in Table 17, it can be observed that based on the derived SSR values, experimental number 2, i.e. $A_1B_2C_2D_2$ emerges out as the best parametric combination for the said NTM process.

Process parameters	Symbol	unit	Level		
			1	2	3
Voltage	A	V	45	60	75
Electrolyte concentration	B	g/l	90	100	110
Inter-electrode gap	C	mm	100	120	140
Duty factor	D		0.5	0.66	0.75

Table 15: Process parameters with their levels for the ECDD process [1]

Run	A	B	C	D	MRR	Overcut	Taper
1	45	90	100	0.5	1.092	0.121	0.0560
2	45	100	120	0.66	1.023	0.112	0.0490
3	45	110	140	0.75	1.025	0.113	0.0590
4	60	90	120	0.75	1.016	0.098	0.0500
5	60	100	140	0.5	1.019	0.088	0.0510
6	60	110	100	0.66	1.005	0.064	0.0491
7	75	90	140	0.66	1.015	0.179	0.0562
8	75	100	100	0.75	1.017	0.196	0.0610
9	75	110	120	0.5	1.012	0.103	0.0480

Table 16: Experimental details for the ECDD process [1]

Now using the calculated SSR values, the corresponding response table and response graph are developed for the ECDD process and presented in Table 18 and Figure 6, respectively. Based on these observations, the setting $A_2B_2C_2D_1$ (i.e. voltage = 60 V, electrolyte concentration = 100 g/l, inter-electrode gap = 120 mm, and duty factor = 0.5) can be noticed as the optimal parametric mix for the considered NTM process for simultaneous optimization of all the three responses. In Table 18, the highest max-min value of 77.6666 indicates voltage as the most influencing factor among the four ECDD process parameters, followed by inter-electrode gap.

	S/N ratio			Rank			Squared rank				
Run	MRR	Overcut	Taper	MRR	Overcut	Taper	MRR	Overcut	Taper	SSR	SR
1	0.7645	18.3443	25.0362	1	7	6	1	49	36	86	5
2	0.1975	19.0156	26.1961	3	5	2	9	25	4	38	1
3	0.2145	18.9384	24.5830	2	6	8	4	36	64	104	7
4	0.1379	20.1755	26.0206	6	3	4	36	9	16	61	3
5	0.1635	21.1103	25.8486	4	2	5	16	4	25	45	2
6	0.0433	23.8764	26.1784	9	1	3	81	1	9	91	6
7	0.1293	14.9429	25.0053	7	8	7	49	64	49	162	8
8	0.1464	14.1549	24.2934	5	9	9	25	81	81	187	9
9	0.1036	19.7433	26.3752	8	4	1	64	16	1	81	4

Table 17: S/N ratios and rank calculations for the ECDD process

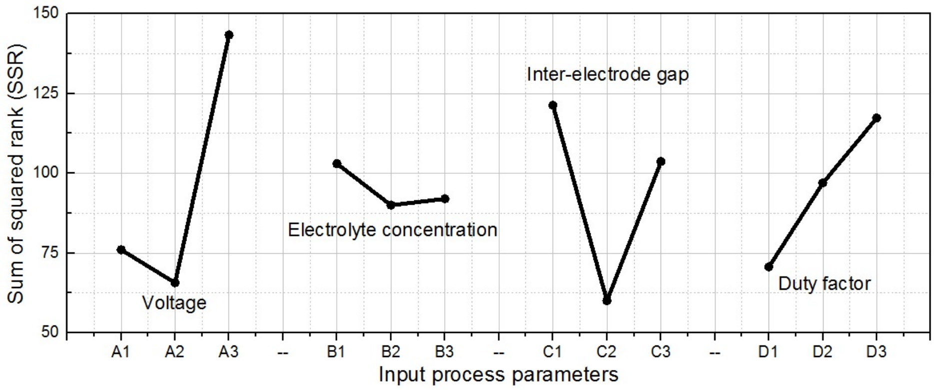


Figure 6: Response graph for SSR values for the ECDD process

Process parameters	Level			Max-Min	Rank
	1	2	3		
Voltage	76	65.6667	143.3333	77.6666	1
Electrolyte concentration	103	90	92	13	4
Inter-electrode gap	121.3333	60	103.6667	61.3333	2
Duty factor	70.6667	97	117.3333	46.6666	3

Table 18: Response table for SSR values for the ECDD process

Like the previous examples, in order to understand the significance of each of the ECDD process parameters on the computed SSR values, ANOVA is performed in Table 19. It can be revealed from this table that the corresponding number of degrees of freedom (DoF) for the residual error has a value of zero, showing lack of sufficient data and it usually occurs when four process parameters, with three levels each, are considered for experimentation using L_9 orthogonal array. Hence, to overcome this problem, pooling is made [27]. Pooling is a technique of revising and re-estimating the ANOVA results in order to neglect a factor which is of less significance as compared to others. It can be noticed from Table 19 that electrolyte concentration has an adjusted mean square (Adj. MS) value of 147 which is quite low as compared to the other ECDD process parameters, identifying it as the least influencing factor. The same can also be revealed from the max-min column of the response table and its less steep slope in the response graph. Hence, electrolyte concentration is pooled in Table 20. This table also confirms voltage as the most influencing process parameter with 52.75% contribution, followed by inter-electrode gap having 29.55% contribution.

Source	DoF	Adj SS	Adj MS	f-value	% contribution
Voltage	2	10672.7	5336.3	*	*
Electrolyte concentration	2	294.0	147.0	*	*
Inter-electrode gap	2	5980.7	2990.3	*	*
Duty factor	2	3284.7	1642.3	*	*
Error	0	*	*		
Total	8	20232.0			

Table 19: ANOVA for SSR values (before pooling) for the ECDD process

Source	DoF	Adj SS	Adj MS	f-value	% contribution
Voltage	2	10672.7	5336.3	36.30	52.75
Inter-electrode gap	2	5980.7	2990.3	20.34	29.55
Duty factor	2	3284.7	1642.3	11.17	16.25
Error	2	294	147.0		1.45
Total	8	20232			100

Table 20: ANOVA for SSR values (after pooling) for the ECDD process

Now, the two parametric combinations, i.e. $A_2B_2C_2D_1$ and $A_2B_3C_2D_2$ are compared based on the predicted SSR values. It is observed that there is a decrement of 28.3334 in the predicted SSR value for the proposed setting of $A_2B_2C_2D_1$ against $A_2B_3C_2D_2$ as derived by Antil et al. [1]. To fully justify the above observations, the corresponding regression equations are developed for all the considered responses. The estimated response values, derived from these regression equations, and presented in Table 21, show improvements by 1.43%, 38.78% and 2.14% in MRR, overcut, and taper, respectively.

Figure 7 shows the corresponding response surface plots to highlight the influences of various ECDD process parameters on the computed SSR value.

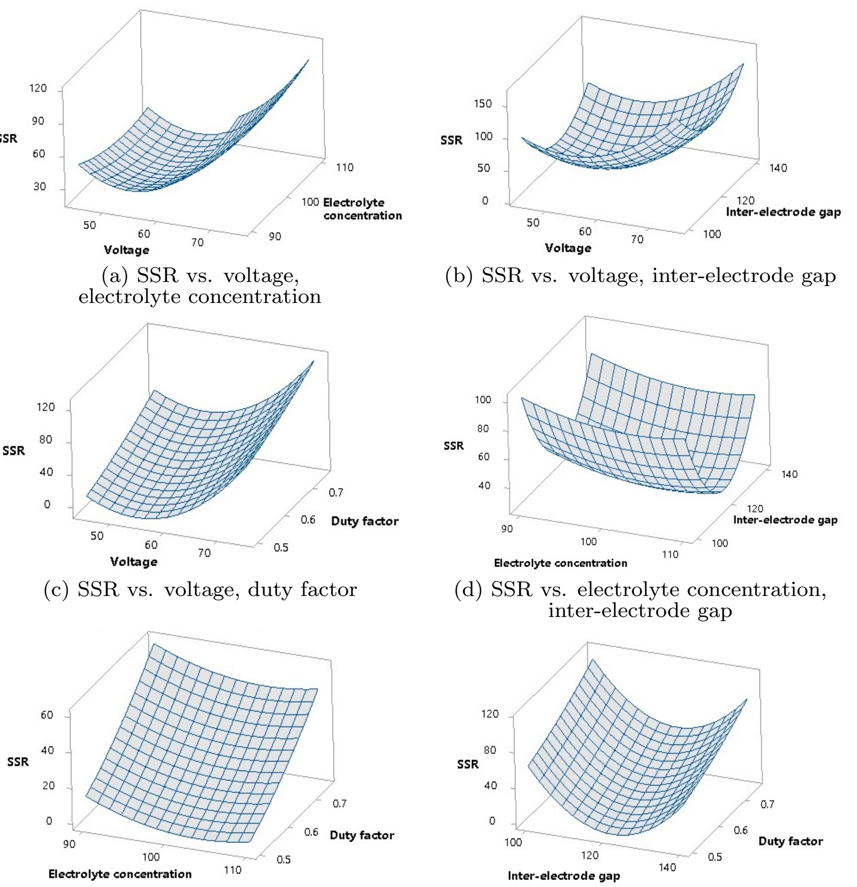
$$MRR = 1.3400 - 0.001067 \times A - 0.001350 \times B - 0.000458 \times C + 0.0960 \times D \quad (14)$$

$$Overcut = 0.151 + 0.00147 \times A - 0.00197 \times B - 0.000008 \times C + 0.122 \times D \quad (15)$$

$$Taper = 0.0514 + 0.000013 \times A - 0.00012 \times B + 0.000001 \times C + 0.00175 \times D \quad (16)$$

Optimization method	MRR	Overcut	Taper
Taguchi method and super ranking concept ($A_2B_3C_2D_2$)	1.134	0.10224	0.0411
GRA technique ($A_2B_3C_2D_2$) [1]	1.118	0.167	0.042
Improvement (%)	1.43	38.78	2.14

Table 21: Estimated responses for the ECDD process



(a) SSR vs. voltage, electrolyte concentration

(b) SSR vs. voltage, inter-electrode gap

(c) SSR vs. voltage, duty factor

(d) SSR vs. electrolyte concentration, inter-electrode gap

(e) SSR vs. electrolyte concentration, duty factor

(f) SSR vs. duty factor, inter-electrode gap

Figure 7: Surface plots showing the effects of different ECDD process parameters on SSR value

5. CONCLUSIONS

In this paper, a novel technique combining Taguchi method and super ranking concept is applied to determine the optimal parametric combinations for three different NTM processes. It can be clearly observed that the proposed approach provides better parametric combinations for all the considered NTM processes with respect to the predicted SSR values. Moreover, the developed regression equations for the individual responses also confirm the superiority of this approach over the other popular methods while proving its competency as a multi-objective optimization tool. This approach is quite simple, easy to implement and free from any complex mathematical computation. As the entire analysis is based on the secondary experimental data of the past researchers, thus, there is no scope of conducting any confirmatory experiment so as to validate the derived results. It can also be applied to other conventional, as well as non-conventional, machining processes for determination of the optimal parametric combinations for achieving their better machining performance.

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