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 Proc-
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 To overcome these problems, the conventional machining processes have gradually been replaced by the non-traditional machining (NTM) processes.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 al. [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.

\[
S/N = -10 \log_{10} \left[ \frac{1}{n} \sum_{i=1}^{n} \frac{1}{x_i(k)^2} \right]
\]  

(1)
S/N = $-10\log_{10}\left(\frac{1}{n}\sum x_i(k)^2\right)$ \hspace{1cm} (2)

S/N = $10\log_{10}\frac{\mu^2}{\sigma^2}$ \hspace{1cm} (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 $\mu$ and $\sigma$ 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 \( \text{mm}^3/\text{min} \)), EWR (in \( \text{mm}^3/\text{min} \)), Ra (in \( \mu \text{m} \)), surface crack density (SCD) (in \( \mu \text{m}/\mu \text{m}^2 \)), white layer thickness (WLT) (in \( \mu \text{m} \)) and micro hardness (MH) (in \( \text{HV}_{0.05} \)) 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 |
|--------------------|--------|------|-------|
| Gap voltage        | A      | V    | 50 60 70 80 90 |
| Peak current       | B A    | µs   | 3 5 7 9 11 |
| Pulse-on time      | C      | %    | 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 | 100| 65 | 0.2| 8.926014 | 0.111982 | 3.800 | 0.0158 | 19.261 | 439.3333 |
| 2   | 50 | 200| 70 | 0.3| 14.10501 | 0.022396 | 6.333 | 0.0166 | 19.577 | 387.7000 |
| 3   | 50 | 100| 65 | 0.2| 26.92124 | 0.044793 | 8.067 | 0.0152 | 17.523 | 388.9667 |
| 4   | 50 | 200| 70 | 0.3| 79.57041 | 0.067189 | 9.733 | 0.0125 | 19.086 | 390.3000 |
| 5   | 50 | 100| 65 | 0.2| 4.868735 | 0.055991 | 7.667 | 0.0156 | 20.308 | 373.8667 |
| 6   | 50 | 200| 70 | 0.3| 8.926014 | 0.111982 | 3.800 | 0.0158 | 19.261 | 439.3333 |
| 7   | 50 | 100| 65 | 0.2| 26.92124 | 0.044793 | 8.067 | 0.0152 | 17.523 | 388.9667 |
| 8   | 50 | 200| 70 | 0.3| 79.57041 | 0.067189 | 9.733 | 0.0125 | 19.086 | 390.3000 |
| 9   | 50 | 100| 65 | 0.2| 4.868735 | 0.055991 | 7.667 | 0.0156 | 20.308 | 373.8667 |
| 10  | 50 | 200| 70 | 0.3| 8.926014 | 0.111982 | 3.800 | 0.0158 | 19.261 | 439.3333 |
| 11  | 50 | 100| 65 | 0.2| 26.92124 | 0.044793 | 8.067 | 0.0152 | 17.523 | 388.9667 |
| 12  | 50 | 100| 65 | 0.2| 4.868735 | 0.055991 | 7.667 | 0.0156 | 20.308 | 373.8667 |
| 13  | 50 | 100| 65 | 0.2| 4.868735 | 0.055991 | 7.667 | 0.0156 | 20.308 | 373.8667 |
| 14  | 50 | 100| 65 | 0.2| 4.868735 | 0.055991 | 7.667 | 0.0156 | 20.308 | 373.8667 |
| 15  | 50 | 100| 65 | 0.2| 4.868735 | 0.055991 | 7.667 | 0.0156 | 20.308 | 373.8667 |
| 16  | 50 | 100| 65 | 0.2| 4.868735 | 0.055991 | 7.667 | 0.0156 | 20.308 | 373.8667 |
| 17  | 50 | 100| 65 | 0.2| 4.868735 | 0.055991 | 7.667 | 0.0156 | 20.308 | 373.8667 |
| 18  | 50 | 100| 65 | 0.2| 4.868735 | 0.055991 | 7.667 | 0.0156 | 20.308 | 373.8667 |
| 19  | 50 | 100| 65 | 0.2| 4.868735 | 0.055991 | 7.667 | 0.0156 | 20.308 | 373.8667 |
| 20  | 50 | 100| 65 | 0.2| 4.868735 | 0.055991 | 7.667 | 0.0156 | 20.308 | 373.8667 |
| 21  | 50 | 100| 65 | 0.2| 4.868735 | 0.055991 | 7.667 | 0.0156 | 20.308 | 373.8667 |
| 22  | 50 | 100| 65 | 0.2| 4.868735 | 0.055991 | 7.667 | 0.0156 | 20.308 | 373.8667 |
| 23  | 50 | 100| 65 | 0.2| 4.868735 | 0.055991 | 7.667 | 0.0156 | 20.308 | 373.8667 |
| 24  | 50 | 100| 65 | 0.2| 4.868735 | 0.055991 | 7.667 | 0.0156 | 20.308 | 373.8667 |
| 25  | 50 | 100| 65 | 0.2| 4.868735 | 0.055991 | 7.667 | 0.0156 | 20.308 | 373.8667 |

Table 2: Experimental details for the EDM process [20]
Table 3: Correlation coefficients between the EDM responses

|        | 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 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
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= 7 A, pulse-on time = 100 µs, duty factor = 85% and flushing pressure = 0.4 bar, which can also be represented as $A_1B_3C_1D_5E_3$. 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 $A_1B_3C_1D_5E_3$ 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.

| Run | MRR | EWR | Ra | SCD | WLT | MH | SSR | SR |
|-----|-----|-----|----|-----|-----|----|-----|----|
| 1   | 19  | 21.5| 4  | 20  | 18  | 22 | 361 | 462.25 |
| 2   | 17  | 11  | 11 | 22  | 20  | 8  | 289 | 121  |
| 3   | 10  | 11  | 19 | 13  | 2   | 23 | 100 | 121  |
| 4   | 6   | 20  | 23.5| 10.5| 12  | 24 | 36  | 400  |
| 5   | 2   | 21.5| 15 | 12  | 6   | 10 | 4   | 462.25 |
| 6   | 22  | 25  | 3  | 16  | 15  | 14 | 484 | 625  |
| 7   | 16  | 23  | 6  | 14.5| 3   | 25 | 256 | 529  |
| 8   | 11  | 16.5| 17 | 14.5| 4   | 9  | 121 | 272.25|
| 9   | 9   | 18  | 16 | 17.5| 25  | 3  | 81  | 324  |
| 10  | 1   | 24  | 21 | 1   | 8   | 15 | 1   | 576  |
| 11  | 21  | 4   | 2  | 25  | 22  | 16 | 441 | 16   |
| 12  | 18  | 4   | 8  | 21  | 23  | 11 | 324 | 16   |
| 13  | 15  | 4   | 13 | 23  | 24  | 19 | 225 | 16   |
| 14  | 4   | 11  | 18 | 3   | 19  | 18 | 16  | 121  |
| 15  | 3   | 19  | 22 | 9   | 17  | 12 | 9   | 361  |
| 16  | 24  | 4   | 5  | 24  | 11  | 6  | 576 | 16   |
| 17  | 23  | 11  | 7  | 19  | 9   | 1  | 529 | 121  |
| 18  | 13  | 11  | 12 | 5   | 10  | 7  | 169 | 121  |
| 19  | 8   | 11  | 9.5| 2   | 13  | 13 | 64  | 121  |
| 20  | 5   | 4   | 23.5| 6   | 14  | 20 | 25  | 16   |
| 21  | 25  | 4   | 1  | 17.5| 5   | 5  | 625 | 16   |
| 22  | 20  | 4   | 9.5| 1   | 2   | 400 | 16   |
| 23  | 14  | 15  | 14 | 10.5| 7   | 4  | 196 | 225  |
| 24  | 12  | 16.5| 20 | 7   | 21  | 17 | 144 | 272.25|
| 25  | 7   | 11  | 25 | 4   | 16  | 21 | 49  | 121  |

Table 5: Rank, squared rank, SSR and SR for the considered 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 $A_4B_3C_1D_5E_3$, 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).

$$S_p = S_m \sum_{i=1}^{n} (S_i - S_m)$$

where, $S_p$ is the predicted SSR value, $S_m$ is the mean SSR value for all the 25 experiments, $S_i$ 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 $A_4 B_2 C_1 D_5 E_3$ is predicted as 79.02, whereas, for setting $A_4 B_2 C_1 D_2 E_3$, it is estimated to be 245.17. Thus, it can be noticed that for setting $A_4 B_2 C_1 D_2 E_3$, there is a decrement of 166.15 in the predicted SSR value, which justifies the selection of $A_4 B_2 C_1 D_2 E_3$ 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.

$$MRR = -25.7 - 0.0494 \times A + 8.176 \times B - 0.0155 \times C + 0.449 \times D + 11.11 \times E$$

$$EWR = 0.161 - 0.001792 \times A + 0.00134 \times B - 0.000067 \times C + 0.00013 \times D + 0.0358 \times E$$

$$Ra = 6.68 - 0.0107 \times A + 0.7420 \times B - 0.00089 \times C - 0.0472 \times D - 8.19 \times E$$

$$SCD = 0.02274 - 0.000059 \times A - 0.000764 \times B + 0.000011 \times C - 0.000032 \times D - 0.00184 \times E$$

$$WLT = 24.37 - 0.045 \times A + 0.0193 \times B + 0.00090 \times C - 0.0666 \times D - 25.14 \times E$$

$$MH = 427.0 - 1.96 \times A + 0.67 \times B - 0.0137 \times C + 0.239 \times D + 55.6 \times E$$

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 $(A_4 B_2 C_1 D_2 E_3)$ | 68.635 | 0.0457 | 3.641 | 0.00369 | 5.2781 | 316.075 |
| Satisfaction function and distance-based approach $(A_4 B_2 C_1 D_2 E_3)$ [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
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 | 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 \( \mu F \), feed rate = 12 \( \mu m/s \) 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.

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

| Run | Ra     | KW   | MRR  | Ra     | KW   | MRR  | Squared rank | 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 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 $A_3 B_1 C_4 D_4$, whereas, it is estimated as 73.3125 at the parametric mix $A_3 B_1 C_3 D_4$, 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.

\[
\begin{align*}
Ra &= -0.62 + 0.01039 \times A + 0.05244 \times B - 0.0039 \times C - 0.0067 \times D \\
KW &= 168.9 - 0.500 \times A - 0.035 \times B - 1.500 \times C - 1.200 \times D \\
MRR &= 3.36 - 0.0219 \times A - 0.0006 \times B + 0.4856 \times C - 0.0585 \times D
\end{align*}
\]

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.

| 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

| Process parameters | Symbol | unit | Level |
|--------------------|--------|------|-------|
| Voltage            | A      | V    | 45    | 60    | 75    |
| Electrolyte        | 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]
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 77.6667 indicates voltage as the most influencing factor among the four ECDD process parameters, followed by inter-electrode gap.

![Figure 6: Response graph for SSR values for the ECDD process](image)
Table 18: Response table for SSR values for the ECDD process

| Process parameters | Level 1 | Level 2 | Level 3 | Max-Min | Rank |
|--------------------|--------|--------|--------|---------|------|
| Voltage            | 76     | 65.6667| 143.3333| 77.6666 | 1    |
| Electrolyte conc.  | 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    |

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.

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 | *         | *              |
| Electrolyte conc.  | 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| 100    |           |                |

Table 20: ANOVA for SSR values (after 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   | 20232.0| 100    |           |                |

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.

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

\[ \text{Overcut} = 0.1514 + 0.00147 \times A - 0.00197 \times B - 0.000008 \times C + 0.122 \times D \]  
\[(15)\]

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

| Optimization method                        | MRR      | Overcut | Taper   |
|--------------------------------------------|----------|---------|---------|
| Taguchi method and super ranking concept   | 1.134    | 0.10224 | 0.0411  |
| (A_2B_3C_2D_2)                             |          |         |         |
| GRA technique (A_2B_1C_3D_2) [1]           | 1.118    | 0.167   | 0.042   |
| Improvement (%)                            | 1.43     | 38.78   | 2.14    |

Table 21: Estimated responses for the ECDD process

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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