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Multi Response Optimization of Electric Discharge Machining (EDM) of Al 6061 / MoS2 MMC through Response Surface Methodology and Grey Relational Analysis Technique

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Abstract: Molybdenum disulfide (MoS2), has met substantial consideration as a possible reinforcement for metal matrix composites (MMCs) to improve the desired features as well as reducing the fabrication costs. Though, deprived machining features of Aluminum-based MMCs restrict their use. Modern manufacturing demands the fabrication of MoS2 reinforced Al-6061 materials through the stir casting technique. In the present work, Al-6061/MoS2 machinability features were examined through electric discharge machining (EDM). Machining outcomes like MRR, EWR, SR, and OC for different settings of process variables like peak current (I_p), pulse-on time (T_{ON}), pulse-off time (T_{off}), and voltage (V) were considered. Total experiments (31-runs) were performed through the response surface methodology (RSM) based central composite design (CCD). A mathematical model was developed to correlate the process parameters and performance measures. Then, the competencies of the suggested models are confirmed through the analysis of variance (ANOVA). In addition, the significance of key influential parameters on the machining outcomes was measured through ANOVA. Grey relational analysis (GRA) is applied for RSM to confirm the process parameter's optimal settings for satisfying the anticipated multi-response features (like maximized MRR, minimized EWR, SR, and OC) for attaining the best-drilled holes onAl-6061/MoS2 composite. Significant improvement was noticed in the response measures attained through the employment of optimal settings of process parameters. Results attained were validated with the confirmation experiments.

Keywords: Al-6061/MoS2, EDM, RSM, Overcut, GRA

1. Introduction

The present-day modern manufacturing demands novel materials inhibiting superior features like enhanced toughness, higher strength, and resistance to fatigue and wear. These occasioned the improvement of reinforced composite materials to a group of Nano-composites in recent years. The load application for the composite material tends to disrupt the force adhesion in between the matrix and reinforcement by poisoning the frictional forces in between. The de-bonding behavior concerning the constituents starts cracks at the grain boundaries and transmits the let-down. The other matrix feature is to decrease the de-bonding in the stark load circumstances. Therefore the low-density matrix is a crucial apprehension in realizing the lighter composites.

In the viewpoint of the above concerns, novel material researchers have developed cutting-edge materials like exotic composites, ceramics, and other super-alloys that are higher resistant to heat. Aluminum (Al) metal-matrix composites (MMC) find vast consideration in the modern era due to their higher stiffness, strength, higher heat resistance, and wear in contrast to the un-reinforced alloys [1]. Al-alloys with ceramic reinforcement is desired above traditional owing to their high performance at elevated temperature. Such excellent features make these possess far-reaching uses in the automobile arena for manufacturing constituents like pistons, cylinder liners, blocks, disk-brakes, connecting rods, and drive-shafts, etc., Several handling methods such as traditional and specially patented techniques are already developed to formulate the Aluminium-based MMCs with several types of ceramic particle reinforcement that includes metallurgical methods, alloying, friction-stir casting, thermal-spray depositions, and squeeze casting. Molybdenum disulfide (MoS2) is novel graphene that possesses a smart layered structure. This material is very stronger and lighter. It has increased attention in modern manufacturing as a possible alternative for silicon [2].In the present work; Aluminium alloy (Al-6061) was utilized as the matrix and molybdenum disulfide (MoS2) as reinforcement.

Metal matrix composites (MMC) particle integration intensely depends on the method of volumetric composition and reinforcement. As the wide application of ceramic reinforcements like B4C, TiC, MoS2, ZrB2, and Al2O3improve the features of the base alloying material. Between these, MoS2 has grabbed the novel researcher’s consideration for the reason of their exceptional mechanical, thermal, and electrical properties like low density, increased hardness, and good resistance to wear, higher electric conductivity, exceptionally stable, and wettability features. In addition, MoS2 is a capable material in elevated temperature uses owing to its higher melting-point. These paybacks motivated us to study MoS2 in this research as appropriate reinforcement for improving features of Al-6061 alloy [3]. Despite the fact several manufacturing methods are reachable for ceramic particle reinforcement for MMCs; there exist some challenges like higher costs of fabrication, increased production times, and phase strength mechanisms in the base matrix that realizes to be most economical. Therefore a better technique for accurate shape and large production rates could be attained through the stir casting method. Moreover, better-enhanced particle reinforcement in the metal matrix could be attained over the instinctive stirring act implemented in the stir-casting method.

The possible applications of MMCs are restricted by the slow machining conditions owing to the existence of tough abrasive supports. In the course of traditional machining methods like milling, drilling, shaping, and turning the tough and particle reinforcement's occasions in the increased wear of the cutting tool. In this viewpoint, traditional machining of components results in high production costs and deprived surface features. Consequently, the manufacturing of intricate geometries with high precision and accuracy for MMCs is a challenging task through traditional machining processes. In addition, if it is desired for micro and Nano holes of higher aspects through machining for Al-based composites through traditional drilling methods, the drill-bit fails suddenly owing to the low rigidity features. The difficulty in withdrawing from the tool breakage from the micro or Nano holes significantly decreases the productivity in machining. Hole drilling operations in component manufacturing are deliberated as the key engineering application as mostly macro and micro-holes are desired for precise features as well as compacting in the product assembly.

On the other hand, the submissions of prevailing composites are restricted though machinability is a serious issue. Slow or deprived machining conditions the material result in rough surfaces as well as increased wear of the tool. In general machining process for the MMC is a very challenging task through conventional methods owing to the inherent features like exotic hardness as well as reinforcement strengths. Therefore, the EDM process acts as an appropriate technique that does not rely on mechanical forms of energy to eliminate the undesired material from the work [4]. The material erosion in the EDM, do not affect by the features such as strength, hardness, and toughness. Exotic materials such as MMC with MoS2 are very tough to be processed on conventional machining. Moreover, results from the past literature reported that selection of process parameters in EDM play a vital role in deciding the machining outcomes like electrode-wear rates (EWR), material removal rates (MRR), surface roughness (SR), and over-cut (OC). The choice of the process variables for optimal machining outcomes is quite an exciting job. Consequently, the statistical approach for resolving the multi-response optimization problems of EDM has implied enhancing the response measures [5]. One such technique is fulfilled with the response-surface methodology (RSM) to progress the complete mathematical representations for the correlative interactions and also second-order effects of machining process parameters of peak-current, pulse durations, pulse interval on the multiple surface integrity features for M2 steel. Taguchi orthogonal arrays procedure as the experimentation designs in the view of studying the effect of EDM process variables like pulse duration, peak current, and voltage factors, pulse interval, as well as other electrode and surface features in EDM of hot-work DIN1.2714 tool steel material [6]. The robust methods of Taguchi-methods and grey-relational analysis combined to optimize the process variables settings of EDM over the response measures such as MRR, EWR, and SR during studying the machinability features for Ti-6Al-4V [7]. Though, the complications were noticed in understanding the non-linear relations in between the different parameters, whereas GA could not fit for the complication of domain experiments. The RSM-Taguchi technique has been utilized in optimizing the multiple outcomes in several machining operations. Principal-component analysis (PCA) coupled with grey-relational analysis (GRA), an integrated technique, have been noticed effective through multi-objective optimization.

The present work examines and optimizes the impending process variables that effecting the MRR, EWR, SR, and overcut during ED machining Al-6061/MoS2 material. This investigation includes the study of the relations among the different input process parameters like peak current (I_P), pulse on time (T_{ON}), pulse-off time (T_{OFF}), and voltage (v). The response surface methodology (RSM) procedure, an authoritative experimentation design tool, utilizes an easy, operative, and organized technique for developing the optimum conditions for machining parameters. Moreover, this technique involves the least possible experimentation costs and professionally minimizes the variation influence. This technique is very simple but most robust, and operating methodology could be progressed to change the surfaces machined and also for maintaining precision and accuracy. RSM technique by central composite design (CCD) is utilized for performing the design of experiments (DOE) for optimizing the experimentation results for EDM of Al-6061/MoS2 material. In addition, the Grey-relation analysis (GRA) technique is utilized to integrate several responses into a unified single response for optimization in the viewpoint for attaining single operative optimal settings for multiple response measures like MRR, EWR, SR, and OC.

2. Materials and methods

2.1 Method of hybrid composite fabrication

Al-6061/MoS2 material is selected as the matrix material in the present work, and the chemical (%) of the developed matrix were listed in Table 1. The metal-matrix composites (MMCs) were developed utilizing the stir-casting procedure, by altering the MoS2 in wt. % of 2%, 4%, and 6% of 2μm size particles. The MoS2 powder particles were pre-heated to 525° C to eliminate the wetness and added to the molten metal. The mechanical stirrer with 350 rpm was engaged. After the formulated mixture is sent to a die-casting molding to make the essential works. A similar type of procedure was considered to achieve the MMCs of altered composition wt. % i.e. 4 %, and 6% respectively. The experimentation has been performed to analyze the data utilizing a ZNC electric discharge die-sinking EDM apparatus Sparkonix S-35 ZNC presented in Figure 1. Pure graphite electrode of ø 10 mm was utilized to the Al-6061/MoS2, the outlook of the sample is shown in Figure 2, and EDM dielectric fluid (specific gravity = 0.69, freezing-point= 89°C) was utilized as the dielectric-fluid, tool-electrode, and workpiece was placed with the positive.

Fig. 1. Die-Sinker EDM Machine (Make: Sparkonix S-35)

Both workpiece and tool-electrode were immersed in the dielectric-fluid as the phenomenon in die-sinker EDM, in the view of effective-flushing of debris particulates from the machining zone with a pressure 0.3 kg-f/cm^2.

Fig. 2. Graphite tool-electrode

The performance measures of the machined surfaces were determined by the input process parameters such as peak current (I_p), pulse-on time (T_{ON}), pulse-off time (T_{off}), and voltage (v). The experimental runs were planned so that the permissible range of input process parameters as well as categorizing the appropriate lower and upper limits so that the quality of the machined surfaces could be justified with minimal deviations. Response surface methodologies (RSM) like central composite design (CCD) were selected for the combination of three different levels for experimentation. The chemical composition of the selected Al-6061/MoS2 is listed in Table 1 and the property of the tool-electrode is listed in Table 2 respectively. The coded and actual ranges of the experimental runs are listed in Table 3. Servo sensitivity is maintained high and a constant gap was confirmed in between the surfaces of the tool-material and workpiece for every experimental run.

Table 1. Chemical Composition of Al-6061/MoS2

Elements	C	Mg	Si	Fe	Ni	Mn	Ti	Sn	Mn	Al
Weight in %	0.02	0.042	0.36	0.43	0.004	0.15	0.018	0.01	0.17	Balance

Table 2. Properties of Tool-electrode

Material	Properties		
	Density (g/cm^3)	Melting Point (^{o}C)	Thermal Conductivity (W/m.k)
Graphite	2.26	3600	98

The performance measures such as material removal rate (MRR), electrode wear rate (EWR), surface roughness (SR), and overcut were considered for evaluating the machining features. The machining performance for ED-hole drilling for Al-6061/MoS2 MMC is assessed by making an allowance for the performance measures in the characteristics of productivity and qualitative features like MRR, EWR, SR, and OC.

Table 3. Process Parameters and their levels for machining

Process Parameters					
Parameter	Symbol	Units	Levels		
			Low	Medium	High
Peak Current	I_P	A	10	20	30
Pulse-on Time	T_{ON}	µs	100	200	300
Pulse-off Time	T_{OFF}	µs	20	30	40
Voltage	v	V	15	25	35

The formula for calculating the MRR is represented in Equation 1. The formula for calculating the EWR is represented in Equation 2. The MAB 220T accuracy 0.0001 g was utilized for weighing electrodes before and after the experiments.

$$MRR = \frac{Volume\ of\ the\ work\ material\ eroded}{Time} mm^3/min \quad (1)$$

$$EWR = \frac{W_b - W_a}{Time\ *\ Density} mm^3/\ min \quad (2)$$

Where $W_b = Weight\ of\ the\ electrode\ before\ machining$

$W_a = Weight\ of\ the\ electrode\ after\ machining$

Average of the measured surface microscopic-peaks and valleys. The value of RMS is calculated as the Root-Mean-Square of a surface measured microscopic peaks and valleys. The surface roughness has been measured using the Mitutoyo SJ 210 roughness tester. Surface roughness (SR) values are calculated based on Equation 3. In the below equation x denotes the direction of the profile, y denotes the height of the peaks and valleys of profile roughness and L specifies the sampling length. Any machined cavity developed through EDM will be larger than that of the tool-electrode utilized to process it. The actual difference between the size of the tool-electrode and the machined cavity (or hole) is called the overcut. In the present investigation, tool-electrode diameter and workpiece cavity is measured by the profile projector. The formula for determining the overcut is represented in Equation 4. Where $'D_h'$ and 'D_t' denotes the diameters of the machined hole and the tool-electrode. The overcut is measured in millimeters (mm).

$$SR = \frac{1}{L}\int_1^l |y(x)|dx\ (\mu, m) \quad (3)$$

$$OC = \frac{D_h - D_t}{2}\ mm \quad (4)$$

3. Methodology

3.1. Multi-objective optimization using Hybrid grey-response surface methodology

The multi-response optimization methodology is a unique offline model of quality control technique underwriting an applied structure to the prerequisite for increased productivity and better surface finish on the machined surfaces This procedure restitutions the difficulty of regression-based analysis by launching the association in between the elements based on deviations amount or similarity of the tendencies amongst these features. The features of the grey-relation grade are reflected in utilizing the grey-based analysis as a qualitative descriptive of all the machining response features, which is additionally modeled by integrating to RSM-CCD approach equipping the possibility for simultaneous optimization of the response measures [8]. This technique of GRA with response surface methodology (G-RSM) is conveyed in the following sections. The grey-relation analysis (GRA) has been utilized to convert the complicated raw experimentation results into a sequential form to attain the connection between the several response measures and process variables. The measured responses such as EWR, SR, and OC were considered as the 'smaller the better' type feature and the results noticed for MRR have been measured as the 'larger the better' type feature. Linear type of normalization procedure has implied on the attained output responses as well as for the equivalent ideals for pre-processed data and the grey relational grade (GRG) values are recorded. The GRG outcomes attained will represent the individual value for the multiple responses and also the GRG magnified value of the experimental responses. The GRG calculated values are mapped for the several runs of experimentation. The maximum response of the attained GRG values was noticed for the twelfth trial, signifying the closeness of the operative conditions to the optimal setting of the process parameters.

3.2. Grey Relational Analysis Procedure

Grey's relational theory provides resolution for any system with uncertainty or incomplete data. This approach is a conceptually effective means of validating the correlations in between the continuous series with less data as well as it could appraise several parameters that could overcome the difficulty of parameter selection. The advantage of this approach is significant to elucidate the confusing inter-relationship amongst the response measures competently keen on a unique grey-relational grade (GRG). The way of implementing GRA is modest and very effective for controls and optimization processes [9]. The GRA includes these three steps in the optimization:

3.2.1. Step-1: Data pre-processing and Normalization

The raw experimental data is pre-processed is intended when the sequential breakup collection is very large, or else the guidelines of the required goal optimization for the sequences are divergent. The units of the measured responses are different and the requisites also vary from one another, so to satisfy the required unified optimized conditions the raw data needs to be pre-processed. Pre-processing of the raw data refers to the conversion of the raw-sequence into a comparative sequence. In the view of data sequences, there are several methods of data pre-processing available for the GRA procedure. Material removal rate (MRR) will come for larger-the-better quality features, whereas EWR, SR, and OC will group under smaller-the-better type quality features. The corresponding formula for both maximization and minimization types of characteristics are given in Equation (5) and Equation (6):

Larger the better characteristic, $$x_{ij} = \frac{y_{ij} - \min\limits_{j} y_{ij}}{\max\limits_{j} y_{ij} - \min\limits_{j} y_{ij}} \quad \text{……......………..(5)}$$

Smaller the better characteristic, $$x_{ij} = \frac{\max\limits_{j} y_{ij} - y_j}{\max\limits_{j} y_{ij} - \min\limits_{j} y_{ij}} \quad \text{………………(6)}$$

where 'x_{ij}'is the normalized value after grey-relational development.

'y_{ij}' for the i^{th} experimentation results in the j^{th} experiment.

3.2.2. Step-2: Development of Grey-Relational Coefficient

By utilizing the normalized data attained from the step-1 normalization process (pre-processing step), the grey-relational-coefficients are developed. The grey-relational- coefficient (ξ_{ij}) is developed utilizing the formulae mentioned in Equation (7),

$$\xi_{ij} = \frac{\min\limits_{i}\min\limits_{j} |x_i^o - x_{ij}| + \zeta \max\limits_{i}\max\limits_{j} |x_i^o - x_{ij}|}{|x_i^o - x_{ij}| + \zeta \max\limits_{i}\max\limits_{j} |x_i^o - x_{ij}|} \quad \text{………………………………………………(7)}$$

where, 'x_i^o' is the ultimate normalized value for the i^{th} experimention result

'ζ' refers to the distinguishing-coefficient normally nominated as 0.5.

3.2.3. Step-3: Development of Grey-Relational Grade

The grey-relational-grade (GRG) is calculated by considering the mean of the attained grey- relational co-efficient (GRC) values of all the experimental outcomes and it is developed utilizing the formulae represented in Equation (8),

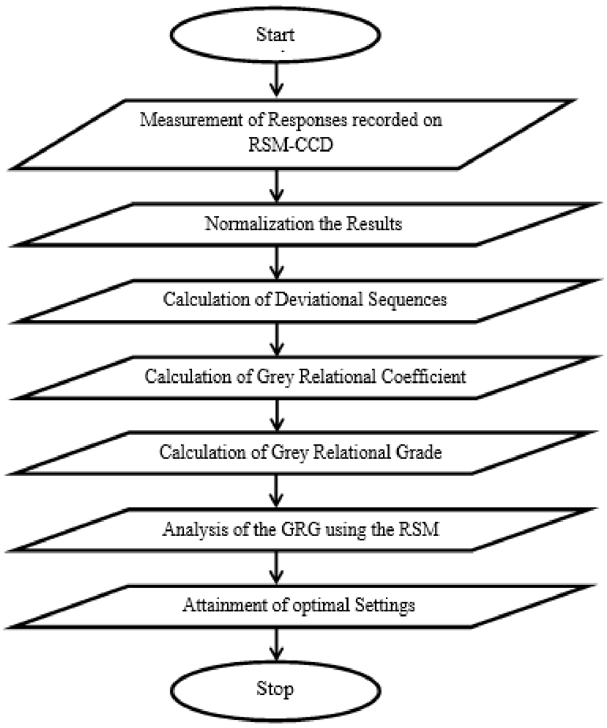

Fig. 3. Flow chart for Response measures using GRG Technique

$\gamma_j = \frac{1}{m}\sum_{i=1}^{m}\xi_{ij}$ ……..…...(8)

where 'γ_j' denotes the grey-relational-grade of the 'j^{th}' experiment

'm' denotes the numbers of response characteristic

The complete procedure for the hybrid approach for optimized results is represented in Figure 3. The quadratic model and the response plots generated with the design-expert software using the response-surface-methodology (RSM) revealed the relation of the process parameters and the response measures. The 3D response graphs for showing the influence of process parameters on grey relational grade (GRG): (i) Influence of I_P and T_{ON} (ii) Influence of T_{OFF} and v (c) influence of I_P and v. Several graphs of RSM were generated and presented, equivocating the interaction plots with the least significant influence. It has been witnessed that I_P at elevated levels and low T_{ON} durations are preferred as closely in line with the past researches in the viewpoint to improve the grey grades and which in turn the response measures. This phenomenon is accounted to intensified sparking at peak current, and occasioning in stable melting, re-solidifying phenomenon, resulting in the surface finish of the EDM'ed work. The controlled discharges in-between the tool-electrode and workpiece are attained through the stable flushing pressure during machining. From the experimental results, it has been noticed that increased voltage conditions develop the stable pulses, which in turn decreases EWR, enhanced surface finish with better MRR. Similar results were noticed for the GRG for this parametric combination.

4. Effect of independent process variables on measured responses

4.1. Effect of independent process variables on material removal rate (MRR)

The higher MRR response denotes the more rate of erosion. It is always desired to have higher MRR in terms of productivity. As of the results from the developed empirical model, it is witnessed that the peak-current (I_P) shown a higher influence on the MRR. The MRR values tend to increase with the increase in the peak current (I_P) and pulse-on time (T_{ON}). This could be possibly accounted for the reason as an increase in I_P, the pulse-discharge energies in the diameter channel upsurges which in turn increases the developed crater-depth and diameter. As the crater dimension increases, this occasions the MRR improvement. Whereas, the increase in T_{ON} results in extended durations for the heat flux developed this, in turn, directs towards the plasma channel enlargement, which directly witnesses the increased MRR. Results from Figure 4 show the changes in the MRR values with reference peak current (I_P) and voltage (v).

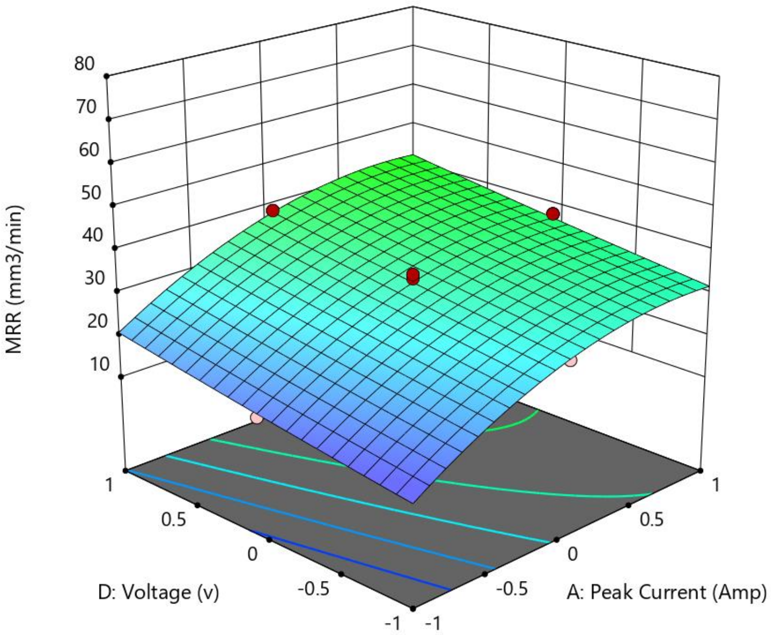

Fig. 4. Interaction Plot (v Vs. I_P) for MRR

It can be witnessed clearly that the MRR increases with the rise of I_P for all levels of v except for at low values of v, somewhere it initially decreases marginally and formerly tends to increase. This figure in addition validates that the MRR non-linear deterioration with the rise of gap-voltage conditions, on the other hand later attaining a minimum value, it shows the increasing tendencies. The regression equation developed for the MRR because of experimental data is represented in Equation 9. This shows that lower gap-voltage values tend to result in increased MRR. Though, the implication of very low values devises the tendency of arcing. Likewise, the higher gap- voltage values could result in comparatively decreased MRR.

MRR = +32.66 +10.86 (I_P) +9.56 (T_{ON}) +2.85(T_{OFF}) +5.31(v) + 1.63(I_P)(T_{ON})- 0.4073 (I_P)(T_{OFF})+0.0048(I_P)(v)+ 2.99 (T_{ON})(T_{OFF})-0.0527(T_{ON})(v)+3.32 (T_{OFF})(v)-6.67 (I_P^2) + 7.79 (T_{ON}^2) + 3.84 (T_{OFF}^2) + 0.2635 (v^2) ……..………………………(9)

4.2. Effect of independent process variables on Electrode wear rate (EWR)

Die-Sinker EDM is a method of copying the profile of the tool-electrode to the workpiece, in addition, the profile of the tool-electrode is damaged by the sparking phenomenon. This damage refers to electrode wear. The regression equation developed for the EWR because of experimental data is represented in Equation 10. It is always desired to have the least EWR values, as this directly refers to the tooling economics in machining. Results developed from the established equations from the mathematical models revealed that the influence of the several machining responses has been studied in viewpoint to analyze the possible parameter combinations which could be accounted for attaining the controlled electrode-wear rate (EWR). It can be seen from Figure 5 that the influence of T_{ON} and I_P on the EWR. It has been observed that values for EWR tend to decrease continuously with the increase in the T_{ON} values for all gap-voltage conditions for a pre-set I_P values. This could be possibly accounted for the reason that the low values of pulse-on time T_{ON}, more volumes of negatively charged particles could strike in motion the positive tool-electrode and hence increase in melting rates for the tool-electrode material.

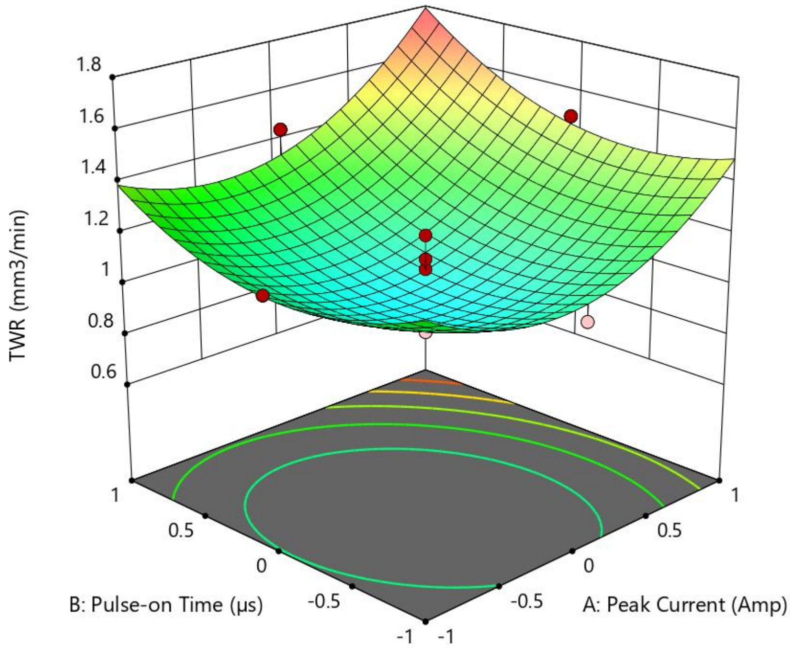

Fig. 5. Interaction Plot (T_{ON}Vs. I_P) for EWR

It is also witnessed that EWR values tend to increase with the increased gap-voltage till it reaches crosses a minimum parametric value and then gradually decreases again. Subsequently, the EWR is directly proportional to the MRR responses, as the existence of the larger volume debris particulates occasions increased wear of tool-electrode in the process of flushing activity. Consequently, the MRR also decreases; the EWR also tends to decrease. The effect of I_P and v on the tool-electrode wears for a pre-determined I_P and v. This represents for every selected gap-voltage (v), the increase in the EWR with the rise in the I_P in a mirror-symmetrical trend. This could be possibly accounted for the reason that the machining phenomenon with higher I_P values results in increased energies and is exposed to both of the electrodes. Therefore molten metal volumes for both the cathode (workpiece) and anode (tool-electrode) tend to increase accordingly.

$$EWR = 1.06 + 0.1507 (I_P) + 0.1004 (T_{ON}) +0.1030 (T_{OFF}) + 0.0432 v+ 0.0500 (I_P) (T_{ON}) + 0.3050(I_P) (T_{ON}) + 0.0215 (I_P) (v) +0.0017 (T_{ON}) (v) – 0.0265 (T_{OFF})(v) +0.2542 (I_P)^2+0.1778 (T_{ON})^2-0.0735 (T_{OFF})^2 -0.2280 (v)^2 \ldots\ldots (10)$$

4.3. Effect of independent process variables on Surface roughness (SR)

The regression model developed for the SR is presented in Equation (11) reflects that the peak current has a key influence on the SR. The SR values tend to increase with the increase in peak current (I_P) and pulse-on time (T_{ON}) values. Results from Figure 6 shows that an increase in the I_P leads to a rise in heat energy at the specific point of discharge. Consequently, a molten pool and liquefied pool metal are developed as well as agitated. As the material removal in the EDM process is accomplished through vaporization, in this process tiny gas bubbles are formed and are exploded owing to the liquefaction and evaporation of molten metal. Furthermore, these are flushed away under the influence of dielectric fluid. It is also noticed for the high pulse-on durations, greater spark energies are produced. Owing to the listed reasons, the increased SR values are noticed.

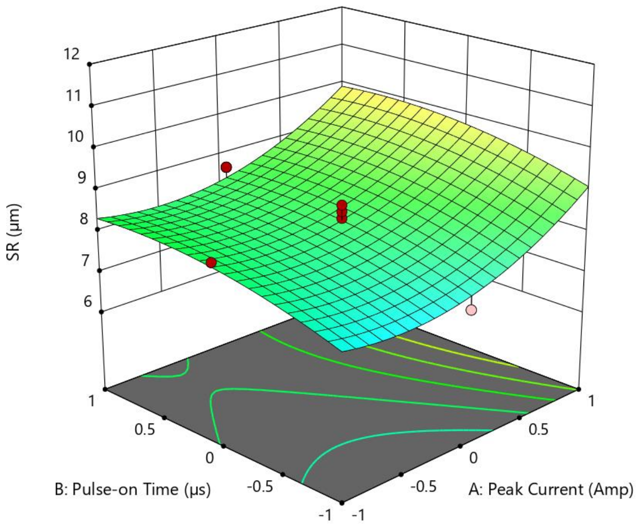

Fig. 6. Interaction Plot (T_{ON}Vs. I_P) for SR

The influence of peak current I_P and voltage delivers to the significant decrease in the SR, although the SR tends to decline with the increase in the T_{OFF} and I_P values. Although the past researches reported that the increase in peak current I_P results in intensified heat discharges at the point of the discharge. The regression equation developed for the MRR given experimental data is represented in Equation 11. Consequently, molten pools are formed as well as the overheating phenomenon is noticed. The developed molten metal initially evaporate as well as resulting in the formation of tiny gas- bubbles which tend to burst over the instance of discharges, flushing the molten material and creating the fresh gap for sparking. Consecutive discharges could occasion the formation of pockmarks and craters, therefore an increase in the surface roughness (SR) values are noticed.

$SR = 8.28 + 0.8087\ (I_P) + 0.4208\ (T_{ON}) -0.3713\ (T_{OFF}) +0.6547\ (v) - 0.0133\ (I_P)\ (T_{ON}) – 0.1216\ (I_P)\ (T_{OFF}) - 0.0128\ (I_P)\ (v) + 0.0881\ (T_{ON})\ (T_{OFF}) - 0.5882\ (T_{ON})\ (v) -0.1267\ (T_{OFF})\ (v) + 0.7386\ (I_P)^2 - 0.3175\ (T_{ON})^2 - 0.4130\ (T_{OFF})^2 – 0.4379\ (v)^2$………..…..(11)

4.4. Effect of independent process variables on overcut (OC)

Any EDM cavity is quite large than the tool-electrode utilized in machining. The variation between the tool-electrode size and the cavity-size (or formed hole) is termed over-cut. The increase in the pulse-discharge energies, in turn, results in the increased magnitude of overcut owing to the higher rates of thermal-energy transmission into the machining region [11]. This occurrence directs to the melting and vaporization of more material from the work surface. Over-cut on the machined hole is possibly occasioned for the magnitude of material removal through electric sparks. It has been witnessed from Figure 7 that I_P and T_{ON} are key influential process variables for OC.

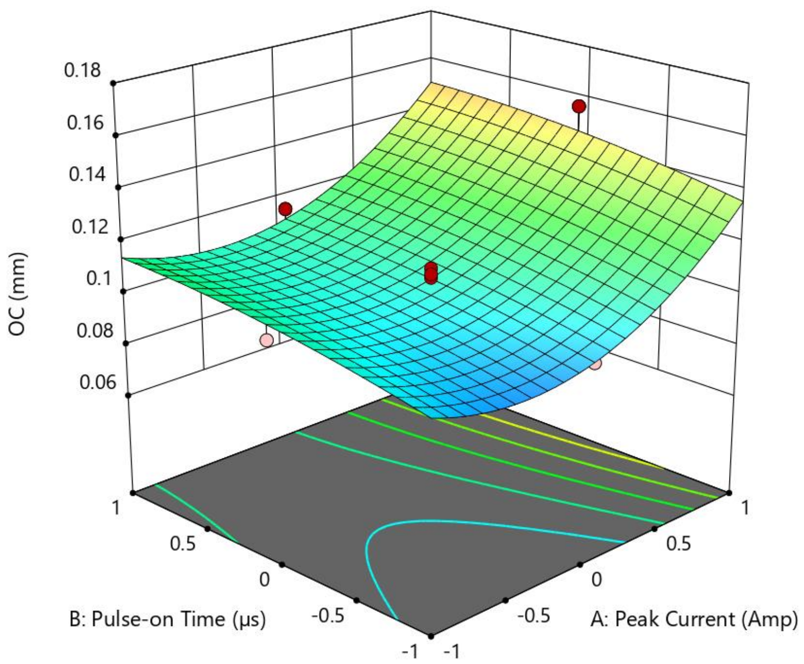

Fig. 7. Interaction Plot (T_{ON}Vs. I_P) for OC

It is also witnessed that the over-cut of machined holes tends to increase with the increase in the levels of I_P and T_{ON}. This phenomenon is attributed to increased attentiveness of electrons and also heat transfer at the elevated current, which in turn resulted in increased melting and vaporization from the work surface. Similar trends are noticed for the instance of an increase in the pulse-on times. Better ionization is possible at higher levels of pulse-on-time. In turn, this ionization develops a broader plasma channel, as well as the area witness the elevated temperatures and consequently result in a larger overcut. Whereas, the shallow plasma channel is developed at the low pulse-on time, in turn occasioning the minimized overcut. Likewise, the effect of I_P and T_{ON} is considerably high on overcut is noticed to be considerably high as matched to the T_{OFF} and v parameters. The regression equation developed for the OC given experimental data is represented in Equation 12. It is also noticed that the influence of interactions of I_P and T_{OFF} on overcut responses. It is witnessed that overcut of machined holes tends to be reduced with the rise in the T_{OFF} for all the levels of I_P. This can be accounted for the debris particle's effective evacuation in the machining region that in return restricts the arcing phenomenon at the debris boundaries and machined hole surface in the process of clearing the detached particles through the effective dielectric flushing media [12].

$$OC = 0.1062 + 0.0183\,(I_P) + 0.0075\,(T_{ON}) + 0.0040\,(T_{OFF}) + 0.0131\,(v) - 0.0002\,(I_P)(T_{ON}) + 0.0041\,(I_P)(T_{OFF}) + 0.0083\,(I_P)(v) - 0.0061\,(T_{ON})(T_{OFF}) - 0.0001\,(T_{ON})(v) + 0.0039\,(T_{OFF})\,(v) + 0.0217\,(I_P)^2 - 0.0031(T_{ON})^2 - 0.0131(T_{OFF})^2 + 0.0040\,(v)^2 \qquad (12)$$

On the other hand, at lower levels of T_{OFF} and higher levels of I_P, increased overcut is noticed and this could be possibly accounted for edge arcing conditions. In addition, T_{OFF} is noticed to be the least influential parameter for OC with 1.95 % contribution, and the other process variables, correspondingly I_P and v, show the contribution impact of 40.90% and 21.42%, in turn, on OC. It is clear that with the rise in T_{ON} the OC tends to increase up to the threshold limit and then OC is considerably stable at lower levels of T_{OFF}, compared to alternate settings of T_{OFF}.

5. Results and discussion

5.1 Multi-response optimization using Grey-relational analysis (GRA)

The parametric influence on the performance measures (MRR, EWR, SR, and OC) has been investigated according to the RSM. The regression-based models developed through RSM were noticed to be competent and adequate. For implementing multi-response optimization utilizing the GRA procedure, the process initiates with the normalization process to the experimental EDM results, to style scale-free (unified) response reaching from 0 to 1. The above-mentioned procedure is termed grey-relation development. The process parameters, experimental results, and the intended values from the normalization procedure for output response were utilized to fix the grey-relational coefficient (GRC) value [13].

Table 4. Grey Relational Analysis

Trial No.	Experimental Data				Normalization				Grey Relational Coefficient (GRC)				Grey Relational Grade	Rank
	MRR	EWR	SR	ROC	MRR	EWR	SR	ROC	MRR	EWR	SR	ROC	GRG	Rank
1	15.442	0.908	6.459	0.090	0.059	0.876	0.923	0.881	0.347	0.801	0.866	0.807	0.705	3
2	36.858	1.064	8.389	0.092	0.410	0.713	0.544	0.853	0.459	0.636	0.523	0.773	0.598	8
3	29.387	0.959	8.236	0.109	0.288	0.823	0.574	0.659	0.412	0.739	0.540	0.594	0.571	11
4	51.858	1.186	10.199	0.121	0.656	0.586	0.188	0.515	0.592	0.547	0.381	0.507	0.507	26
5	23.547	1.037	9.266	0.080	0.192	0.742	0.372	1.000	0.382	0.659	0.443	1.000	0.621	6
6	40.355	1.199	11.158	0.134	0.467	0.573	0.000	0.374	0.484	0.539	0.333	0.444	0.450	29
7	28.366	1.027	8.699	0.117	0.271	0.752	0.483	0.561	0.407	0.669	0.492	0.533	0.525	22
8	56.875	1.396	10.499	0.155	0.738	0.367	0.129	0.126	0.656	0.441	0.365	0.364	0.457	28
9	11.845	0.993	6.066	0.084	0.000	0.788	1.000	0.957	0.333	0.702	1.000	0.921	0.739	1
10	28.155	1.269	7.478	0.115	0.267	0.499	0.723	0.594	0.406	0.500	0.643	0.552	0.525	21
11	30.000	1.216	8.159	0.092	0.298	0.555	0.589	0.864	0.416	0.529	0.549	0.786	0.570	12
12	55.699	1.579	9.569	0.118	0.719	0.176	0.312	0.557	0.640	0.378	0.421	0.530	0.492	27
13	26.289	1.057	8.257	0.110	0.237	0.721	0.570	0.653	0.396	0.642	0.537	0.591	0.541	19
14	44.658	1.257	9.741	0.162	0.538	0.512	0.278	0.037	0.520	0.506	0.409	0.342	0.444	30
15	50.549	1.113	8.125	0.105	0.634	0.663	0.596	0.712	0.578	0.597	0.553	0.634	0.590	9
16	72.846	1.747	9.459	0.166	1.000	0.000	0.334	0.000	1.000	0.333	0.429	0.333	0.524	23
17	14.326	1.169	8.326	0.104	0.041	0.604	0.556	0.720	0.343	0.558	0.530	0.641	0.518	24

18	37.857	1.494	9.658	0.156	0.426	0.264	0.295	0.112	0.466	0.405	0.415	0.360	0.411	31
19	28.544	1.070	7.214	0.095	0.274	0.707	0.775	0.818	0.408	0.631	0.689	0.733	0.615	7
20	52.148	1.440	8.658	0.115	0.661	0.321	0.491	0.593	0.596	0.424	0.496	0.551	0.517	25
21	27.388	0.790	8.124	0.097	0.255	1.000	0.596	0.795	0.402	1.000	0.553	0.709	0.666	4
22	38.657	0.909	9.259	0.127	0.440	0.875	0.373	0.452	0.471	0.801	0.444	0.477	0.548	18
23	29.659	0.804	8.157	0.085	0.292	0.985	0.589	0.945	0.414	0.971	0.549	0.901	0.709	2
24	43.542	1.204	7.524	0.106	0.520	0.567	0.714	0.699	0.510	0.536	0.636	0.624	0.577	10
25	32.215	1.064	8.095	0.104	0.334	0.714	0.602	0.722	0.429	0.636	0.557	0.643	0.566	14
26	28.974	1.103	8.335	0.107	0.281	0.672	0.554	0.688	0.410	0.604	0.529	0.616	0.540	20
27	34.569	1.197	8.270	0.097	0.373	0.575	0.567	0.800	0.443	0.540	0.536	0.715	0.559	15
28	29.548	1.057	8.090	0.110	0.290	0.721	0.603	0.645	0.413	0.642	0.557	0.585	0.549	17
29	34.541	1.037	8.237	0.106	0.372	0.742	0.574	0.697	0.443	0.659	0.540	0.622	0.566	13
30	33.578	0.813	8.499	0.100	0.356	0.976	0.522	0.761	0.437	0.954	0.511	0.677	0.645	5
31	34.575	1.040	8.660	0.108	0.373	0.739	0.491	0.673	0.444	0.657	0.495	0.605	0.550	16

Subsequently, in the next step grey-relational coefficient (GRC) is developed depending on the normalization of experimentation data to exemplify the experimentation and estimated data. Afterward, the average of grey-relational-coefficients (GRC) consistent with the designated outcomes grey-relational-grade (GRG) is computed. Therefore, the several responses are renewed into a unified response. The optimum parametric setting is appraised by allowing for the global maximum of GRG response. The calculated deviation sequence orders, GRC's and GRG outcomes are recorded in Table 4. The regression equation developed for the GRG because of experimental data is represented in Equation 13. Consequently, the multi-response optimization difficulties have been renovated into a single-response optimization problem utilizing the hybrid RSM-GRA methodology [14]. Results from Figure 8 show that T_{ON} and I_P play a crucial role in the determination of multiple objective characteristics for GRG. The equivalent parameter in the ED process setting associated with larger GRG values is confined to be closely in line with the optimum solution.

GRG = 0.5707 -0.0541 (I_P) - 0.0270 (T_{ON}) - 0.0078 (T_{OFF}) - 0.0374 (v) +0.0196 $(I_P)(T_{ON})$ -0.0028 $(I_P)(T_{OFF})$ +0.0038 $(I_P)(v)$ +0.0151 $(T_{ON})(T_{OFF})$ +0.0291 $(T_{OFF})(v)$ + 0.0064 $(T_{OFF})(v)$ – 0.1096 $(I_P)^2$ – 0.0083 $(T_{ON})^2$ + 0.0685 $(T_{OFF})^2$ +0.0329 $(v)^2$……….(13)

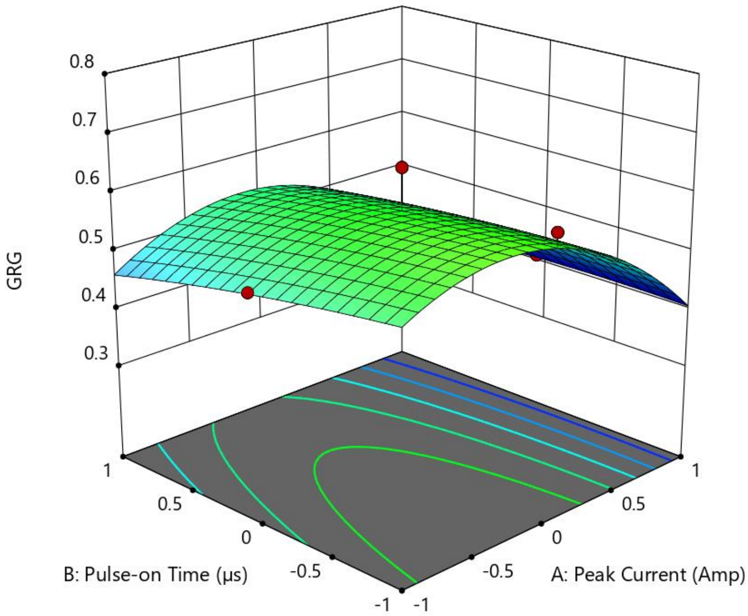

Fig. 8. Interaction Plot (T_{ON}Vs. I_P) for GRG

The main effects plot for GRG values is represented in the Figure 9, that shows optimum parameter setting at I_P = 10 A, T_{ON} = 100 µs, T_{OFF} = 60 µs and v = 60 V.

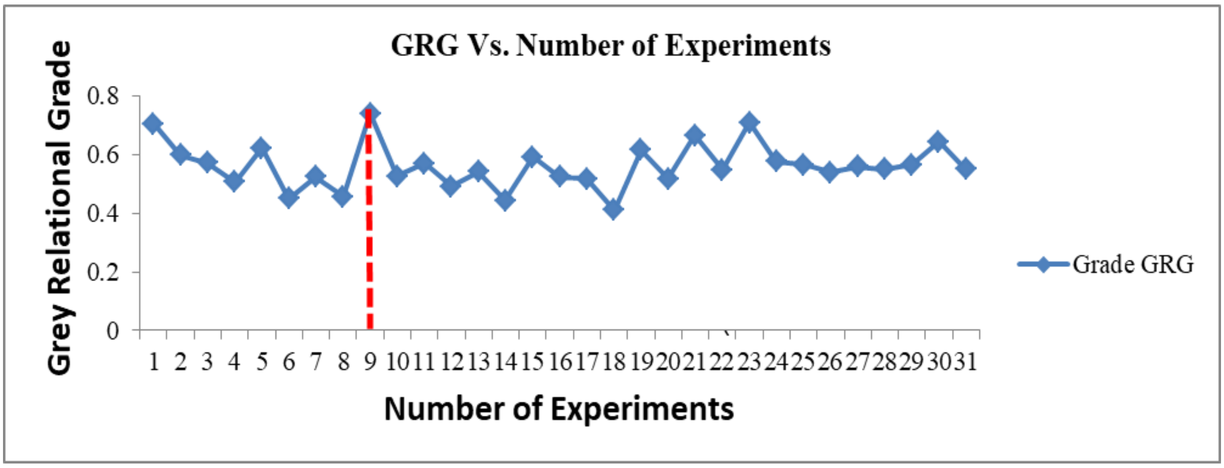

Fig. 9. GRG Vs Number of Experiments

ANOVA statistical analysis for GRG values with the contribution percentage of every process parameter with their interaction combined effects is measured. This represents that process parameters like I_P with 29.65%, T_{ON} with 7.37%, T_{OFF} with 0.67%, v with 14.18%, and the interactions like I_P * T_{ON} with 3.4327, T_{ON} * T_{OFF} 2.02%, T_{ON} * v with 7.65% have shown an influence on GRG. The determination coefficient (R^2) and the adjusted deterministic coefficient (adj-R^2) values were noticed to be 86.46% and 74.61%, correspondingly. P-values less than 0.0500 indicate model terms are significant.

In this case, I_P, T_{ON}, T_{OFF}, v, I_P^2, and T_{OFF}^2 are noticed to be influential model-terms. The values greater than 0.1000 indicate that the model terms were not-significant. The Lack of Fit F-value of 1.34 implies the Lack of Fit is not significant relative to the pure error is good and statistically insignificant at 95% levels of confidence. The mathematical relation among the process variables and the GRG was represented in Equation (9). At the final stage, the confirmatory experiment has been performed to validate and confirm the development of the qualitative characteristics utilizing the optimal levels of the parametric design [15]. The optimal values estimated for GRG for the EDM process have been noticed through Equation (10). Where $'\alpha_m'$ denotes the mean of GRGs for all the experimental trials,$'\alpha_i'$denotes GRG means at the optimal-levels of the process parameters and ‘n’ represents the process parameters selected and considerable influence on GRG. In the view of the qualitative performance improvement, the process parameters at the initial trial selected were at I_P=20A, T_{ON} =300 µs, T_{OFF} =20 µs, and v=15 V. The process parameters at the initial level were randomly selected by the user settings for the accessible options. It has been witnessed that 0.5165 GRG-value at trial 1. It has been noticed that a considerable improvement of GRG-value to 0.7391 for optimal setting at trial 13 (I_P=10A, T_{ON} = 100 µs, T_{OFF} = 40 µs, and v= 15 V). The present work revealed that performance measures enhancement to a considerable level with the optimal setting.

5.2. Evaluating adequacy of the developed models

The developed quadratic models utilizing the RSM are shown for the assessment of MRR, EWR, SR, and OC. In addition, competence examinations for the suggested models are developed utilizing ANOVA analysis done by computing the F-ratio that is the average ratio of the developed regression-model mean-square values to the mean-square error (MSE) [10]. It has been witnessed that the F-value for MRR is 50.05, F-value for EWR 10.44, F-value for SR as 70.48, and F-value for OC as 32.96 correspondingly. The ANOVA responses indicate that the measured model responses are significant as well as the larger numerical occasioned through noise-factors by a probability of 0.01 %. On the other hand, these ANOVA measures are confirmed at 95%-confidence levels besides the expressions in the regression-based models that have a p-value ($P \leq 0.05$) are measured as statistically substantial influences. The responses measured by ANOVA noticeably represent the possible significance of the model-terms that comes under 0.05 for the measured outcomes. Therefore the suggested quadratic models are quite sufficient for MRR, EWR, SR, and OC estimates. The MRR instance showed that I_P and T_{ON} are measured as the key influential parameters whereas T_{OFF} and v are witnessed to be the least influential parameters. The second-order terms of I_P and T_{ON} are measured to be significant as their p-value lies under 0.05. Similarly, the results of ANOVA for EWR revealed that I_P, T_{ON}, and v are significant factors for second-order terms of I_P, and T_{ON} showed a substantial influence. Similarly, ANOVA results of SR measured I_P and T_{ON} as the influential factors as well as and second-order terms of T_{OFF} and v as key influential parameters. In addition, the word adequate-precision for the model represents the signal-to-noise (S/N) ratio. This associates the choice of value prediction with the average prediction error. The more F-ratio indicates that model adequacy and perception. The F-ratio for adequacy for MRR, EWR, SR, and OC is 50.05, 10.44, 70.48, and 32.96 correspondingly.

6. Conclusion

1) In the present work, the combined Grey-RSM technique was noticed to be operational, model adequacy and fits in estimating the optimal settings of EDM process parameters for Al-6061/ MoS2 composite (peak current of 10 A, pulse-on time of 100 µs, pulse-off time 60 µs, voltage of 60 volts)

2) The experimentation attained values of grey-relational grade (GRG), as well as the estimated values, are closely in line with each other, representing the model adequacy for the applied design.

3) The process parameters examined in the EDM process (I_P, T_{ON}, T_{OFF}, and v) were noticed to be considerable in influencing the machining responses exemplified by GRG. The model developed through a response-surface methodology (RSM) has been witnessed as acceptable as well as significant in developing the relations between the different process variables.

4) The RSM-GRA has been used effectively for the prediction of MRR, EWR, SR, and OC occasioning from the EDM of Al-6061/ MoS2. In addition, this approach yields better outcomes in the experimentation runs in contrast to the regression-based models in the RSM technique.

5) The multi-response optimization technique GRA was engaged to develop the single descriptive (GRG) as of the four process parameters for multiple responses considered in the EDM process and the RSM method was used to develop a robust model for GRG outcomes. Therefore, the contradiction management potential of grey-relation theory has been combined with the regression modelling capabilities of the RSM method, authorizing the execution of the hybrid grey-RSM method for multi-response optimization difficulties in industrial applications.

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