INTERNATIONAL JOURNAL OF ADVANCE RESEARCH AND DEVELOPMENT

(Volume 3, Issue 6)
Available online at: www.ijarnd.com

Some investigations on EDM based hybrid machining process of metal matrix composite

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ABSTRACT

The famous proverb "the necessity is the mother of invention" is highly appropriate in present manufacturing paradigm. In the new age, the technology is continually becoming more advance exponentially. The advanced materials are required in many technological fields. In manufacturing many engineering components, there is a requirement of materials which has high strength at high temperature, good resistance to chemical degradation, good resistance to wear and having low density. Advanced materials such as superalloys and metal matrix composites satisfy these requirements. But machining of these materials with conventional machining is a difficult and sometimes impossible task. Unconventional machining processes (UMPs) such as electric discharge machining, electrochemical machining, ultrasonic machining, laser beam machining, electron beam machining etc. have been developed by people to machine these materials. The performance of these AMPs can further be enhanced by hybridizing it with other conventional and unconventional processes Electric discharge abrasive surface grinding (EDDSG) is such a Hybrid UMP which can be used for machining of advanced materials. EDDSG combined EDM and conventional grinding process in a scientific way. In the present work, hybrid metal matrix composite is chosen to perform numerous experiments using EDDSG. Variables were peak current, pulse-on time, sensitivity and grit number of abrasive to study the effect of control factors on material removal rate and average surface roughness. Multiple regression method has been used to develop the model for material removal rate and average surface roughness. Further, optimization has been done to achieve best performances using AI tools.

Keywords*: EDDSG, Optimization, Regression analysis, Surface roughness, Material removal rate*

1. INTRODUCTION

The present advanced world requires better mechanical components in terms of cost, efficiency, life, and reliability and it has resulted in the emergence of a wide range of advanced engineering materials. These materials have excellent mechanical characteristics like high strength even at elevated temperatures, high strength to weight ratio, hardness and excellent wear resistance [1], these materials offer attractive options for component design. However, converting these materials into a useful product is difficult. The dearth of suitable machining technology is the major reason for commercially exploiting such materials.

It is extremely difficult to machine very complex shapes (such as an aerofoil section of a turbine blade, complex cavities, non-circular, small and curved holes), low rigidity structures, and micro/Nano mechanical components with tight tolerances and fine surface quality with the help of traditional machining processes [2]. If these processes can be used, they require expensive equipment and large labor forces, hence making them economically unviable. To meet above challenges, it's imperative to develop innovative manufacturing techniques.

Electrical discharge abrasive grinding (EDAG) is such an innovative unconventional machining process. EDAG is a hybrid machining process comprising conventional grinding and electrical discharge machining (EDM) as its constituent processes. It has the potential of shaping advanced engineering materials. ***Koshy et al.*** [3] were first to develop the EDDG process and they explored the mechanism of material removal in EDDG, for machining electrically conducting hard materials. They selected high speed steel workpiece for the experimentation. The electrical discharge cut-off grinding set-up was developed and experiments were carried out. The author's effect of current and wheel speed on MRR, grinding forces, and power. In this paper, a simple model is proposed to evaluate the reduction in normal force due to thermal softening of the work material caused by electrical discharges. It was concluded from the paper that the spark discharges thermally soften the work material in the grinding zone, and consequently decrease the normal force and the grinding power. ***Choudhury et al.*** [4] discussed the effect of current, voltage, pulse-on-time and duty factor on the grinding forces and the material removal rate during machining of high speed steel workpiece. The spark discharges facilitate grinding by thermally softening the work material in the grinding zone, and consequently decreasing the normal force. It is observed that the material removal rate increases with an increase in current and pulse on-time while it decreases with an increase in voltage and duty factor. These independent parameters are also found to significantly influence the grinding forces ***Kansal et al.***[5] studied the process performance of powder-mixed EDM using response surface methodology. They concluded that addition of silicon powder in dielectric have positive effects on MRR and SR. They identified peak current and silicon powder concentration as the most significant control factors. ***Mohan et al***. [6] imparted rotation to tool electrode to study the electric discharge machining of Al-SiC MMCs. Peak current, polarity, pulse duration, hole diameter, speed of rotation of electrode were considered as input control factors and their effect was studied on MRR, TWR, and SR. They concluded that increase in volume percentage of SiC has an negative effect on MRR and positive effect on TWR. It was also found that increasing the rotary speed of tool increases the MRR and decreases the TWR and SR. ***Jain and Mote*** [7] did a comparative analysis between EDM with a specially fabricated bronze disk as tool electrode and EDDG with cut-off mode. The specific energy, MRR and average temperature distribution were considered as output parameter. HSS with 10% cobalt was considered as workpiece material. The current, pulse-on time, and wheel speed were chosen as input parameters. It was analysed that pulse current is a significant factor, which affects both temperature and MRR. MRR increases with an increase in wheel speed, but temperature is found to decrease with an increase in wheel speed. An increase in pulse-on time increases both MRR and temperature. It has been found that specific energy required in EDDG is less than that in EDM with a rotating disk electrode.

Xie and Tamaki [8] have introduced a new in-process evaluation method for grit protrusion feature on wheel surface by monitoring discharge current trace during electro-contact discharge (ECD) dressing of metal-bonded fine diamond grinding wheel. First an impulse discharge machining experiment was carried out to investigate the correlation between metal bond removal and discharge parameters, namely discharge current and discharge pulse duration. The result shows that the grit protrusion feature is sensitive to the discharge parameters with reference to mean diamond grit size. ***Kumar and Chowdhary***[9] predicted of wheel wear and surface roughness using two techniques, namely design of experiments and neural network during EDDG process. They used central rotatable composite design of experiment method for machining of high speed steel. They developed response surface model for WWR and SR. Further they developed artificial neural network (ANN) and found that ANN model suitably predict the EDDCG process behaviour. Effect of process parameters, such as pulse current, duty ratio, wheel speed and grain size on output responses, wheel wear and surface roughness were investigated**. *Yadav et al.***[10] developed an innovative setup for electro-discharge diamond cut-off grinding (EDDCG). They considered peak current, pulse-on time, duty factor and wheel speed as input control factors and MRR was taken as output parameter. Experiments were conducted on high speed steel (HSS). The settings of machining parameters were determined by using the Taguchi experimental design method. The contribution of parameters on MRR was decided by analysis of variance (ANOVA). It was observed that wheel speed and current are the most significant factors affecting MRR. ***Singh et al.*** [11] studied the electric discharge diamond face grinding of tungsten carbide-cobalt composite (WC-Co). A face grinding setup was designed and developed. The effect of input parameters such as wheel speed, current, pulse on-time and duty factor on output parameters such as material removal rate (MRR), wheel wear rate (WWR) and surface roughness (SR), are investigated. Taguchi based L_9 OA was used to design the experiments. They concluded that MRR increases with increase in current and wheel speed. The WWR and SR also increase with increase of wheel speed and current. The most significant factor has been found as wheel speed affecting the robustness of electro- discharge diamond face grinding (EDDFG) process.**Shrivastava and Dubey**[12] have investigated the grinding performance of copper–iron–graphite MMCs. Experiments have been performed on a self-developed experimental setup of EDDFG. Taguchi based L_{27}OA was used to design the experiments. Effects of peak current, pulse-on time, pulse-off time and grit number was analysed on two important performances, material removal rate (MRR) and surface roughness (SR). Genetic algorithm-based optimization of MRR and SR models show considerable improvements in both characteristics, as confirmed by verification experiments. Results reveal that the peak current and grit size of diamond wheel is the most significant control factors for MRR while peak current and pulse-on time have been identified as significant factors for SR. In another research Shrivastava and Dubey [13] did simultaneous optimization of MRR, WWR and SR during EDDFG of HSS. As simultaneous optimization of above mentioned quality characteristics is challenging task; they used hybrid approach of ANN-GA for the same. The optimization results show considerable improvements in MRR, WWR and SR.After going through the literature, an interesting aspect has been observed that mostly researchers have considered peak current, pulse-on time and pulse-off time as input control factor during EDM and EDAG. Further, no researcher has considered sensitivity of machine as input control factor. Also maximum researches on MMCs were mainly concentrated on aluminium-based MMCs. Very little work on EDAG of copper–iron–graphite composite has been reported in the literature. Keeping above in the mind, present work, is an attempt to analyse the process performance of copper–iron–graphite composite during EDAG, while considering sensitivity of machine as one of the input control factor. The other input control factors are peak current, pulse-on time and grit number. The output process parameters considered are MRR and SR.

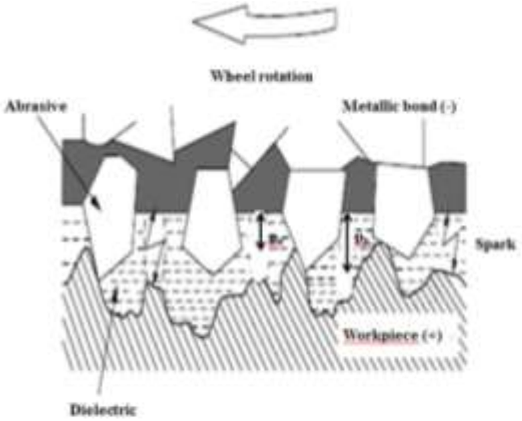

Fig. 1: Mechanism of material removal in EDAG [4]

2. METHODOLOGY

2.1 Taguchi methodology

Taguchi methodology (TM) for robust parameter design is a unique statistical experimental design technique, which greatly improves the engineering productivity. In this method, the main process parameters or control factors which affect the result are taken as input parameters and experiments are performed by specially designed orthogonal arrays (ORs). Compared to conventional experimental design, the TM based OA examined the quality characteristics through a minimum number of experiments so there is huge reduction in number of experiments to be performed, thus saving experimental effort and data analysis is also easier.

Taguchi has suggested that the production process must be applied at optimum levels with minimum variation in its functional characteristics. Functional characteristics of a manufacturing process are affected by controllable factors and uncontrollable factors or noise factors. Uncontrollable factors are very difficult to control or sometimes impossible to control. The levels of controllable factors can be specified and controlled during experimentation. According to TM, the main parameters of a manufacturing process are located in different rows of a designed orthogonal array (OA). Selection of the OA is based on the calculation of the total degree of freedom of all the factors related to the manufacturing process. The number of rows of an OA selected should be greater than or equal to the total degree of freedom calculated for the process. The total degree of freedom (dof) related to a process is computed as follows [16]:

$$\text{dof} = (\text{number of levels} - 1) \text{ for each factor} + (\text{number of levels for factor A} - 1) \times (\text{number of levels for factor B} - 1) \text{ for each interaction} + 1$$

Here, A and B are the interacting control factors.

2.2 Response surface methodology

Response surface methodology or RSM is a collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response, For example, suppose that a chemical engineer wishes to find the levels of temperature (x_1) and pressure (x_2) that maximize the yield (y) of a process. The process yield is a function of the levels of temperature and pressure, say

$$y = f(x_1, x_2) + \epsilon \tag{1}$$

Where ϵ represents the noise or error observed in the response y. If we denote the expected response by E(y) = $f(x_1, x_2)$ = η, then the surface represented by equation (2) is called a response surface [13].

$$\eta = f(x_1, x_2) \tag{2}$$

We usually represent the response surface graphically where η is plotted versus the levels of x_1 and x_2. We have seen response surface plots such as this before, particularly in the chapters on factorial designs. To help visualize the shape of the response surface, we often plot the contours of the response surface. In the contour plot, lines of constant response are drawn in the x_1 and x_2 plane. Each contour corresponds to a particular height of the response surface. We have also previously seen the utility of contour plots. In most RSM problems, the form of the relationship between the response and the independent variables is unknown. Thus, the first step in the RSM is to find a suitable approximation for the true functional relationship between y and the set of independent variables. Usually, a low order polynomial in some region of the independent variables is employed. If the response is well modeled by a linear function of the independent variables, then the approximating function is the first order model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \epsilon \tag{3}$$

If there is curvature in the system, then a polynomial of the higher degree must be used, such as the second order model

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum\sum_{i<j} \beta_{ij} x_i x_j + \epsilon \tag{4}$$

Almost all RSM problems use one or both of these models. Of course, it is unlikely that a polynomial model will be a reasonable approximation of the true functional relationship over the entire space of the independent variables, but for a relatively small region, they usually work quite well.

2.3 Genetic Algorithm

GA is based on Darwin's principle of natural selection and the concepts of natural genetics, especially "survival of the fittest". GA is able to search very large solution spaces efficiently by providing a lower computational cost since they use probabilistic transition rules instead of deterministic ones and most effectively applied to problems in which small changes result in very non-linear behavior in the solution space [17-18]. The mechanism of GA is simple, involving copying of binary strings. The computations are carried out in three stages to get a result in one generation or iteration. The working of GA has been shown with the help of block diagram.

A genetic algorithm is one of a class of algorithms that searches a solution space for the optimal solution to a problem. This search is done in a fashion that mimics the operation of evolution – a "population" of possible solutions is formed, and new solutions are formed by "breeding" the best solutions from the population's members to form a new generation. The population evolves for many generations; when the algorithm finishes the best solution is returned. Genetic algorithms are particularly useful for problems where it is extremely difficult or impossible to get an exact solution or for difficult problems where an exact solution may not be required.

A genetic algorithm is a type of searching algorithm. It searches a solution space for an optimal solution to a problem. The key characteristic of the genetic algorithm is how the searching is done. The algorithm creates a "population" of possible solutions to the problem and lets them "evolve" over multiple generations to find better and better solutions [17].

The population is the collection of candidate solutions that we are considering during the course of the algorithm. Over the generations of the algorithm, new members are "born" into the population, while others "die" out of the population. A single solution in the population is referred to as an individual. The fitness of an individual is a measure of how "good" the solution represented by the individual is. The better the solute on, the higher the fitness – obviously, this is dependent non the problem to be solved.

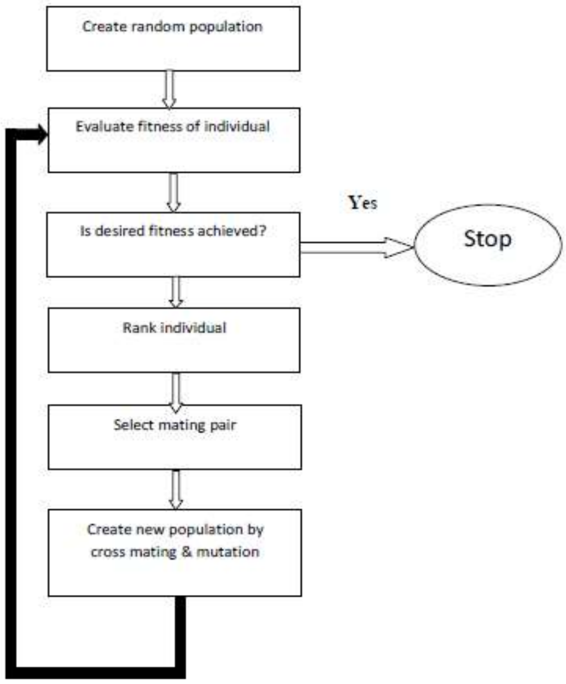

Fig. 2: Block diagram for the genetic algorithm

The size of the population is highly variable. The larger the population, the more possible solutions there are which means that there is more variation in the population. Variation means that it is more likely that good solutions will be created. Therefore, the population should be as large as possible. The limiting factor is, of course, the running time of the algorithm. The larger the population, the longer the algorithm takes to run.

3. EXPERIMENTAL DETAILS

3.1 Development of experimental setup

The EDASG setup consists of a metal bonded grinding wheel with diamond as abrasive, motor, shaft, V-belt, pulleys, and bearing. The shaft is a rotating element of the attachment and is held between the two bearings. At one side of shaft, diamond grinding wheel is mounted and another side V-pulley is mounted for rotation. Design of the shaft requires the selection of some input parameters like material, motor power, and motor RPM. Here, mild steel is used for the shaft [12]. A motor of 0.9 kW and 1,440 RPM is used. The diameter of shaft taken is 14 mm. Two pulleys are used to transmit the power. The diameter of pulleys was selected accordingly to manage the speed of grinding wheel in the permissible limit. Pulley with diameter 30 mm is attached to the shaft and other with diameter 20 mm is attached to the shaft of the motor. The smaller pulley is connected to the motor for speed reduction at grinding wheel. Proper alignment of the pulleys is very important factor otherwise belt will wear out quickly.

The primary function of V-belt is to transmit power from driver to driven pulley. The belt is provided with a certain amount of initial tension to avoid slip. The V-belt has a trapezoidal cross-section so that it is contacted to the side of pulley also. Belt of width 13 mm and thickness of 8 mm is selected. The length of V-belt is 25 inches. The size of the belt is decided by hit and trail method, which is selected, is safe. The bearing is used to support the movement of the shaft. It permits a relative motion between the contact surfaces of the members while carrying the load. Selection of the bearing needs the weight of the shaft, grinding wheel and pulley. Based on the values of equivalent load and dynamic capacity the selected bearing is 15BC02 [12].

Table 1: Chemical composition of iron-copper-graphite metal matrix composite

Iron	Copper	Graphite
60	30	10

3.2 Orthogonal array experiments

This study considered four potential factors: peak current, pulse on time, Sensitivity, and grit number as input parameters, each at level three (Table 2). The wheel speed was kept constant at 900 rpm. The range of the process parameters was decided by extensive pilot experiments. The total degree of freedom, without considering interaction is (3–1)×4+1=9 so a minimum of nine experiments is required as per orthogonal array; however, to get higher resolution, the L27 orthogonal array was selected. The degree of freedom for experiments is 26. Each experiment was performed for 30 min and amount of material removed was obtained by finding mass difference before and after machining using precision electronic digital weight balance with 0.1-mg resolution. The MRR (in grams per minute) was calculated by the following formula:

$$MRR = \frac{mi - mf}{t}$$

Where m_i is the initial mass of the workpiece before carrying out the experiment, m_f is the final mass of the workpiece after conducting experiments, and t is the time for which the experiment was conducted. Each experiment was conducted for 30 minutes.

Table 2: Control factors and their Levels

Factors	Peak current	Pulse on time	Sensitivity	Grit Size
Level 1	1	10	2	80
Level 2	3	20	4	120
Level 3	5	30	6	240

Table 3: Grinding Wheel Specifications

Wheel diameter	120 mm
Thickness of wheel	6.2 mm
Concentration	C80
Bonding material	Bronze
Bore diameter	14 mm
Abrasive used	Diamond

Table 4: Experimental observation using L_{27} OA

Experiment No.	Control factors				MRR (g/min)	SR (µm)
	A	B	C	D		
1	1	1	1	1	0.0785	1.430
2	1	1	2	2	0.0821	1.170
3	1	1	3	3	0.0835	1.131
4	1	2	1	2	0.0818	1.222
5	1	2	2	3	0.0863	1.173
6	1	2	3	1	0.0873	1.691
7	1	3	1	3	0.0807	1.755
8	**1**	**3**	**2**	**1**	0.1058	1.846
9	**1**	**3**	**3**	**2**	0.1113	1.756
10	**2**	**1**	**1**	**2**	0.1279	1.157
11	**2**	**1**	**2**	**3**	0.1339	1.099
12	**2**	**1**	**3**	**1**	0.1442	1.757
13	**2**	**2**	**1**	**3**	0.1175	1.222
14	**2**	**2**	**2**	**1**	0.1262	1.798
15	**2**	**2**	**3**	**2**	0.1056	1.651
16	**2**	**3**	**1**	**1**	0.1405	1.885
17	**2**	**3**	**2**	**2**	0.1559	1.833
18	**2**	**3**	**3**	**3**	0.1612	1.703
19	**3**	**1**	**1**	**3**	0.1339	1.833
20	**3**	**1**	**2**	**1**	0.1400	1.989
21	**3**	**1**	**3**	**2**	0.1556	1.898
22	**3**	**2**	**1**	**1**	0.1504	2.184
23	**3**	**2**	**2**	**2**	0.1667	2.0280
24	**3**	**2**	**3**	**3**	0.1772	1.8210
25	**3**	**3**	**1**	**2**	0.1344	2.301
26	**3**	**3**	**1**	**2**	0.0878	2.106
27	**3**	**3**	**3**	**1**	0.1358	2.509

4 ANALYSIS of MATERIAL REMOVAL RATE (MRR)

4.1 Modeling

Equation 5 shows the second order response model for MRR. It has been developed by using the data of all 27 runs as given in Table 4. The results of analysis of variance (ANOVA) for model MRR is shown in Table 5. The model F value 10.83implies that the quadratic model is statically significant. There is negligible chances that a model F value of this much magnitude could occur due to noise. The value of coefficient of determination Rsq and adjusted Rsq are 92.66and 88.12, respectively, which means a very high percent of the variation in the response variable can be explained by the explanatory variable. The negligible variation can be explained by unknown or inherent variability. The S value of the regression analysis is 0.0259, which is smaller. The associated p-value for the model, as well as linear and square term, is lower than 0.05 (i.e. α=0.05, or 95 % confidence) indicates that the model is considered to be statistically significant. Further ANOVA of MRR (Table 6) identifies peak current as most significant factor affecting MRR followed by, pulse-on time, Sensitivity and grit size. The final response surface equation for MRR (in grams per minute), after removing the non-significant terms is given as follows:

$$MRR= 0.0889 + 0.0302x_1 + 0.0021x_2 + 0.0050x_3 - 0.00004x_4 - 0.0030x_1 * x_4 - .00001{x_1}^2 + 0.0013{x_2}^2 - 0.0002{x_4}^2 \quad (5)$$

Table 5: Analysis of variance for developed model of MRR

Source	Degree of freedom	Seq SS	Adj SS	Adj MS	F	P
Regression	8	0.256593	0.032074	0.032064	10.83	0.000
Residual Error	18	0.079087	0.004394			
Total	26	0.335680				
S=0.0259	R-Sq = 92.66	R-Sq (adj) = 88.12				

Table 6: ANOVA for MRR

Source	Degree of freedom	Sum of square	Mean square	F	Contribution (%)
Peak Current	2	0.0217	0.01085	66.81	86.55
Pulse-on time	2	0.00173	0.00087	5.33	6.9
Sensitivity	2	0.01157	0.00079	4.85	6.29
Grit Number	2	0.00007	0.00003	0.2	0.02
Error	18	0.00292	0.00018		
Total	26	0.02799			

Experimental results show that composite can be effectively machined by EDASG. High-electrical conductivity and low-thermal resistance of all the constituents of composite promotes good MRR. Figure 3, 4,5 shows the estimated response surface for MRR in relation to the design parameters of peak current, pulse on time and Sensitivity since these parameters have the most significant influence on MRR. It can be seen that as peak current increases, MRR also increases. With the increase in peak current, the overall kinetic energy of electrons increases, thus more heat is developed per spark and that ultimately results in more melting and vaporization from the workpiece surface and hence more MRR. There is a slight deviation from the above-mentioned trend at the pulse-on time of 10 µs and 30 µs. EDM is a very complex process, and the reason for that may be due to arcing, instead of sparking, there is a reduction in MRR. It can also be concluded from the figure that with an increase in pulse-on time the MRR increases. It can also be concluded that with an increase in pulse-on time the MRR increases. With the increase in pulse-on time more energy is supplied during given cycle, so MRR increases. It is evident that as sensitivity increase, more material is removed in a given time span. The increase in sensitivity prompts the servomechanism to respond quickly and hence there is an increase in MRR.

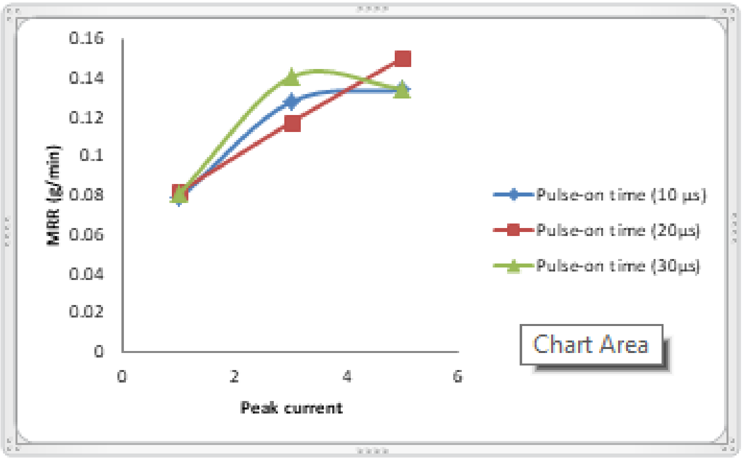

Fig. 3: Variation of MRR with peak current and Pulse-on time

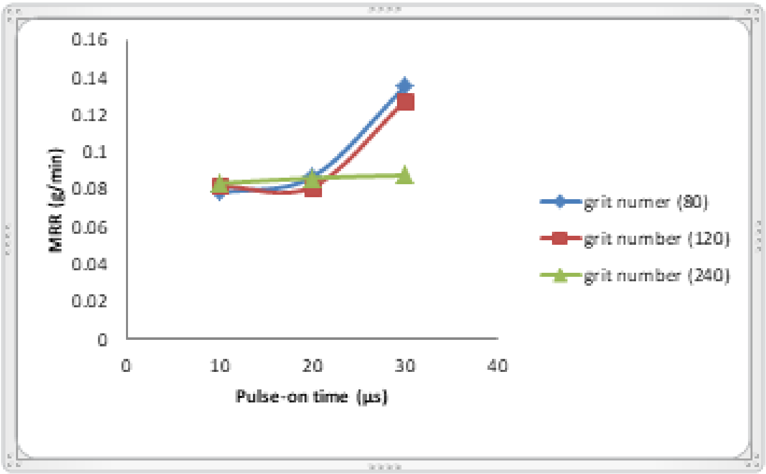

Fig. 4: Variation of MRR with Pulse-on time and Grit number

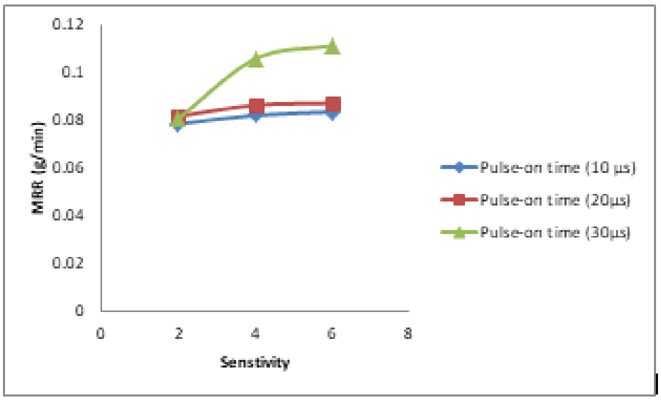

Fig. 5 Variation of MRR with Sensitivity and a Pulse-on time

4.2 Optimization

The standard optimization problem definition requires an objective function to be minimized or maximized and may require the constraint functions to be satisfied in term of optimization parameters. In the present case, the objective function of optimization problem can be stated as below:

Find: x1, x2, x3 and x4

Maximize:

$$\text{MRR}= 0.0889 + 0.0302x_1 + 0.0021x_2 + 0.0050x_3 - 0.00004x_4 - 0.0030x_1 * x_4 - .00001{x_1}^2 + 0.0013{x_2}^2 - 0.0002{x_4}^2 \quad (6)$$

With a range of process input parameters:

$1 \le x_1 \le 5$

$10 \le x_2 \le 30$

$2 \le x_3 \le 6$

$80 \le x_4 \le 240$

The critical parameters of GA are the size of the population, mutation rate, cross-over rate and a number of generations. After trying different combinations of GA parameters, the population size 40, cross-over rate 1.0, mutation rate 0.01 and number of generation 60 have been taken for MRR. The objective function in Eq. (6) has been solved without any constraint. In Fig. 6, the best and mean fitness curves are illustrated in the search space. The fitness function is optimized when the mean curve converges to the best curve after 25 generation. The corresponding values of control factors peak current, pulse-on time, sensitivity and grit number have been found as 1.015 A, 29.81 µs, 5.647 and 240. Hence these are the optimum values of control factors. Using these values, the value of MRR has been obtained as 0.1823 g/min.

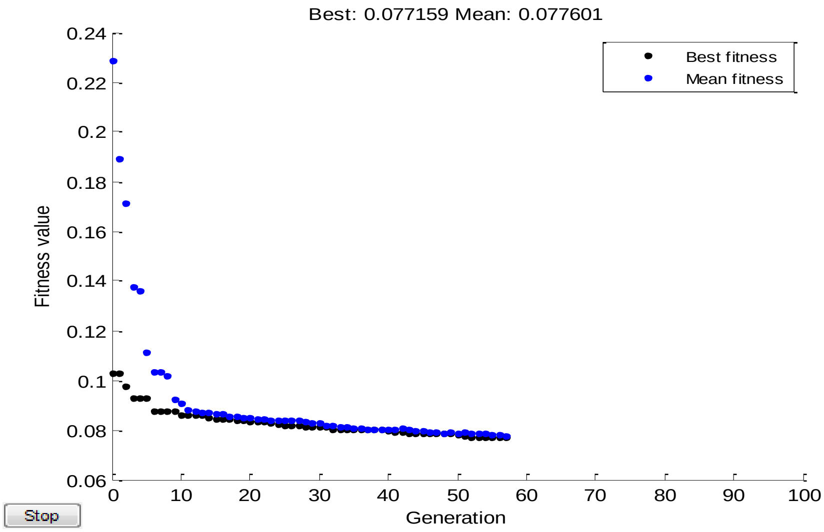

Fig. 6: Generation-fitness graphics for MRR

5. ANALYSIS OF SURFACE ROUGHNESS (SR)

Equation (7) shows the second order response model for SR. It has been developed by using data of all 27 runs as given in Table 4. The results of ANOVA for model SR is shown in Table 7. The model F value 24.36implies that the quadratic model is statically significant. There is negligible chances that a model F value of this much magnitude could occur due to noise. The value of coefficient of determination R2 and adjusted R2 are 96.78 and 87.19, respectively, which means a very high percent of the variation in the response variable can be explained by the explanatory variable. The negligible variation can be explained by unknown or inherent variability. The S value of the regression analysis is 0.0059, which is smaller. The associated p value for the model and square term is lower than 0.05 (i.e., α=0.05, or 95 % confidence) which indicates that the model is considered to be statistically significant. ANOVA of SR (Table 8) identifies peak current as most significant factor affecting SR followed by pulse-on time, grit size, and pulse-off time. The final response surface equation for SR (in micrometer), after removing the non-significant terms is given as follows:

$$SR= 0.054 + 0.1064x_1 - 0.0122x_2 + 0.0268x_3 - 0.0002594x_4 + .0008{x_1}^2 + 0.0088{x_2}^2 - 0.0000142{x_4}^2 + 0.0518x_1 * x_2 \quad (7)$$

Although the linear terms are non-significant, they have been included in the response surface equation following the hierarchy principle. The hierarchy principle indicates that if a model contains a higher-order term, it should also contain all the lower-order terms that compose it. The variation in the SR with the peak current and pulse-on time is shown in the response surface plot (Fig. 7). It is evident that as the peak current increases, the MRR increases, which increase the depth of the crater formed and hence surface roughness increases. It can also be concluded from the fig. 7 that as pulse-on time increases from 10 µs to 30 µs, the surface roughness increases.

Fig. 8 shows the variation of surface roughness with pulse-on time at different values of grit numbers. It is evident from the fig. That with an increase in pulse-on time the surface deteriorates. As the grit number increases, the quality of the surface in terms of surface roughness improves. With the increase in grit number, the number of cutting edges in a grain reduces, which results in the fine surface.

Fig. 9 shows the variation of surface roughness with the sensitivity. It is clear that there is no fixes pattern of variation of surface roughness with sensitivity. EDM is a very complex process involving many variables. Sometimes simultaneously two factors are working and acting in different directions. So then there may not be any fixed trend of variation for the quality characteristic.

Table 7: Analysis of variance for a developed model of SR

Source	Degree of freedom	Seq SS	Adj SS	Adj MS	F	P
Regression	8	0.256593	0.032074	0.032064	24.3680	0.000
Residual Error	18	0.079087	0.004394			
Total	26	0.335680				
S=0.0059	R-Sq = 98.78	R-Sq (adj) = 87.12				

Table 8: ANOVA of SR

Source	Degree of freedom	Sum of square	Mean square	F	Contribution (%)
Peak Current	2	1.93773	0.96886	83.44	53.21
Pulse-on time	2	1.04909	0.52454	45.18	28.96
Sensitivity	2	0.08311	0.03155	2.72	1.701
Grit Number	2	0.58603	0.29301	25.24	16.02
Error	18	0.209	0.01181		
Total	26	3.84495			

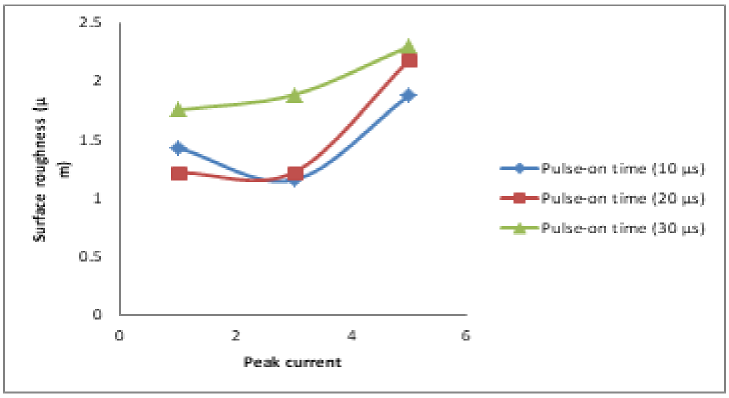

Fig 7: Variation of SR with peak current and Pulse-on time

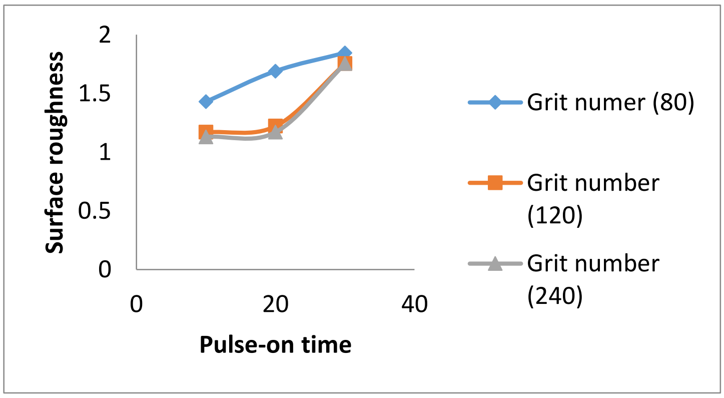

Fig. 8: Variation of SR with Pulse-on time and Grit number

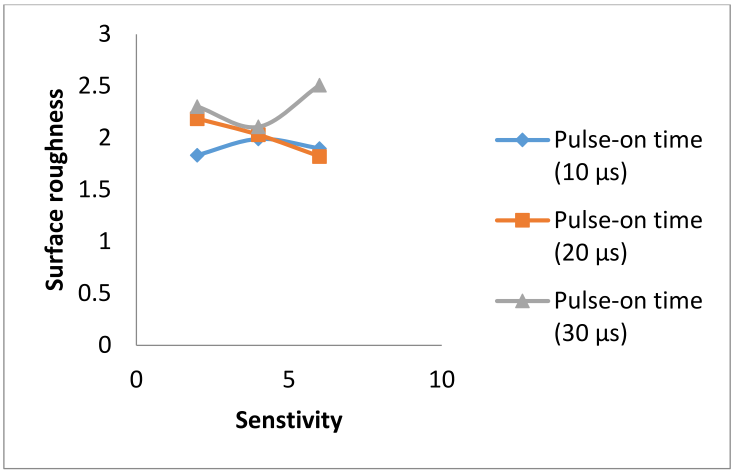

Fig. 9: Variation of SR with Sensitivity and a Pulse-on time

In the present case, the objective function of optimization problem can be stated as below:
Find: x_1,x_2,x_3 and x_4
Maximize:

$$SR= 0.054 + 0.1064x_1 - 0.0122x_2 + 0.0268x_3 - 0.0002594x_4 + .0008{x_1}^2 + 0.0088{x_2}^2 - 0.0000142{x_4}^2 + 0.0518x_1 * x_2 \quad (8)$$

With a range of process input parameters:
$1 \leq x_1 \leq 5$
$10 \leq x_2 \leq 30$
$2 \leq x_3 \leq 6$
$80 \leq x_4 \leq 240$

The critical parameters of GA are the size of the population, mutation rate, cross-over rate and a number of generations. After trying different combinations of GA parameters, the population size 40, cross-over rate 1.0, mutation rate 0.01 and number of generation 60 have been taken for MRR. The objective function in Eq. (8) has been solved without any constraint. In Fig. 10, the best and mean fitness curves are illustrated in the search space. The fitness function is optimized when the mean curve converges to the best curve after 25 generation. The corresponding values of control factors peak current, pulse-on time, sensitivity and grit number have been found as 1.0 A, 10 µs, 3.44 and 168. Hence these are the optimum values of control factors. Using these values, the value of SR has been obtained as 1.0914 µm.

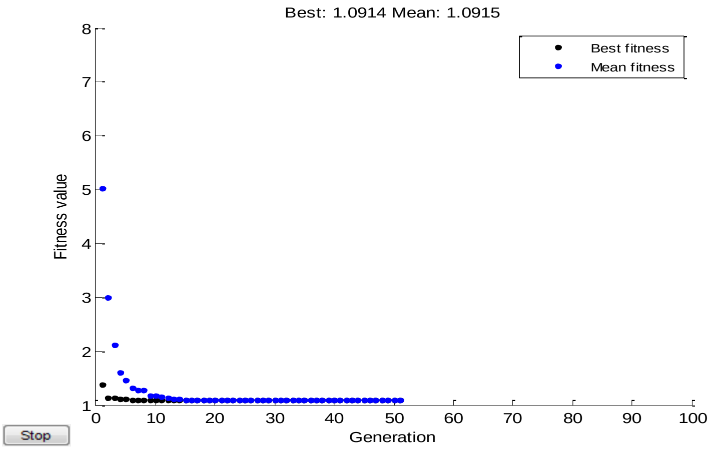

Fig. 10: Generation-fitness function graphics for SR

6. CONCLUSION

The innovative experimental setup has been used to study the effect of EDAG on the metal matrix composite has been investigated for the analysis of various factors influencing the Performance characteristics, following the Taguchi method of experimental design. It has been successfully applied for finding out the relative contributions of various factors such as current, sensitivity, pulse-on time and grit number on MRR and SR.

1. The peak current has been identified as most significant control factor affecting MRR followed by pulse-on time and sensitivity. The contribution of Peak current, pulse-on time and sensitivity in MRR is 66.81 %, 5.33 % and 4.85 %, respectively.
2. The peak current, pulse-on time and grit number of the grinding wheel has been identified as significant factors for SR. Their contribution in surface roughness has found to be 83.44 %, 45.18%, and 25.24 %, respectively.
3. The MRR has been found to increase with the increase in peak current, pulse-on time, sensitivity whereas it decreases with the increase in the grit number.
4. The SR has increasing trend with the increase in peak current and decreasing trend with the increase in grit number.
5. The developed response surface models for MRR and SR have been found adequate.
6. Optimization results show improvements of 125 % and 22.4 % in MRR and SR, respectively.

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