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Data driven surrogate model-based optimization of the process parameters in electric discharge machining of D2 steel using Cu-SiC composite tool for the machined surface roughness and the tool wear

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ABSTRACT: Electrical discharge machining (EDM) is mainly utilized for the die manufacturing and also used to machine the hard materials. Pure Copper, Copper based alloys, brass, graphite, steel are the conventional electrode materials for EDM process. While machining with the conventional electrode materials, tool wear becomes the main bottleneck which led to increased machining cost. In the present work, the composite tool tip comprises 80% Copper and 20% silicon carbide was used for the machining of hardened D2 steel. The powder metallurgy route was used to fabricate the composite tool tip. Electrode wear rate and surface roughness were assessed with respect to the different process parameters like input current, gap voltage, pulse on time, pulse off time and dielectric flushing pressure. During the analysis it was found that Input current (I_p), Pulse on time (T_{on}) and Pulse off time (T_{off}) were the significant parameters which were affecting the tool wear rate (TWR) while the I_p, T_{on} and flushing pressure affected more the surface roughness (SR). SEM micrograph reveals that increase in I_p leads to increase in the wear rate of the tool. The data obtained from experiments were used to develop machine learning based surrogate models. Three machine learning (*ML*) models are random forest, polynomial regression and gradient boosted tree. The predictive capability of *ML* based surrogate models was assessed by contrasting the R^2 and mean square error (*MSE*) of prediction of responses. The best surrogate model was used to develop a complex objective function for use in firefly algorithm-based optimization of input machining parameters for minimization of the output responses.

KEYWORDS: Data driven modeling; Electric discharge machining; Firefly algorithm; Machine learning; Surface roughness; Tool wear

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RESUMEN: *Optimización de los parámetros de proceso en el mecanizado por electroerosión del acero D2 utilizando una herramienta compuesta de Cu-SiC basada en un modelo sustitutivo basado en datos para la rugosidad superficial y el desgaste de la herramienta después del mecanizado.* El mecanizado por electroerosión (*EDM,* del inglés *electrical discharge machining*) se utiliza principalmente para la fabricación de matrices y también para el mecanizado de materiales duros. Materiales como el cobre puro, las aleaciones de cobre, el latón, el grafito y el acero son utilizados de manera convencional como electrodos en el proceso de electroerosión. Durante el mecanizado con estos electrodos convencionales, el desgaste de la herramienta se convierte en el principal cuello de botella que conduce a un mayor coste de mecanizado. En el presente trabajo, la punta de la herramienta compuesta por un 80% de cobre y un 20% de carburo de silicio se utilizó para el mecanizado de acero D2 endurecido. Para fabricar la punta de la herramienta de material compuesto se utilizó la vía de la pulvimetalurgia. La tasa de desgaste del electrodo y la rugosidad de la superficie se evaluaron con respecto a los diferentes parámetros del proceso como la corriente de entrada, el voltaje de separación, el tiempo de pulso encendido, el tiempo de pulso apagado y la presión de lavado dieléctrico. Durante el análisis se encontró que la corriente de entrada (I_p), el tiempo de pulso (T_{on}) y el tiempo de pulso (T_{off}) eran los parámetros significativos que afectaban al índice de desgaste de la herramienta mientras que el I_p, T_{on} y la presión de lavado afectaban más a la rugosidad de la superficie. La caracterización con microscopía electrónica de barrido revela que el aumento de I_p conduce a un aumento en la tasa de desgaste de la herramienta. Los datos obtenidos en los experimentos se utilizaron para desarrollar modelos sustitutivos basados en el aprendizaje automático. Los tres modelos de aprendizaje automático son el bosque aleatorio, la regresión polinómica y el árbol de gradiente reforzado. La capacidad predictiva de los modelos sustitutos basados en aprendizaje automático se evaluó contrastando el R^2 y el error cuadrático medio (*ECM*) de predicción de las respuestas. El mejor modelo sustitutivo se utilizó para desarrollar una función objetivo compleja para su uso en la optimización basada en el algoritmo de la luciérnaga de los parámetros de mecanizado de entrada para la minimización de las respuestas de salida.

PALABRAS CLAVE: Modelización basada en datos; Mecanizado por electroerosión; Algoritmo Firefly; Aprendizaje automático; Rugosidad superficial; Desgaste de herramientas

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1. INTRODUCTION

Electro discharge machining (EDM) is a category of non-conventional machining process which basically operates on the electro thermal principal in which the material is removed by an electric current and a thermal spark between two electrically conductive materials, i.e., the work material and the electrode which are submerged in the dielectric fluid. High frequency electric pulses are used to machine the work material so the hardened conductive material which is difficult to be machined by conventional processes, can be easily machined. As the heat is generated on the electrode and subsequently on the workpiece, the material gets eroded from both electrodes as well as the work piece (Pay *et al.*, 1995; Li *et al.*, 2001; Dimla *et al.*, 2004; Somani *et al.*, 2021a). As the EDM is also known as a replica process, the wear of tool profile has a direct effect on the finally machined cavity. As a result of this, there is variation in the shape and dimension of the final product. To overcome this, the tool has to be re-prepared for machining again and again. It has been reported that the tool cost in the EDM process has the major share in total machining cost (Zaw *et al.*, 1999; Somani *et al.*, 2021b). It makes the choice of material selection for tool very important. Copper is the highly preferred material for EDM tool adhering to its high thermal and electrical conductivity but it disintegrates at a very high rate especially in the machining of hardened steels. Hence, there is a need to identify either an additive or reinforcements which can enhance the wear resistance of the tool.

In this modern era of technology which demands reducing the machining time as well saving the money, the optimization of the process variables is required. The major limitation of the EDM process is that it can machine only conductive materials as well as it consumes high power which leads to higher machining cost as compared to the conventional machining processes like turning (Singh *et al.*, 2004). So, proper selection of the process variables is required before machining on the EDM in order to achieve the optimum results (Norasetthekul *et al.*, 1999; Tsai *et al.*, 2003; Khanra *et al.*, 2007; Mishra and Routara, 2018). From literature it is evident that the performance of the EDM process depends on the process parameters like input current, gap voltage, pulse on time (T_{on}), pulse off time (T_{off}), and the flushing pressure. The performance of this process is mainly rated by criteria like electrode wear rate, surface roughness and material removal rate of the machined part.

Kumar *et al.* (2021) experimentally investigated the process parameters of wire electrical discharge machining (WEDM) through both integrated desirability and machine learning (ML) technique on implant material (CP-Ti G2). The material removal rate (MRR) was considered as an output response. Moreover, machined surface topography was also analyzed. The Pulse on time, pulse of time, spark voltage and peak current were the significant parameters that affect the response. Various surface defects are also observed in terms of debris and crater. From the results it was observed that there is a good agreement between experimental and predicted results. Wang *et al.* (2018) used deep learning techniques to detect geometrical defects of a fir-tree slot in WEDM. From the outcomes, it was observed that, despite of using a tolerance band of (+/−) 5 µm, results are predicted with an accuracy of 80%. Weiwen *et al.* (2018) detected the break out in highspeed small hole drilling EDM based on ML technique. Support vector machine (SVM) was the ML approach used in the modelling. Through hole machining was conducted in the experimental analysis. The input parameters are discharge pulsed duration, pulse interval, peak current, effective discharge frequency and electrode feed rate. The results are compared with actual machining operation on test specimens having various thicknesses. It was observed that both the cycle time and the accuracy were precisely predicted by the ML techniques. Surleraux *et al.* (2020) optimized the tool shape in die-sinking micro-EDM through ML based reverse modelling approach. The authors have proposed a new reduced modeling optimization framework as a reverse ML model. Two artificial neural network (ANN) models were trained, one with a modification and other one without any kind of modification. From the results, it was found that using the ML technique, the tool shape can be produced instantly and it can be optimized with a deviation of only 6%. Saha *et al.* (2022) studied the uncertainty of wire EDM performance features through the data-driven approach. Various uncertainties were taken care of, such as gap state, control action, power fluctuation and frictional forces. Six different types of process parameters were considered such as pulse on time, pulse of time, peak current, servo voltage, wire feed rate and wire tension. The surface roughness and the cutting rate were the responses. Four different ML techniques were used like linear regression (LR), regression trees, support vector machines and Gaussian process regression. Pulse on time and peak current were the two dominating parameters affecting the responses. Gaussian process regression technique was found to be the most efficient technique in the EDM process modelling. Yogesh *et al.* (2021) predicted the MRR and surface roughness in wire EDM using decision tree and Naive Bayes algorithm and the results were compared with the LR model. From the outcomes, it was observed that both algorithms predicted the MRR and surface roughness accurately. Sanchez *et al.* (2018) predicted the unexpected event (change of material thickness) in wire EDM using deep learning techniques. From the outcomes it was observed that by applying combined convolutional layer with gated recurrent units, the material thickness was predicted with 97.4% accuracy. Walia *et al.* (2021) predicted the tool shape (roundness) in EDM of EN-31 steel using ML techniques. From the experimental outcomes it was found that input parameters such as pulse on time, pulse off time and current were the most significant parameters. Four ML algorithms are used like decision trees, random forest (RF), generalized linear model and neural network. Better results are predicted using RF. Paturi *et al.* (2021) optimized the surface roughness in WEDM through both ML and statistical approach for Inconel-718. Three ML techniques were used, i.e. SVM, GA and ANN. Pulse on time, pulse of time, peak current, servo voltage and wire feed rate were the input variables. From the outcomes it was divulged that better results are predicted through the SVM technique. Shanmugasundar *et al.*, (2021) compared three ML algorithms such as LR, RF and AdaBoost (AB) regression in non-traditional machining. From the experimental outcomes it was observed that, RF and AB regression model performed better compared to the LR model. Wang *et al.* (2019) used unsupervised ML for the desired tolerance in WEDM machining of disk turbine Fir-Tree Slots. The distribution of ionization time was taken as the variable. It was observed that there was a strong correlation between ML predicted and coordinate measuring machine (CMM) based results. Total five clusters were observed and the tolerance limit was observed as ± 15 µm for clusters 3 and 5. The short circuit situation was observed for clusters 1 and 2. Ulas *et al.* (2020) predicted the surface roughness of machined aluminum alloy with WEDM machining using various ML algorithms. Four input parameters were considered, i.e. voltage, pulse on time, dielectric pressure and wire feed. Four ML algorithms were utilized such as extreme learning machine (ELM), Weighed-Extreme Learning Machine (WELM), SVR and quantum support vector classification (QSVR). Better results are predicted through WELM compared to the other algorithms. Shukla and Priyadarshini (2018) optimized various response variables in wire EDM machining of Haste alloy (C276) using ML techniques. The input parameters considered are pulse on time, pulse off time, servo voltage, wire feed rate, and wire tension. Three responses were considered, such as roughness, kerf width and material removal rate (MRR). The optimization algorithm used in this analysis was the gradient descent method. From the outcomes it was observed that pulse on time, pulse off time and peak current were observed to be the most dominating parameters for both surface roughness and kerf width and by applying this method both outcomes are optimized effectively. Naik *et al.* (2021) studied the surface integrity aspects of Aluminum metal matrix composite through EDM machining. The sustainability analysis was also accomplished. Flushing pressure, pulse on and off time, gap voltage and discharge current were considered as input variables. Discharge current was found to be the dominating one for the degradation of machined surface quality. Vegetable oil was observed to be an effective die electric for sustainable machining.

It is clear from the literature that he optimization of process parameters in EDM is a challenging task due to the complex interactions between various input variables, such as pulse on-time, pulse off-time, peak current, electrode material, and tool geometry. Traditional optimization approaches often rely on trial-and-error methods, which are time-consuming, expensive, and do not guarantee optimal results. Moreover, these methods are limited by their inability to consider the intricate relationships among the process variables and their effects on surface roughness and tool wear.

To address these challenges, a data-driven approach based on surrogate modeling has emerged as a promising solution for optimizing process parameters in EDM. By utilizing historical data and advanced machine learning techniques, surrogate models can effectively capture the complex relationships between process parameters and performance measures. These models serve as efficient approximations of the EDM process, enabling rapid evaluation and optimization of various parameter combinations without the need for extensive experimental trials.

In this article, the experimental data for different input machining parameters and output responses were collected and a dataset was prepared for in a ML model based development of the surrogate models for predictive modeling of output responses in terms of the input machining parameters. The full dataset was divided into training, testing and validation dataset in appropriate ratio. Three ML models e.g. random forest, polynomial regression and gradient boosting regression trees are used for the surrogate model development. The predictive capabilities of all the three ML models were assessed in terms of the R^2 and mean square error (MSE) of predictions. The best ML surrogate model was used to develop a complex objective function. The complex objective function was used in a swarm based optimization (firefly) algorithm to find the optimal values of input machining parameters for the minimization of the output responses. The rest of the article is arranged as follows: in section 2 the experimental setup of the electric discharge machining is presented. In section 3, the experimental results are discussed. In section 4, the ML algorithms are discussed. In section 5, the multi-objective optimization technique is described. Finally, the conclusions are discussed in detail.

2. MATERIALS AND METHODS

2.1. Workpiece material

In this work, hardened D2 steel having a hardness of 62 HRC was selected as the workpiece material as it is very difficult to machine because of its high hardness as well as good abrasion resistance. D2 steel has wide applications in shear and planer blade industries, industrial cutting tools, die and punch fabrications etc. For the experimentation, the samples of D2 steel having a size of 50×50×10 mm^3 were used. Energy dispersive x-ray spectroscopy (EDX, model KETEK VITUS H150) attached to a scanning electron microscope () was done to identify the elemental composition. Chemical composition of the material is shown in Table 1 while the EDX is shown in Fig. 1.

TABLE 1. Chemical composition (wt. %) of D2 steel

Element	C	Cr	Co	Mn	Mo	P	S	Si	Fe
Wt. (%)	1.5	13	0.7	1.56	0.8	0.02	0.03	0.6	81.7

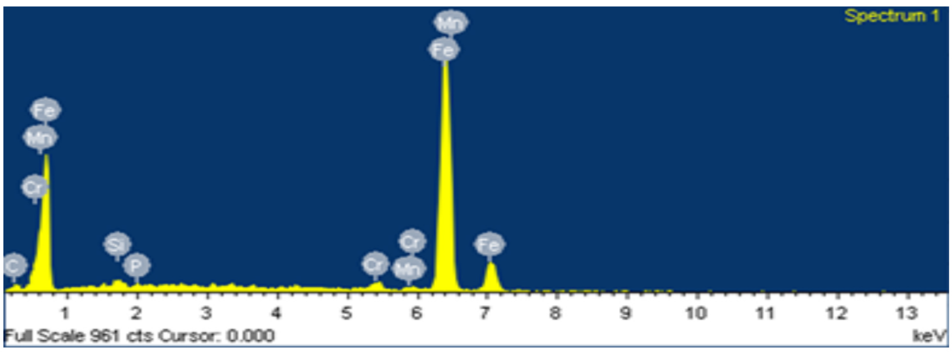

FIGURE 1. EDX of D2 steel.

2.2. Electrode material and fabrication

Powder metallurgy route was used to fabricate the electrode tip. Copper (Cu) powder (80% by weight) was used as base metal and the Silicon carbide (SiC) (20% by weight) was used as the reinforcement material. Copper has the major share in composition due to its high thermal and electrical conductivity properties. Higher hardness and wear resistance properties of SiC made it a very good choice for the reinforcement material. Both the powders were having the average particle size of 44 μm. Figure 2 represents the schematic diagram of the complete procedure.

Scanning electron microscopy (SEM) micrographs of the Cu and SiC powder are shown in Fig. 3 (a-b). From the micrographs it is clear that the copper powder particles are dendritic in nature while the SiC particles are having sharp edges.

Initially the powders were mixed in a V shape blender (Bionics, BST/VB-50) at a speed of 240 rpm for 20 min to get the homogeneous mixture. From Fig. 3c it is clearly visible that the Cu and SiC powder particles are homogeneously dispersed. A hydraulic press (Jackman, KHPL-HF-HOP) was used to compact the powers in cylindrical shapes of 10 mm diameter at a pressure of 250 MPa for 30 min. Further, a three stage sintering of pellets was done in a tubular furnace (Victory Sensors, HTF- 006) for the heating rate of 3 $°C \cdot min^{-1}$. Initially the temperature was increased till 600 °C for degassing purpose and then it was raised till 850 °C followed by 950 °C for the purpose of stabilization and to recover the properties. Sintering micrographs are shown in Figs. 3 (d-e) for two different magnifications. It is evident from the micrographs that due to sintering process, the Cu and SiC elements form a homogeneous network structure which is an added advantage of the powder metallurgy route. The prepared pellets were polished and brazed to the copper rod to fabricate the composite tool tip electrode which was further used to machine the D2 steel on die sinking EDM.

3. EXPERIMENTAL SETUP AND PROCESS PARAMETERS

Die-sinking EDM (ZNC, EIL, 3144-R50) machine was used to perform the experimental part shown in Fig. 4. Kerosene was used as dielectric fluid during the machining operation. From the literature, it is clear that EDM machining of hardened steel is dependent on various input process parameters like pulse on time, pulse off time, peak current, gap voltage, duty cycle and flushing pressure, etc. In this study, five variables were selected as process parameters i.e. pulse on time, pulse off time, gap voltage, flushing pressure and input current. The selection of these process variables and their level had been decided based on the machine capability and exploratory pilot experiments. The process variables for the experiments should be determined in such a way so as to cover the significant processing conditions (Pandey and Jilani., 1986; Pradhan and Biswas, 2009; Khan *et al.*, 2015). The process variables used for the experimental work with the respective levels has been presented in Table 2. The machining time was kept constant for all the experiments, i.e. 30 min.

Two important parameters i.e. tool wear rate (TWR) and surface roughness (μm) for the tool tip were measured after the machining operation.

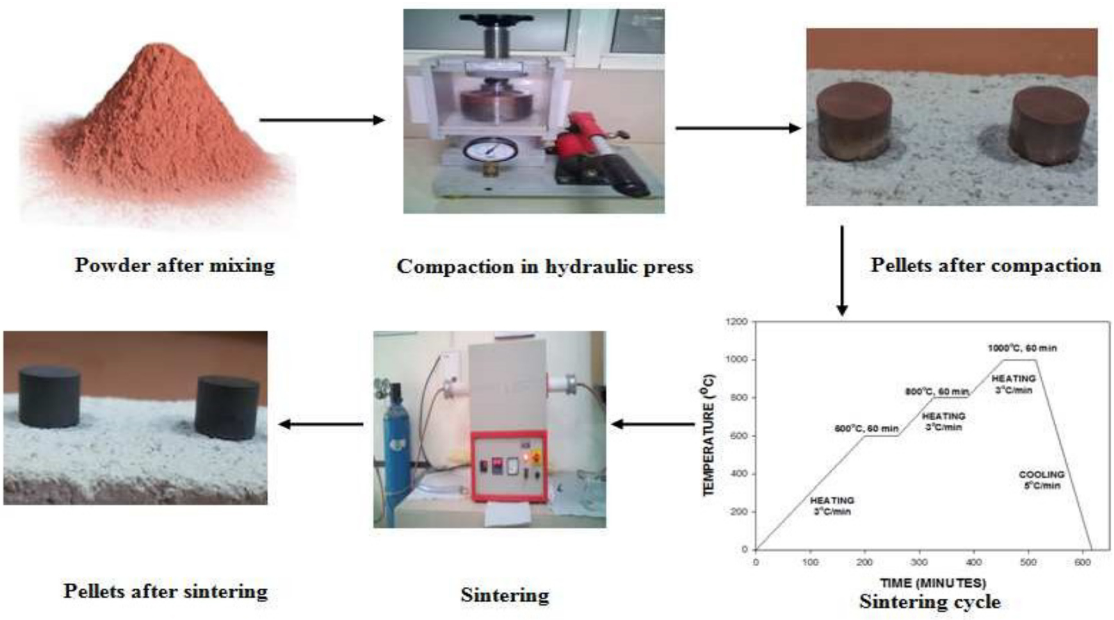

FIGURE 2. Composite tool tip fabrication procedure.

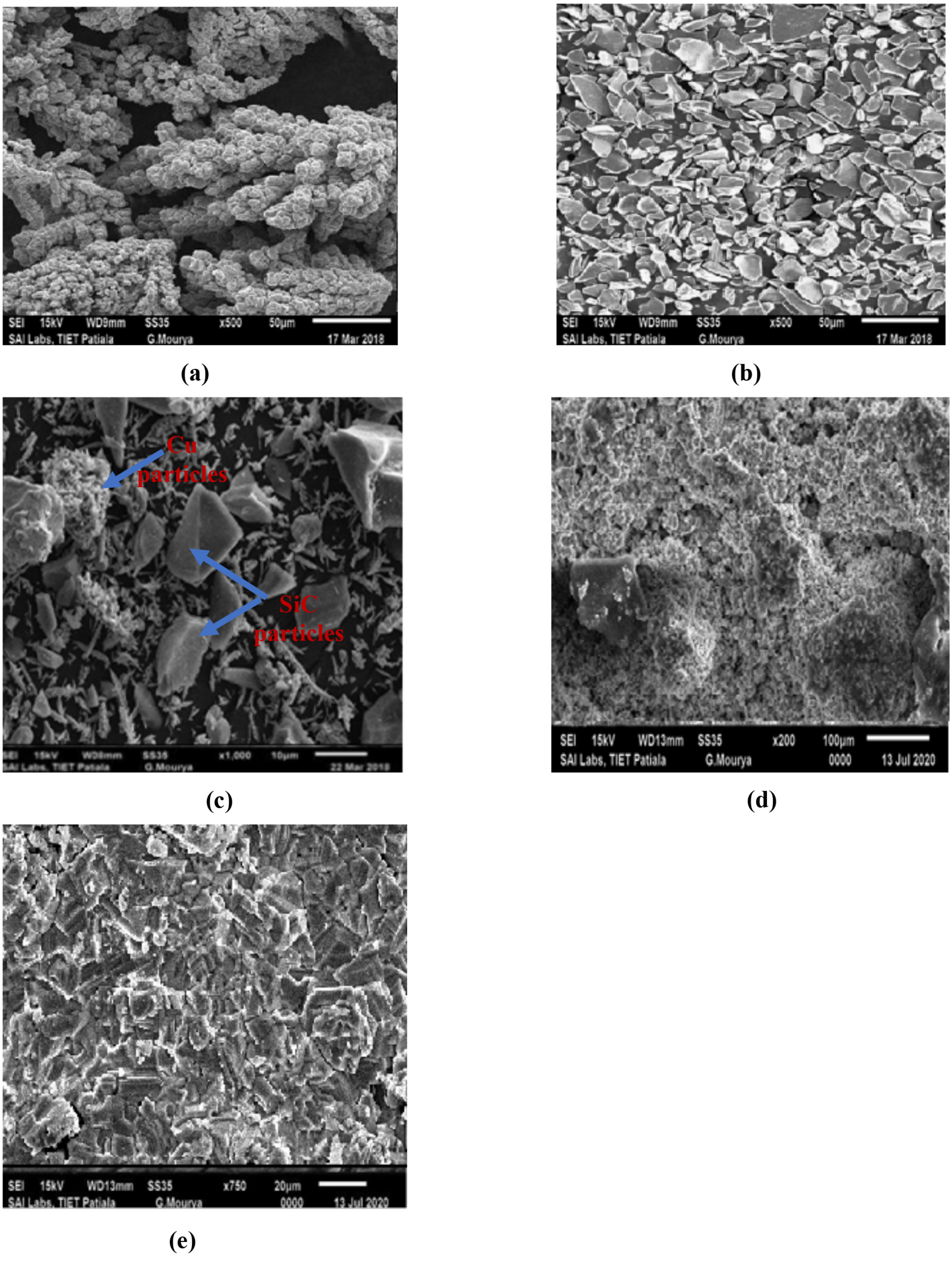

FIGURE 3. SEM micrographs of **(a)** Cu powder **(b)** SiC powder **(c)** dispersion of Cu-SiC powder particles after mixing (**d and e)** sintered pellets.

FIGURE 4. Die Sinking EDM machine.

Equation (1) shows the formula used to calculate the TWR.

$$TWR = (W_{BM} - W_{AM}) / T \qquad (1)$$

where, W_{BM} and W_{AM} is the weight of the electrode before and after the machining and T is the machining time (30 min). To measure the weight, weighing machine of accuracy 0.001 gm was used. Surface roughness tester (SJ-210, Mitutoyo) was used to measure the surface roughness and for that, the readings were taken at six different locations and the average of six readings was taken as the surface roughness.

4. DESIGN OF EXPERIMENT

Central composite rotatable design (CCRD) technique was used for the design of experimental plan. CCRD can predict quadratic, independent and interaction influence of various variables on the response. Central composite design has three set of experiments. First one is the factorial design set experiments which can be represented by 2^n where 'n' is number of process variables. In the present study 'n' equals five, therefore, the number of experiments in the first set are 32. In the second set of experiments, a set of axial points which is equal to 2^n is used. In present study, in this set, the total number of experiments is 10. The third set of experiments is centre points denoted by 'k' and in this set contains 10 experiments. In total, 52 experimental observations, involving five independent variables, were conducted at five levels as given in Table 1. The experimental conditions and the outputs are provided in Table 3.

Table 2: Machining variables and their level

Parameters	Levels				
Discharge current, I_p (A)	4	6	8	10	12
Pulse on time, T_{on} (μs)	150	250	350	450	550
Pulse off time, T_{off} (μs)	15	25	35	45	55
Flushing Pressure (Kgf/cm^2)	22	24	26	28	30
Gap Voltage Vg (V)	45	55	65	75	85

5. RESULTS AND DISCUSSIONS

5.1. Effect of process parameters on the tool wear rate (TWR)

During the machining process, the tool must be able to resist the deformation from impact the force produced during the operation. The optimum combination of thermal, electrical and mechanical properties of EDM tool may increase the resisting capacity of tool to disintegrate. During the experimentation it was found that I_p, T_{on} and T_{off} were the significant parameters which were affecting the TWR as shown in Fig. 5.

Figure 5a shows the variation of mean the TWR with respect to input current. It is evident that the increment in supply of input current increases the TWR. This is due to the fact that the increase in the current leads to an increase in spark at inter electrode gap which tends to raise the temperature and, subsequently, increases the TWR (Hosseini and Kishawy, 2014; Kumar and Kumar, 2017)

Effect of the T_{on} on TWR is shown in Fig. 5b which clearly represents that increase in T_{on} leads to decrease in the TWR. The discharge column diameter increase with increase in T_{on} which leads to decrease in the energy density at the discharge point which helps to decrease the TWR (Patowari *et al.*, 2015).

Effect of T_{off} on TWR is shown in Fig. 5c. It can be observed that increase in T_{off} leads to decrease in TWR. Increase in pulse off time results in increment of the duration between the subsequent pulses which leads to pressure drop and ultimately the unstable arc will produce which will reduce the discharge efficiency and finally the TWR decreases (Patowari *et al.*, 2015; Khan *et al.*, 2015; Kumar and Kumar., 2017).

Table 3. Experimental design and output

Exp. No.	I_p (A)	T_{on} (μs)	T_{off} (μs)	P (Kgf/cm^2)	Gap voltage (V_g)	TWR (gm/min)	SR (μm)
1	10	450	25	24	55	3.11	10.4
2	12	350	35	26	65	3.89	12.2
3	6	450	25	28	75	0.97	3.5
4	10	250	45	28	55	2.86	9.2
5	8	350	35	30	65	2.09	6.1
6	6	250	25	24	55	1.21	5.4
7	10	250	45	28	75	3.20	10.2
8	8	550	35	26	65	1.92	4.7
9	4	350	35	26	65	0.31	2.8
10	6	450	45	24	55	1.26	5.4
11	8	350	35	26	65	2.07	5.9
12	10	450	25	24	75	3.26	7.6
13	8	350	35	26	65	1.98	6.6
14	6	450	25	28	55	1.04	3.2
15	10	250	45	24	75	3.19	9.2
16	6	450	25	24	75	0.89	4.1
17	8	350	35	26	65	2.11	6.1
18	8	350	35	26	65	2.09	5.8
19	8	350	35	26	45	1.79	6.5
20	10	250	45	24	55	2.91	8.5
21	10	450	45	28	75	2.50	6.9
22	10	450	45	24	75	2.69	7.5
23	8	350	35	26	85	2.11	6.6
24	6	450	45	28	55	0.78	4.2
25	6	450	45	28	75	0.97	3.9
26	8	350	35	26	65	2.05	6.2
27	6	450	25	24	55	1.19	5.2
28	6	250	45	24	55	1.31	3.8
29	8	350	35	22	65	1.94	6.8
30	8	350	35	26	65	2.11	5.9
31	10	450	25	28	55	3.18	8.1
32	8	350	35	26	65	1.99	6.6
33	8	350	55	26	65	1.88	6.1
34	6	450	45	24	75	1.37	4.9
35	6	250	25	28	75	1.69	7.3
36	10	250	25	24	75	3.71	10.8
37	8	350	35	26	65	2.11	6.4
38	10	250	25	28	75	4.18	12.5
39	8	350	15	26	65	2.59	7.4
40	10	250	25	28	55	3.89	11.6
41	6	250	45	28	75	1.59	5.5
42	10	450	25	28	75	3.29	7.1
43	10	450	45	24	55	2.59	9.2
44	6	250	25	28	55	1.49	4.5
45	6	250	25	24	75	1.31	5.6
46	8	150	35	26	65	2.90	8.1
47	8	350	35	26	65	2.01	6.4
48	8	350	35	26	65	2.11	6.6
49	10	450	45	28	55	2.21	7.8
50	6	250	45	24	75	1.70	4.2
51	10	250	25	24	55	3.36	11.1
52	6	250	45	28	55	1.18	3.2

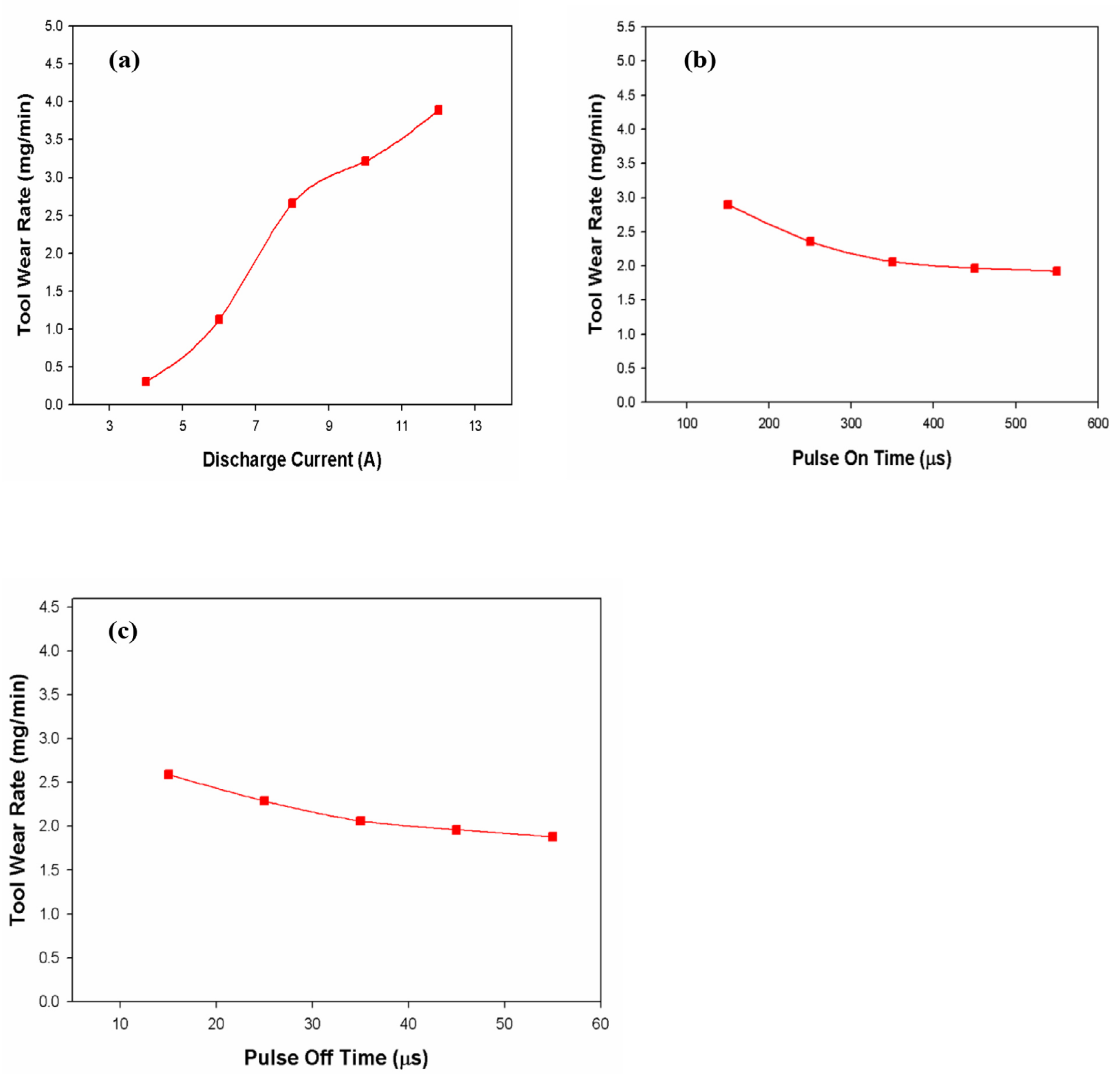

Figure 5. Effect of **(a)** I_p **(b)** T_{on} **(c)** T_{off} on the tool wear rate (TWR).

5.2. Effect of process parameters on the surface roughness

As the EDM process is a replica process, the shape of the tool is obtained on the work material after the machining operation. Higher surface roughness (SR) on the tool leads to impart the rough surface on the work material. During the experimentation, it was observed that the I_p, T_{on} and flushing pressure were the most relevant parameters which were affecting the SR as shown in Fig. 6.

Figure 6a represents the effect of the I_p on the SR of the tool. It was observed that increase in the I_p leads to an increase in the SR because at higher current supply, current density and the impulsive force increases, which ultimately leads to the formation of craters on the surface. Besides, at higher currents, the suspended molten metal between tool work interface increases and these factors tends to increase the SR (Hewidy *et al.*, 2005; Prabhu *et al.*, 2014).

The effect of the T_{off} on the SR is shown in Fig. 6b. It can be observed that the increase in the pulse on time leads to increase in surface roughness. The increase in the pulse on time increases the formation of plasma channel that reduces the current density and also decreases the impulsive force. Due to decrement in the force, the debris collected in the cavity was not effectively flushed out, leading to the formation of globules, which ultimately increases the SR.

Figure 6c demonstrates the effect of the flushing pressure (P) on the SR. It is evident from the figure that there is a small increment in the SR with the increase in flushing pressure. At lower flushing pressures, the flushing is not able to remove the debris

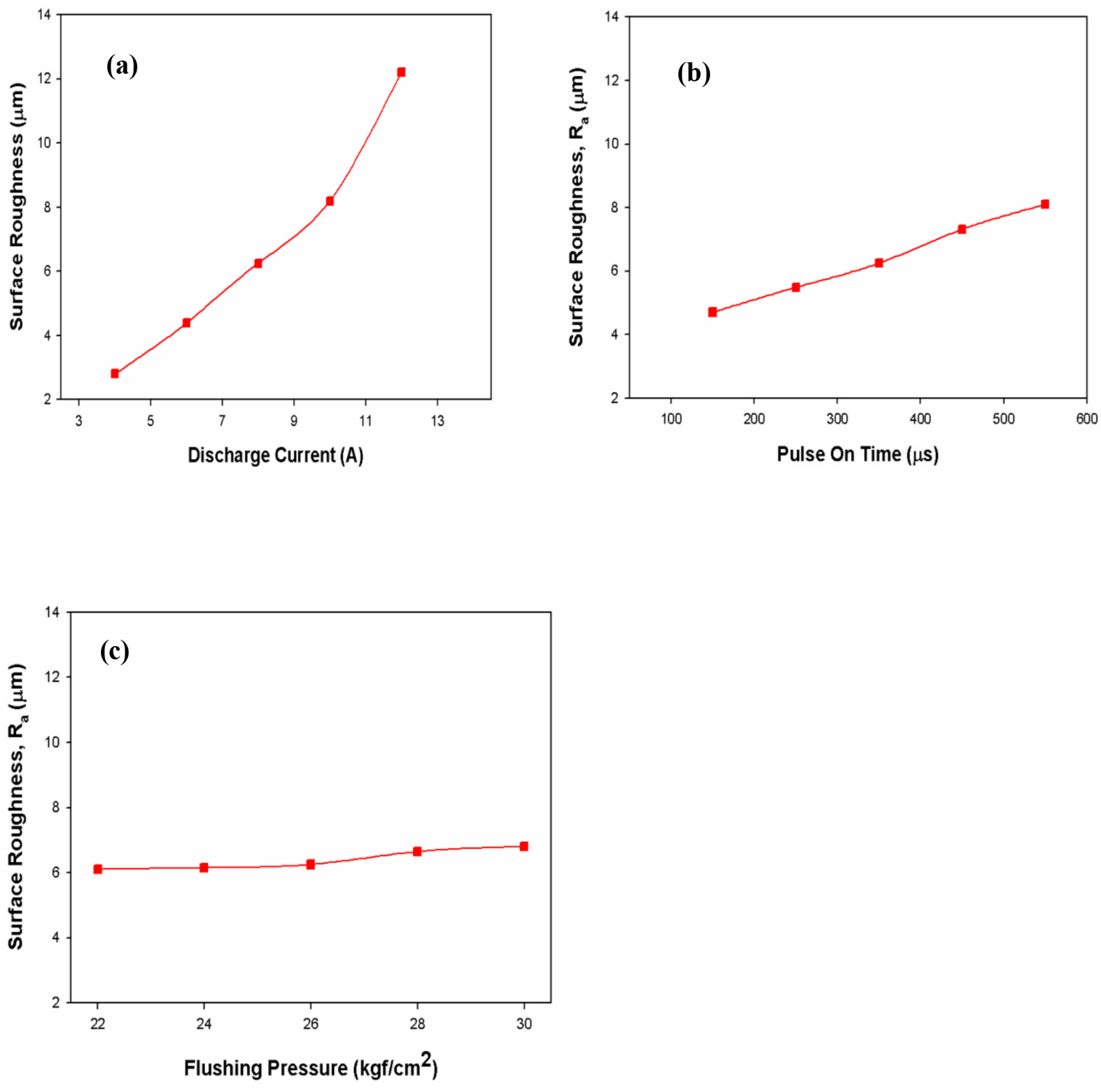

Figure 6. Effect of **(a)** I_p **(b)** T_{on} **(c)** Flushing pressure on the surface roughness (SR).

formed after the discharge. For high flushing pressures, it was observed that proper machining was not done as the ionized channel was continuously washed away leading to an increase in the relative wear ratio. Higher flushing pressures may also increase the turbulence in the inter electrode gap (Kumar *et al.*, 2009; Munz *et al.*, 2013; Nain *et al.*, 2017).

6. WORN SURFACE ANALYSIS

6.1. Microstructural analysis of the tool wear

Figure 7 represents the SEM micrographs of the composite tool tip after EDM machining of hardened D2 steel for experiment no. 9 and 2. It is evident from these micrographs that increase in I_p leads to increase in the wear rate of the tool. At higher discharge currents, more electrical energy will be liberated at the inter electrode gap which produce higher temperatures between the electrode and work-piece and, ultimately, will increase the edge wear and the rounding of the cutting edge (Nain *et al.*, 2017; Kumar *et al.*, 2009).

6.2. Surface texture of tool tip

Figure 8 shows the SEM micrographs for surface roughness of the tool surface obtained after machining of workpiece for experiment no. 9 and 2. EDM

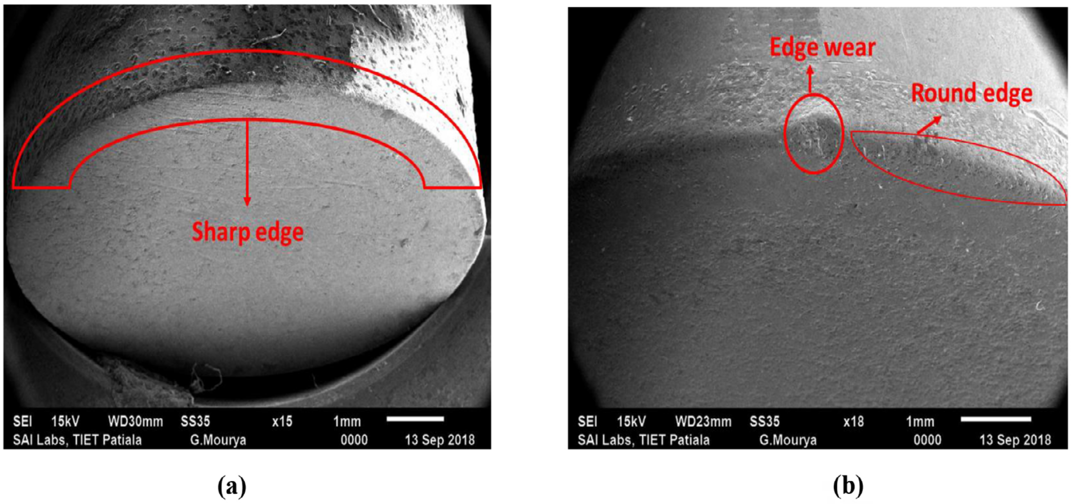

Figure 7. SEM micrographs of the tool after machining for **(a)** expt. Nº 9 and **(b)** expt. Nº 2.

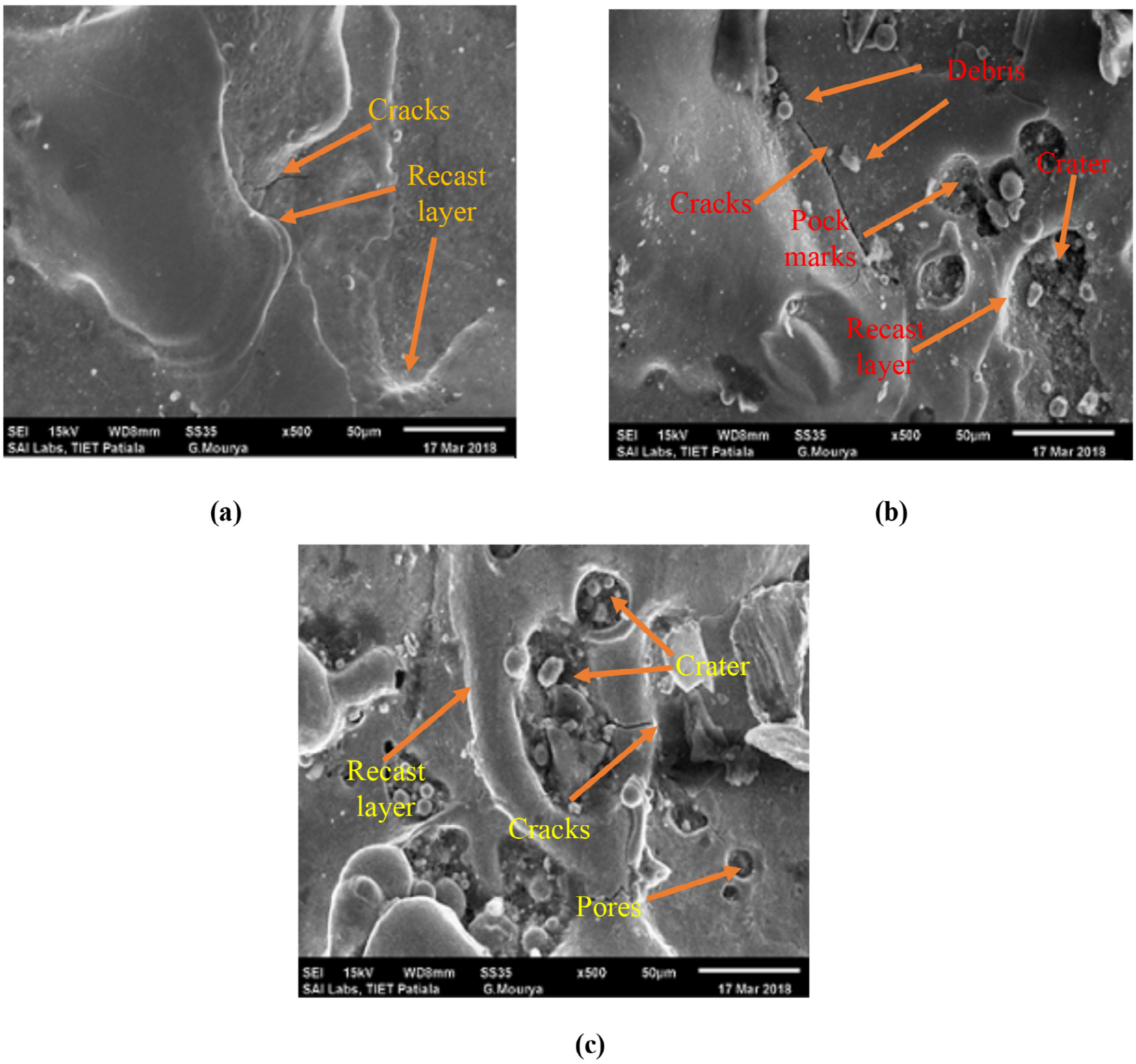

Figure 8. SEM micrographs of the tool after machining for **(a)** expt. Nº 9 **(b)** expt. Nº 17 and **(c)** expt. Nº 2.

is a kind of replica process in which the surface quality of the tool will be directly reflected on the work material (Somani *et al.*, 2022). A higher surface roughness of tool leads to higher rough surface of the counter material. It can be observed that fewer cracks are present as well as the recast layer is also present on the work material surface. Micropores as well as the pock marks are also visible on the surface which increments in the surface roughness (Gill and Kumar., 2016; Klocke *et al.*, 2016; Upadhyay *et al.*, 2017; Hadad *et al.*, 2018).

7. DATASET PREPARATION FOR ML MODEL DEVELOPMENT

The experimental dataset collected for different EDM parameters and responses were kept in a excel sheet as shown in the Table 3. The machining parameters such as discharge current, pulse on time, pulse off time, flushing pressure and gap voltage were used as features and the T (related to the TWR) and the S (related to the SR) were considered as labels for the ML models respectively. The total numbers of samples used were 52. For the development of ML model, the full dataset is divided into train, test and prediction datasets. First, eight data samples were separated from the dataset, those were kept for prediction purpose. Those are I_p, *Ton, Toff, P* and *G* (10, 450, 25, 24 and 55) (6, 450, 25, 28 and 75) (8, 350, 35, 30 and 65) (10, 250, 45, 24 and 55) (10, 450, 25, 28 and 55) (8, 350, 55, 26 and 65) (8, 350, 15, 26 and 65) (6, 250, 45, 24 and 75). The rest of the 42 data samples were kept in a separate excel sheet for training and testing purpose. Among the 42 data samples, 80% were used in the training and the rest (20%) were used in the model testing. All the features used in ML model development were scaled into a common range using the minmax scaler. The formula for feature scaling is defined as follows:

$$\phi_s = \frac{\phi - \phi_{min}}{\phi_{max} - \phi_{min}} \quad (2)$$

7.1. ML based prediction of responses

7.1.1. ML algorithms

7.1.2. Random forest (RF)

It is a supervised machine learning approach (Chung *et al.*, 2021). It is made off decision trees. This algorithm is applied to predict results in many industrial sectors from banking to e-commerce. Both regression and classification problems can be easily obtained through the technique. It is a group learning technology that combines classifiers for giving solution to the complex problem. Many decision trees are associated with this algorithm. The algorithm is mainly trained through combining several individual elements. By such technique, the accuracy of the algorithm improved. The effectiveness of the prediction mainly depends upon the number of trees. If the number of trees increases, the outcome will improve. The predicted result is calculated on the basis of the mean value provided by each tree. A better prediction can be obtained with the reduction of data over fitting in this algorithm. The RF algorithm begins by training multiple decision trees on the given dataset. Each decision tree undergoes a process where it branches out based on various features in the dataset. This process continues recursively until a leaf node is reached, where further division is not possible. The decision nodes within each decision tree play a crucial role in predicting the outcomes by distributing the dataset among the leaf nodes. Each decision node evaluates specific features and makes decisions based on them, directing the data flow towards the appropriate leaf nodes. In the RF algorithm, the final prediction is made by aggregating the predictions of all the decision trees. Each tree independently predicts the outcome, and the most common prediction or the average prediction (depending on the problem type) is chosen as the final result.

7.1.3. Gradient boosting (GB)

It is a well-known and effective methodology in machine learning technique. In machine learning technique, there are two types of errors available. One is the error related to the bias and the other is the error related to the variance. In gradient boosting (GB), the error related to the bias will be minimized. The base estimator is not normally mentioned in this technique. Normally a fixed value will be chosen for the base estimator in the GB model. The base estimator is normally called as the *n* estimator. The value of the *n* estimator is normally taken by the algorithm in a default manner if not assigned. The default value is normally taken as 100. The values of both regressors and classifiers can be easily predicted through the GB algorithm. Regressors are known as continuous target variable and classifiers are called as categorical target values. When the algorithm is used to predict the continuous variable, the cost function will be the mean square error. When it is used to predict categorical variables, the cost function will be the log loss (Panda and Warrior, 2022).

7.1.4. Polynomial regression (PR)

The polynomial regression (PR) (Ostertagová, 2012) is a special case of multiple LRs. In polynomial regression a, n^{th} order polynomial can be used to find a suitable relationship between the features and labels. By using the PR, a nonlinear relationship can be modeled. The PR normally applies to predict human interpretable models. The linear combinations of base functions of the input parameters for the target variable are represented by a PR. These base functions can be as complex as the complexity of the problem. The mathematical expression for the second-order polynomial regression model can be written as follows:

$$y = \beta_0 + \sum_{i=1}^{k} B_i x_i + B_{ii} x_i^{\,2} + \sum_i \sum_j B_{ij}\ x_i x_j + \varepsilon \qquad (3)$$

8. FIREFLY ALGORITHM FOR MULTI OBJECTIVE OPTIMIZATION

The firefly algorithm (Yang, 2008) which was developed in 2008 by Dr. Xin-She Yang mainly belongs to the nature inspired algorithm and mainly relies on lighting bugs of fireflies used to find the optimal solutions. The firefly algorithm is based on the flashing patterns as well as on the behavior of the tropical fireflies. This technique is quite simple, efficient and can be easily implemented for solving various optimization problems with respect to conventionally used algorithms, like the genetic algorithm. This algorithm has many kind of resemblance with other types of algorithms that are related to the swarm intelligence. Real random numbers are mainly used in this kind of algorithm so it is more effective especially in the case of the multi objective optimization problems. So, in this study the firefly algorithm was used for the optimization of the process parameters for the EDM machining of the hardened D2 steel.

This algorithm has three precise idealized regulations which might be primarily based on a number of the predominant flashing traits of real fireflies like all fireflies are unisex whose attractiveness is directly proportional to its brightness as well as the intensity of the light is directly dependent on the objective function's value.

The firefly attractiveness functions are denoted as:

$$\beta(r) = \beta_0 \exp(-\gamma r^m), \text{ with } m \geq 1 \qquad (4)$$

where, r denotes the distance between two adjacent fireflies, γ represents the light absorption coefficient and the initial attractiveness is represented by β_0. The values of β_0, γ, and m are taken as 2, 0.001 and 2 respectively. If the two adjacent fireflies are represented by the i and j for two different positions such as x_i and x_j than the Cartesian distance can be represented as:

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d} (x_i, k - x_j, k)2} \qquad (5)$$

where, d represents the number of dimensions and $x_{i,k}$ and $x_{j,k}$ is the kth component of the spatial coordinate x_i and x_j of the i_{th} and j_{th} firefly.

9. RESULTS AND DISCUSSIONS (ML MODELS)

The predictive capability of the three ML models (polynomial regression, random forest and gradient boosting) is discussed in this section. For assessing the predictive capability, R^2 and MSE of predicted responses were calculated as presented in Tables 4 and 5. The R^2 and MSE can be defined as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (\phi_i - \phi_i)^2}{\sum_{i=1}^{n} (\phi_i - \phi_i)^2} \qquad (6)$$

Table 4. R^2 and MSE of estimations of the ML models for the testing dataset for the tool wear rate (T) and the surface roughness (S).

Testing	Tool wear rate (T)		Surface roughness (S)	
Models	**R^2**	**MSE**	**R^2**	**MSE**
RF	0.9029	3.61e-08	0.7759	0.7005
PR	0.9692	1.14e-08	0.9513	0.2136
GB	0.8854	4.25e-08	0.5935	1.2705

Table 5. R^2 and MSE of estimations of the ML models for the prediction dataset for the tool wear rate (T) and the surface roughness (S).

Testing	Tool wear rate (T)		Surface roughness (S)	
Models	**R^2**	**MSE**	**R^2**	**MSE**
RF	0.9482	2.74e-08	0.7605	1.0931
PR	0.9555	2.35e-08	0.9532	0.2136
GB	0.9013	5.22e-08	0.8829	0.5343

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(\phi_i - \phi_i)^2 \qquad (7)$$

Tables 4 and 5 correspond to testing and prediction results respectively. In Table 4: the highest value of R^2 was observed for the PR. The R^2 values are 0.9692 and 0.9513 for the prediction of T (refers to the TWR) and S (refers to the SR), respectively. For the predictions of T, the R^2 values for RF and GB predictions are 0.9029 and 0.8845 respectively. Similar is the case for the prediction of S. From Table 5, it is also clear that the R^2 of T and S predictions are higher for PR. The actual and predicted values of different responses are also plotted in Fig. 9 and Fig. 10. Hence, we have used PR, for generating a regression equation, which can be used for the development of a complex objective function to be used in metaheuristic algorithms.

9.1. ML based modeling of response equations:

To model the responses of T and S, i.e. tool wear and surface roughness, in terms of current, pulse on time, pulse off time, gap voltage and die electric pressure, polynomial regression was employed. For the two responses, mathematical models are formulated. Mathematical models are developed considering the first data set. Mathematical models are utilized to formulate the complex objective function. The objective function was considered in the optimization process. The mathematical models for each response were written as follows.

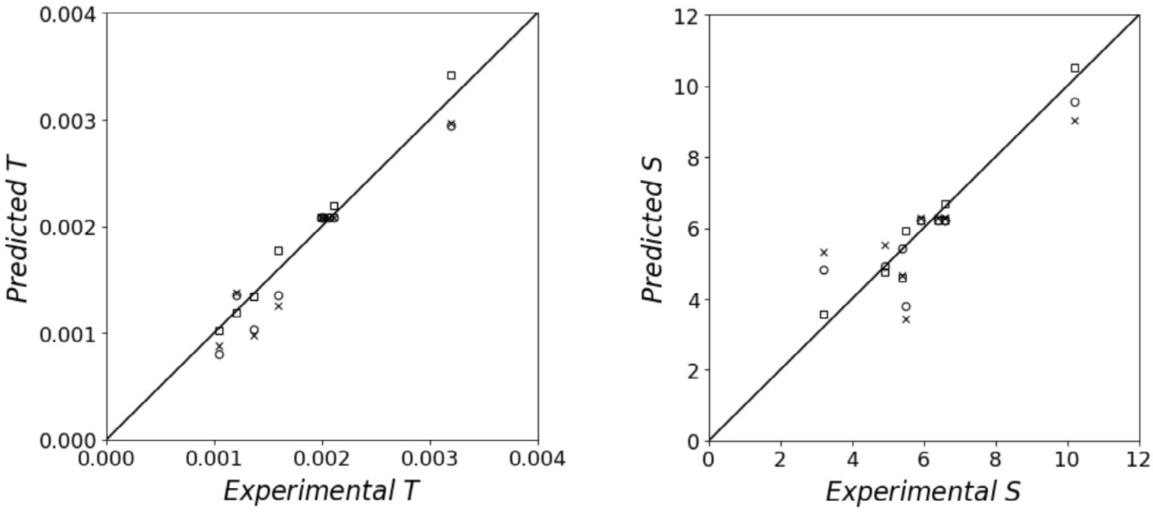

Figure 9. Actual vs. Predicted values of the output responses with different ML surrogate models for the testing dataset.

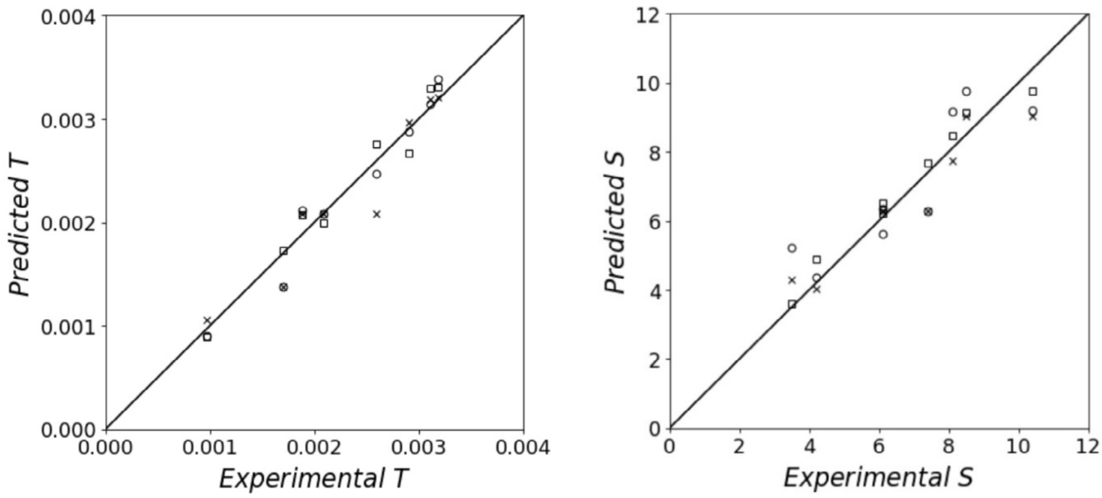

Figure 10. Actual vs. Predicted values of the output responses with different ML surrogate models for the prediction dataset.

T equation:

Beta_0=2.01529461e-03

Array (0.00000000e+00, 1.80965432e-03, -2.69356240e-04, -1.66148902e-04, 4.66876563e05, 1.67649128e-04, 2.00000000e-05, -1.00861590e-04, -4.27620206e-04, 1.21409116e04, 8.16734992e-05, 3.30000000e-04, -7.56739855e-06, -3.34152307e-04, -2.69454906e04, 8.34387160e-05, -1.23962097e-04, 1.06782761e-04, -6.20727661e-05, 5.07914987e05, -4.93805586e-05)

S equation:

Beta_0=6.36124794e+00

(0.00000000e+00, 4.87344755e+00, -6.02969408e-01, -3.65307363e-01, -4.79808971e01, -2.75964325e-01, 1.27142857e+00, -1.83373303e+00, -4.40927499e-01, 1.86091479e01, -9.11691019e-01, 1.71428571e-01, 7.74193004e-01, -1.27550921e+00, -1.66341072e+00, 1.79759589e-01, -9.93409037e-02, 8.68466112e-02, 2.37812922e-01, 6.29338472e-01, 2.06079891e-01)

The coefficient arrays are the coefficients of the following terms in the polynomial regression equation in the respective order:

$$[1, x_0, x_1, x_2, x_3, x_4, x_0^2, x_0x_1, x_0x_2, x_0x_3, x_0x_4, x_1^2, x_1x_2, x_1x_3, x_1x_4, x_2^2, x_2x_3, x_2x_4, x_3^2, x_3x_4, x_4^2]$$

9.1.1. Multi-objective optimization

The equations learned through RF and GB regression are not interpretable; hence we have used the equations learned through polynomial regression to prepare a complex objective function for optimization of the machining parameters. Here the objective function is to minimize the responses of EDM. The following complex objective function has been proposed:

$$\text{COF}\ (x_0, x_1, x_2, x_3, x_4) = w1(T/T_m)+w2(S/S_m)$$

In the above equation, x_0, x_1, x_2, x_3 and x_4 are the five input machining parameters. T_m and S_m are the minimum values of tool wear rate (T) and surface roughness (S). Here we have considered the w_1 and w_2 as 0.5. The constraints of the machining operation were applied for minimization of the objective function. Those constraints are as follows: $4<=x_0<=12$, $150 <=x_1<=550$, $25 <=x_1<=45$, $22 <=x_1<=28$, $45 <=x_1<=85$. For optimization, the firefly algorithm was used. The optimized input machining parameters are found to be 4.86, 155.50, 30.19, 23.73 and 71.97.

10. CONCLUSIONS

- In the present research, pure copper and Cu-SiC composites were successfully sintered by using powder metallurgy technique. Brazing process was used to braze the composite tip on the copper rod which was further used to machine the hardened D2 steel. The Central composite rotatable design (CCRD) technique was used for design of experimentation.
- Result indicates that the tool wear rate (TWR) was significantly affected by the I_p, T_{on} and T_{off} while the I_p, T_{on} and flushing pressure had a greater influence on the surface roughness. From the SEM micrographs it was observed that the increase in the I_p leads to increase in the wear rate of the tool. The dataset collected from the experiments were used to model the EDM responses in terms of discharge current, pulse on time, pulse off time, flushing pressure and gap voltage. The output responses are the tool wear rate (T) and surface roughness (S). Three ML algorithms are used in the modeling of the output responses, those are random forest, polynomial regression and gradient boosted trees. The R^2 of testing and predictions of T and S were found to be maximum for polynomial regression.
- The R^2 value of prediction was found to be more than 0.95, hence we used the learned correlation function for T and S for developing a complex objective function, for optimization of input machining parameters. For the optimization, the firefly algorithm was used. The optimized input machining parameters are found to be 4.86, 155.50, 30.19, 23.73 and 71.97.

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