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MULTI-OBJECTIVE OPTIMIZATION OF MACHINING PARAMETERS FOR EDM OF MAGNESIUM ALLOY- ZE41 USING MARCOS ALGORITHM AND DIFFERENT WEIGHING METHODS: SD, CRITIC AND MEREC

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Abstract: This paper presents multi-objective optimization of machining parameters, i.e., electrode materials, peak current, pulse on time and pulse off time in EDM of magnesium alloy-ZE41. The objectives such as metal removal rate, tool wear rate, surface roughness, recast layer thickness and radial overcut were optimized using MARCOS algorithm and three objective weighing methods, i.e., SD, CRITIC and MEREC. Taguchi's $L_{27}(3^4)$ orthogonal array was used for conduction of experiments. ANOVA results showed that electrode material, interaction of electrode material and peak current and pulse on time were the most significant parameters for all weighing methods. Comparative study indicated that the percentage improvement in performance at optimal parameter setting were 37.21%, 32.30% and 10.68% for SD, CRITIC and MEREC respectively. Confirmation results indicated that all objectives except tool wear rate were improved positively for SD and CRITIC, but all objectives except metal removal rate deteriorated for MEREC.
Key words: Magnesium alloy ZE41, Measurement alternatives and ranking according to compromise solution (MARCOS), standard deviation (SD), Criteria importance through inter-criteria correlation (CRITIC), Method based on the removal effects of criteria (MEREC), EDM.

1. INTRODUCTION

With the advancement of modern manufacturing technologies, it is far easier to meet the requirements of manufacturers and customers. The manufacturing industries are looking at many objectives simultaneously as customer demands are increasing day by day. Multi-objective optimization is therefore becoming more significant in the modern and rapidly changing world. Additionally, multi-objective optimization problems are present in the bulk of real-world processes. However, identifying the optimum process can be challenging considering a number of parameters such as productivity, economy, surface integrity, dimensional accuracy of a part, etc. involved in the decision-making process [1, 2]. EDM is one such modern manufacturing process widely used for machining difficult-to-cut and complex parts. It is stochastic in nature and its performance is influenced by many electrical and non-electrical parameters. The prime requirements in EDM are improving productivity, surface integrity and dimensional accuracy as these are very important during manufacturing as well as in service [3]. However, these requirements are conflicting in nature. In EDM, higher levels of electrical parameters may result in more material removal rate (MRR) while degrading the surface integrity and dimensional accuracy of the produced part and vice versa [4]. It calls for maximising the MRR, minimising the tool wear rate (TWR), improving surface integrity and achieving higher dimensional accuracies. Surface integrity can be improved by reducing surface roughness (SR) and recast layer thickness (RLT). A recast layer is formed due to the re-solidification of removed material and deposition on the machined surface. RLT may consist of globules of debris, cracks and appendages which may damage the surface integrity. In EDM, dimensions may become oversized due to side sparking by the electrode. Hence, it is inevitable to control the dimensional inaccuracies like radial overcut (ROC) of machined hole size.
It is crucial to determine the optimum parameters and their levels for achieving the best objective values using the right mathematical tools because these objectives are conflicting in nature. Hence, engineers and researchers are constantly in the hunt of new tools that can solve and provide better solutions to such problems. In this direction, multi-criteria decision-making (MCDM) techniques have been serving as effective tools to solve multi-objective optimization problems in many manufacturing processes [5]. They are capable of providing the best optimum

settings of machining parameters and their levels among available options/alternatives. Consequently, this leads to fulfilment of the requirements of both manufacturers and customers.

Among all MCDM techniques, technique for order preference by similarity to ideal solution (TOPSIS) and grey relational analysis (GRA) were widely adopted methods for the multi-objective optimization of many manufacturing processes [6-8]. The authors of [9] optimized process parameters of the micro EDM process while machining titanium alloy with tungsten carbide electrode using the Taguchi method and TOPSIS. In [10], research on optimization of die sink EDM of AISI420 stainless steel with copper electrode using GRA was carried out. [11] looked at the optimization of process variables for MRR, TWR, and depth in EDM for Al-2050 utilizing various rotating tool electrodes such as Cu, W, and Cu-W alloy. [12] applied the response surface methodology-based GRA to examine the effects of machining settings experimentally on TWR and MRR in EDM with the copper electrode. [13] used TOPSIS and GRA to optimise several responses for MRR, TWR, SR, form tolerances, taper cuts, circularity, and cylindricity during the EDM machining of biodegradable AZ31 alloy. In a recent study [14], authors carried out optimization of SR, tool wear and MRR in turning of Inconel 718 with ceramic composite tools using TOPSIS, GRA and data envelopment analysis ranking and compared the results based on the equal weighing method. Authors of [15] attempted to improve machining performance in terms of surface quality, cutting forces and tool wear in micro-milling of magnesium alloy using equal weights, GRA and TOPSIS. [16] performed optimization of cutting force, SR and temperature during end milling of magnesium metal matrix composites through TOPSIS and GRA and compared their performances with equal importance to responses. [17] applied analytical hierarchy process (AHP) and TOPSIS for parametric optimization of micro EDM of titanium alloy with tungsten carbide electrode and compared these results with other MCDM techniques. In [18], cuckoo search was applied to improve machining performance in sustainable EDM of Nimonic263 alloy using three electrodes copper, copper tungsten and tungsten. In [19], Taguchi method, TOPSIS and AHP weight were used to maximize MRR and minimize TWR in EDM of Al-Fe-Si alloy with copper, brass and EN8 steel electrodes. AHP and CRITIC weight approaches were used by authors in a study [20] to optimize the mechanical properties of ceramic cutting tool while turning 300M ultra-high-strength steel. The research study [21] concentrated on the concurrent optimization of energy-related objectives, SR and MRR for sustainable turning operation utilizing TOPSIS. For assigning weights to the objectives, the authors used the equal weighing method, AHP, and the entropy weight method (EWM). [22] analyzed MCDM tools such as TOPSIS, complex proportional assessment and preference ranking organization method (COPRAS) for enrichment evaluation-II using weighing methods like CRITIC and best worst method to derive the best optimum results in the micro drilling process. Using a unique integrated approach of best worst method-Tomada-de-Decisao-Interativa-Multicriterio, wear parameter optimization for CrN/TiAlSiN coating was carried out by authors of [23] to obtain the best and the worst alternatives among many choices. [24] employed combined compromise solution and integrated step-wise weight assessment ratio analysis methodologies for parametric optimization of milling processes. In 2018, [25] described a location optimization problem using new MCDM techniques and compared their outcomes with existing MCDM techniques.

The weights given to various criteria (objectives) are of utmost important while utilizing any of the MCDM techniques to solve any multi-objective optimization problem in any machining process. As varying weights to different objectives may lead to different results, this has a significant impact on optimization and the ranking of alternatives. Based on the literature survey, it is revealed that some authors gave equal weightage to criteria [9, 10, 12, 13, 14, 16, 29]. But such weight assignment may not be correct because one objective may weigh more than the other in real-life complex machining processes. To overcome this difficulty, few authors employed subjective weights like the Delphi method, AHP [17-21], best-worst method [22-23], step-wise weight assessment ratio analysis [24] and decision-making trial and evaluation laboratory [25], etc. in various machining processes and other fields. In these methods, the weight of each objective is provided by the decision maker/expert. Though these methods provide better-optimized results than the equal weighing method, these too suffer from the fact that the accuracy of these methods depends on the knowledge and subjective thought process of the decision maker and the experience of the experts in a particular domain of study. In addition, the weights determined by these methods may vary from one person to another and are prone to high bias in decision-making process. Lastly, they are time-consuming and involve high costs [5-7]. Due to such limitations of subjective weights, some authors determined realistic objective weights through some mathematical models and computational processes based on initial experimental data. Such weights are independent of the decision maker/expert and avoid the bias.

The authors of the research work [26] performed simultaneous optimization of processing time, electrode wear ratio, process energy and consumption of dielectric using EWM-GRA and compared these results with fuzzy-TOPSIS and Taguchi-VIKOR models. It was observed that all three methods yielded the same optimization results. For improving the EDM performance of RENE80 nickel superalloy, [27] suggested and verified the hybrid approach of Taguchi method and principle component analysis based on GRA. [28] utilized two MCDM tools to optimise various correlated objectives while cutting Nickel 233 alloy in abrasive jet machining. [29] facilitated the comparison among various MCDM techniques like GRA, TOPSIS and COPRAS by using CRITIC weights and derived optimum solutions for hard turning of medium carbon steel. [30] elaborated on optimization studies in turning by utilizing SD weight and the VIKOR method. Recently, a few authors advocated new optimization tools and weighing methods. [31] adopted two weighing methods - EWM and MEREC and four latest MCDM methods for minimization of SR and maximization of MRR in turning. [32] examined the output responses in the machinability study of Zn-Al-TiC composite in wire EDM and optimized machining parameters by applying EWM-based MARCOS algorithm.

From the literature review, it can be observed that the majority of the machining processes were optimized by TOPSIS and GRA with equal weights or subjective weights. Very few authors carried out optimization with other than TOPSIS and GRA methods. Some authors compared the outcomes of MCDM techniques based on either equal weights or subjective weights [20-22]. Such comparisons may not yield fruitful results. Hence, researchers are now in need of better optimization tools to further enhance the machining performance. In [5], the authors concluded that objective weights should be preferred over subjective weights for better performance and more accuracy of results. The review emphasized focusing more on applications of objective weighing methods and novel MCDM techniques because of potentiality of these methods. In recent studies [2, 33, 34], a new objective weighing method namely MEREC was proposed to determine the criteria weights in a MCDM problem and established the fact that this method can yield equal or better results as compared to others. Further, the MARCOS algorithm is a relatively new MCDM technique suggested by Stević in 2020 [35]. It is being explored for parametric optimization in various machining processes. This method has been applied to turning, milling and grinding [36], wire EDM [32] and powder-mixed EDM [34] only. So far, there has been no research work on the application of MARCOS to optimise the die-sink EDM process. Also, no comparative work of MARCOS with different objective weighing methods, i.e., SD, CRITIC and MEREC is available in the current literature on any machining process. The rationale behind using three objective weighing methods is that occasionally the greatest solution might not be the best when MARCOS is implemented using just one weighting method. As a result, MARCOS must be used in conjunction with a variety of weighing methods to determine which choice is the best. Additionally, various weighing methods can alter the outcomes of optimization because they use different concepts to calculate objective weights. Literature review suggests that many research works considered objectives like MRR, TWR and SR in machining processes. RLT and ROC were rarely considered although they are equally important in terms of surface integrity and dimensional accuracy of a part. Finally, it was revealed that no work has been carried out on the EDM of ZE41 to date.

The present study applied the MARCOS algorithm and objective weighing methods - SD, CRITIC and MEREC for multi-objective optimization of machining parameters in EDM of ZE41 considering five objectives - MRR, TWR, SR, RLT, and ROC. The machining parameters included electrode materials (copper, brass, and EN8), peak current, pulse on time and pulse off time. The organization of the rest of this research paper is structured as follows: Section 2 presents experimental details; Section 3 presents multi-objective optimization methodology; Section 4 presents results and discussion, ANOVA, optimization of utility functions, comparative study and confirmation of results and Section 5 presents the conclusions.

2. EXPERIMENTATION

2.1. Design of Experiments

Based on the results of the pilot study, the investigation showed that the process became unstable and arcing occurred with an increase of peak current and pulse on time. Ranges of peak current and pulse on time were carefully selected to prevent this. The manufacturer of the EDM machine suggested using a constant voltage of 30V. As a result, the pilot study and EDM requirements led to select the machining parameters and their levels as shown in Table 1. In addition, electrode material (copper, brass and EN8) was taken into account as a parameter because each electrode offers a varied level of machining performance due to different material characteristics. Also, these materials are widely used in industries due to ease of availability and economy [37]. Taguchi's L27 (34) orthogonal array was selected for experimentation because the total degrees of freedom were eight (4 x (3-1)), which was less than twenty-six (27-1) that of Taguchi's L27 (34) orthogonal array. Taguchi's experimental design was selected due to its simplicity, reliability, competency and economy. It examines the main effects and interaction effects of input parameters on objectives [38].

Table 1. Machining parameters and their levels

Level	Machining Parameters			
	Electrode material A	Peak current (A) B	Pulse on time (µs) C	Pulse off time (µs) D
1	Copper	6	100	20
2	Brass	12	200	50
3	EN8	18	500	100

Table 2. Experimental results

Exp. no.	A	B	C	D	MRR (mg/min)	TWR (mg/min)	SR (µm)	RLT (µm)	ROC (mm)
1	Copper	6	100	20	16.700	0.200	3.466	32.957	0.457
2	Copper	6	200	50	18.400	0.330	4.062	40.597	0.465
3	Copper	6	500	100	25.875	0.350	4.371	26.203	0.515
4	Copper	12	100	50	55.275	0.450	4.266	28.877	0.525
5	Copper	12	200	100	121.050	0.600	6.132	39.467	0.525
6	Copper	12	500	20	82.875	0.750	5.541	37.077	0.565
7	Copper	18	100	100	179.375	1.675	5.782	58.687	0.655
8	Copper	18	200	20	232.825	2.975	5.546	65.803	0.617
9	Copper	18	500	50	196.100	3.375	5.787	47.940	0.661
10	Brass	6	100	20	28.500	11.425	3.427	17.640	0.108
11	Brass	6	200	50	41.650	15.650	3.501	30.550	0.118
12	Brass	6	500	100	32.925	14.950	3.914	14.077	0.160
13	Brass	12	100	50	176.975	56.225	4.380	18.303	0.478
14	Brass	12	200	100	163.850	61.475	5.947	32.367	0.254
15	Brass	12	500	20	129.725	69.275	5.723	25.183	0.213
16	Brass	18	100	100	282.075	85.525	6.032	18.297	0.122
17	Brass	18	200	20	262.800	98.350	5.737	23.107	0.341
18	Brass	18	500	50	243.075	128.675	5.057	42.443	0.479
19	EN8	6	100	20	13.350	1.600	4.099	97.387	0.309
20	EN8	6	200	50	35.775	4.250	3.233	80.193	0.456
21	EN8	6	500	100	25.350	3.450	3.761	93.940	0.343
22	EN8	12	100	50	95.150	21.775	5.318	35.743	0.472
23	EN8	12	200	100	116.000	7.275	5.191	33.413	0.502
24	EN8	12	500	20	66.625	25.950	3.261	54.367	0.568
25	EN8	18	100	100	183.150	15.825	5.141	39.913	0.485
26	EN8	18	200	20	72.625	18.025	4.714	32.977	0.580
27	EN8	18	500	50	77.425	14.770	4.761	55.510	0.752

2.2. Materials

ZE41 Magnesium alloy was selected as the workpiece material due to its wide applications in the aerospace industry - aircraft components, airframe skin, brake systems, transmission systems, helicopter gearboxes, etc; automotive industry – engine cradles, front-end structures, cam covers, etc; video cameras, power tools and others due to lightweight property. The chemical composition by wt.% is: Ce/Tr-50.4, Cu - > 0.005, Fe - 0.003, Mn-0.02, Ni- <0.0005, Si - < 0.005, Tr-1.2, Zn-4.2, Zr-0.54, O_e- < 0.050, To- < 0.05 Mg-Balance. The workpieces of dimensions 150 x 50 x 12 mm^3 were cut on milling machine and polished before experimentation. Three electrodes – copper, brass and EN8 were turned to Φ12 mm.

2.3. Equipment, instruments and measurements

EDM machine tool – Die-sink EDM machine tool (Make-Askar Microns, model - V3525, India) was used for the conduction of experiments. It has a servo-head for precise control of electrode movement into workpiece, control panel with various settings, dielectric circulation system and work table with T-slots for fixing the workpiece.

Digital weighing balance – After each experiment, the initial and final weights of workpieces and electrodes were measured using a digital weighing balance (Make-Shimadzu, Japan) with 0.1 mg accuracy and 200 gm

capacity. MRR and TWR were measured as the weight difference before and after machining divided by machining time.
Surface roughness tester - SR value (Center line average and cut-off length of 0.8 mm) was measured with the tester (Make-Surftest, Mitutoyo-SJ210, Japan). The average value of three random readings was considered for analysis.
Optical microscope - The diameters of machined holes were measured by image analysis software with an accuracy of 0.001mm linked to an optical microscope (Make-Olympus, CX23, Japan). Two diameters were measured in two perpendicular directions per experiment and the average of these two diameters was considered for calculation. ROC was measured as the difference between the radii of the machined hole (R) and electrode (r). Later, the machined holes were cut at the center for the measurement of RLT. The cut portions of each hole were mounted for metallographic observations. Each specimen was polished by applying the diamond paste on the polishing machine. Later, Nital etchant was used to reveal the microstructure with a recast layer. The same microscope was used to capture images of the recast layer at three different locations with a magnification of 500X. Three readings of RLT on each image were recorded and the average values were considered for analysis. These measurements were repeated for all 27 experiments.

2.4. Experimental Procedure

The voltage of 30 V was kept constant throughout the experimentation. After fixing the workpiece on the table and electrode in the head of EDM, the parameters were set as per the experiment number. Silicon carbide abrasive sheets in the sizes #400, #600, and #800 were used to polish the top surface of the workpiece and the bottom surface of the electrode to a surface finish of 1µm.The dielectric tank was filled with commercial EDM oil (grade 30) using a motor pump. Side flushing with the pressure of 1.5 kg/cm^2 was employed to remove the debris formed during machining. The machining time of each experiment was set to four minutes on a digital watch. Later, every experiment was repeated twice according to the $L_{27}(3^4)$ orthogonal array. Table 2 displays the experimental results.

3. MULTI-OBJECTIVE OPTIMIZATION

3.1. Objective weighing methods

3.1.1. SD weight

It is a statistical method for calculating how much variance or dispersion exists in a set of data. Quantifying how far each data point deviates from the data set's mean is useful. The weights of the criteria are established in terms of their SDs. It has following steps [30],
Step 1: Establish the decision matrix (X) consisting of *n* feasible alternatives and *m* objectives.

$$X = [x_{ij}]_{nxm} = \begin{bmatrix} x_{11} & \cdots & x_{1m} \\ x_{21} & \cdots & x_{2m} \\ \vdots & \vdots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{bmatrix} \qquad i = 1, 2, \ldots, n; \; j = 1, 2, \ldots, m \tag{1}$$

Step 2: Normalize the defined decision matrix X in the ranges between zero and one using equations (2) and (3). Normalization is done for objectives as different objectives have different units and ranges.

$$R_{ij} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}} \qquad \text{for beneficial/maximization criteria} \tag{2}$$

$$R_{ij} = \frac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}} \qquad \text{for non-beneficial/minimization criteria} \tag{3}$$

Step 3: Calculate weights for each objective using equations (4) and (5).

$$\Sigma_j = \sqrt{\frac{\sum_{i=1}^{n} (x_{ij} - \bar{x}_j)^2}{n}} \tag{4}$$

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$$w_j = \frac{\sigma_j}{\sum_{j=1}^{m} \sigma_j} \tag{5}$$

Here, w_j, and σ_j are weight and SD of jth objective respectively.

3.1.2 CRITIC Weight

The CRITIC method is based on the SD approach proposed by Diakoulaki et al. It derives weight fractions based on the contrast intensity and conflict, i.e., objective functions comprise both beneficial and non-beneficial nature involved in decision-making problems. It involves the following steps [39],

Step 1: Same as step 1 in 3.1.1

Step 2: Same as step 2 in 3.1.1

Step 3: Determination of objective contrast intensity based on SD of normalized objective values (columns) using equation (4).

Step 4: Establish the symmetric matrix (*m* x *m*) with correlation coefficients (r_{jk}) between objectives using equation (6).

$$r_{jk}=\frac{\sum_{i=1}^{m}(r_{ij}-\overline{r_j})(r_{ik}-\overline{r_k})}{\sqrt{\sum_{i=1}^{m}(r_{ij}-\overline{r_j})^2\sum_{i=1}^{m}(r_{ik}-\overline{r_k})^2}} \qquad j, k = 1,2,\ldots,m \tag{6}$$

Here, $\overline{r_j}$ and $\overline{r_k}$ are the average values of j^{th} and k^{th} objectives

Step 5: Determine the objective information (O_j) using equation (7).

$$O_j = \sigma_j \sum_{k=1}^{m}(1-r_{jk}) \tag{7}$$

Step 6: Determine weights of objectives by applying the normalizing technique with the help of objective information as shown in equation (8).

$$w_j = \frac{O_j}{\sum_{k=1}^{m} O_j} \tag{8}$$

3.1.3. MEREC weight

MEREC is a recent method and it examines whether there is a performance difference between alternatives by eliminating each criterion. The criteria with a greater impact on performance are given greater weights. MEREC has the following steps [33],

Step 1: Same as step 1 in 3.1.2

Step 2: Normalize the decision matrix (N) by simple linear normalization method using equations (9).

$$\eta_{ij}=\begin{cases}\frac{\min_i ij}{x_{ij}} & \text{if } j \in B\\ \frac{x_{ij}}{\max_i x_{ij}} & \text{if } j \in NB\end{cases} \tag{9}$$

Here, B and NB are beneficial and non-beneficial criteria respectively.

Step 3: Calculate the overall performance S_i of an alternative by considering the logarithmic measure with equal weights using the equation (10).

$$S_i = \ln\left[1+\left(\frac{1}{m}\sum_j^m\left|\ln(\eta_{ij}\right|\right)\right]` \tag{10}$$

Step 4: Calculate each alternative's performance S'_{ij} by removing each criteria using equation (11).

$$S'_{ij} = \ln\left[1+\left(\frac{1}{m}\sum_{k,\,k\neq j}^{m}\left|\ln(\eta_{ij})\right|\right)\right] \tag{11}$$

Step 5: Determine the removal effect of the j^{th} criteria E_j using the equation (12).

$$E_j = \sum_i^m\left|S'_{ij} - S_i\right| \tag{12}$$

Step 6: Determine the weight of each criteria using the equation (13).

$$w_j = \frac{E_j}{\sum_k E_k} \tag{13}$$

3.2. MARCOS algorithm

MARCOS is a novel MCDM technique and it has been demonstrated that it can handle numerous objectives and options while upholding the stability of the process. In this, utility function ($f(K_i)$) represents all objectives with their weights and expects it to be as maximum as possible. To analyse $f(K_i)$ and the ranking of alternatives, it compares alternatives with the best solution, i.e., ideal alternative (AI) and the worst solution, i.e., anti-ideal alternative (AAI) values. Finding the most ideal and anti-ideal reference values is made easier by $f(K_i)$. MARCOS has the following steps [35],

Step 1: Same as step 1 in 3.1.1

Step 2: Build an extended initial matrix (EM) by adding AI and AAI into the initial decision matrix.

$$EM = \begin{array}{c} AAI \\ A_1 \\ A_2 \\ \vdots \\ A_m \\ AI \end{array} \begin{bmatrix} x_{aa1} & \cdots & x_{aan} \\ x_{11} & \cdots & x_{1n} \\ x_{21} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots \\ x_{m1} & \cdots & x_{mn} \\ x_{ai1} & \cdots & x_{ain} \end{bmatrix} \tag{14}$$

Equations (15) and (16) define AAI and AI based on the type of criteria. Here, B and NB are for beneficial and non-beneficial criteria respectively.

$$AAI = \min_j x_{ij} \quad \text{if } j \in B \quad \text{and} \quad \max_j x_{ij} \quad \text{if } j \in NB \tag{15}$$

$$AI = \max_j x_{ij} \quad \text{if } j \in B \quad \text{and} \quad \min_j x_{ij} \quad \text{if } j \in NB \tag{16}$$

Step 3: Normalize EM using equations (17) and (18).

$$n_{ij} = \frac{x_{AI}}{x_{ij}} \quad \text{if} \quad j \in NB \tag{17}$$

$$n_{ij} = \frac{x_{AI}}{x_{ij}} \quad \text{if} \quad j \in B \tag{18}$$

Step 4: Determine the weighted normalized matrix using equation (19).

$$d_{ij} = n_{ij} \text{ x } w_j \tag{19}$$

Here, w_j is the weight of j^{th} objective.

Step 5: Find the utility degree of each alternative K_i^- and K_i^+ in relation to AAI and AI using equations (20), (21) and (22).

$$K_i^- = \frac{S_i}{S_{AAI}} \tag{20}$$

$$K_i^+ = \frac{S_i}{S_{AI}} \tag{21}$$

$$S_i = \sum_{i=1}^{m} d_{ij} \tag{22}$$

Step 6: Compute the $f(K_i)$ of each alternative using equation (23).

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}} \tag{23}$$

Here, $f(K_i^-)$ and $f(K_i^+)$ are utility functions related to AAI and AI. Equations (24) and (25) are used to find them,

$$f(K_i^-) = \frac{K_i^+}{\left(K_i^+ + K_i^i\right)} \quad \text{for anti-ideal solution} \tag{24}$$

$$f\left(K_i^+\right) = \frac{K_i^-}{\left(K_i^+ + K_i^i\right)} \quad \text{for ideal solution} \tag{25}$$

Step 7: Rank the alternatives based on values of $f(K_i)$.

Figure 1 depicts a multi-objective optimization methodology. Equation (1) and experimental values of objectives from Table 4 were used to form the initial decision matrix. Later, equation (2) was used to obtain the normalised decision matrix. Here, MRR is considered as a 'higher the better' type objective and SR, TWR, RLT and ROC as 'lower the better' type objectives. This matrix has been utilized in all calculations for optimization. To accomplish step 4 in the MARCOS algorithm, the weights of objectives were determined by following the procedures explained in sections 3.1.1, 3.1.2 and 3.1.3 respectively. Some important parameters of these methods are shown in Tables 3, 4 and 5. The obtained weights of all objectives are consolidated in Table 6. The variations in weights according to the method are shown in Figure 2. Such variations in weights using different methods were observed in research works [8, 9, 20, 36]. Subsequently, $f(K_i)$ s were calculated for each experiment using equations (14) – (25) explained in section 3.2. Results of some parameters and $f(K_i)$s by MARCOS using SD is shown in Table 7. A similar procedure is followed for CRITIC and MEREC. The $f(K_i)$s and ranks according to SD, CRITIC and MEREC are shown in Table 8.

Table 3. Standard deviations (σj) and weights (wj) - SD

Objectives	MRR [mg/min]	TWR [mg/min]	SR [µm]	RLT [µm]	ROC [mm]
σ_j	0.306	0.266	0.323	0.259	0.271
w_j	0.215	0.187	0.226	0.181	0.190

Table 4. Correlation coefficients (rjk) and weights (wj) - CRITIC [29]

Objectives	r_{jk}					1- r_{jk}	O_j	w_j
	MRR [mg/min]	TWR [mg/min]	SR [µm]	RLT [µm]	ROC [mm]	-	-	-
MRR	1	-0.665	-0.755	0.210	-0.089	5.299	1.623	0.251
TWR	-0.665	1	0.349	-0.345	-0.326	4.987	1.327	0.205
SR	-0.755	0.349	1	-0.202	0.193	4.414	1.425	0.220
RLT	0.210	-0.345	-0.202	1	0.311	4.026	1.041	0.161
ROC	-0.089	-0.326	0.193	0.311	1	3.911	1.059	0.164

Table 5. Removal effects of objectives (Ej) and weights (wj) - MEREC

Objectives	MRR	TWR	SR	RLT	ROC
E_j	4.688	7.982	0.666	2.386	1.652
w_j	0.270	0.459	0.038	0.137	0.095

Table 6. Obtained weights (wj) - SD, CRITIC and MEREC

-	Objectives	MRR	TWR	SR	RLT	ROC
Objective weighing method	SD	0.215	0.187	0.226	0.182	0.190
	CRITIC	0.251	0.205	0.220	0.161	0.164
	MEREC	0.270	0.459	0.039	0.137	0.095

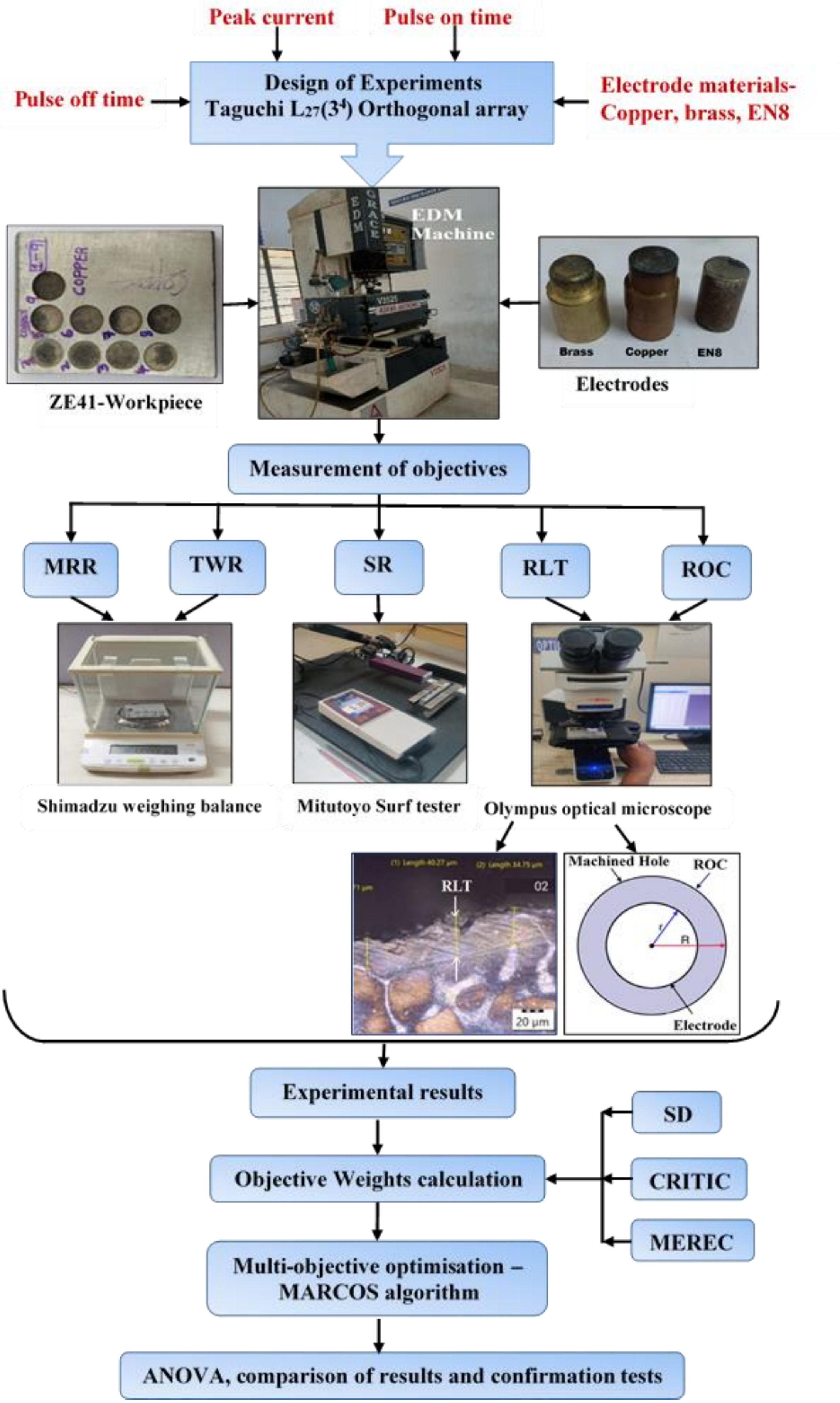

Fig. 1. Proposed multi-objective optimization methodology

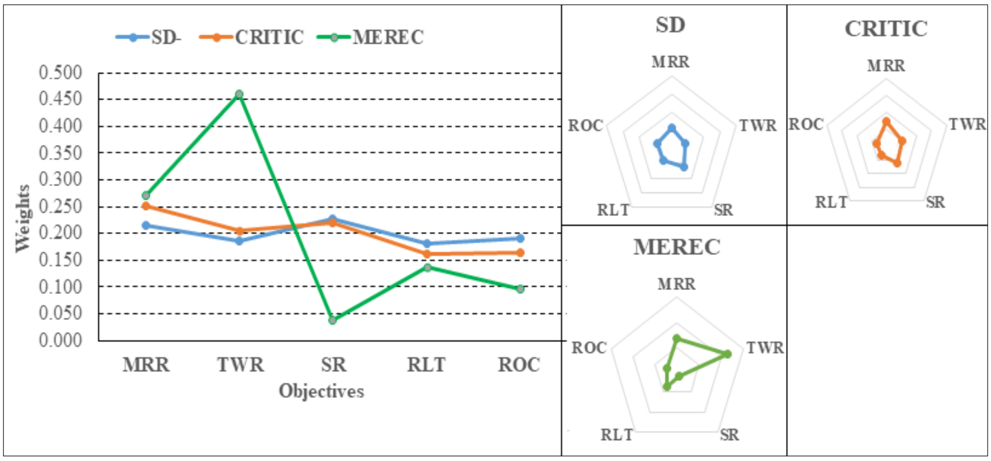

Fig. 2. Variations in weights of SD, CRITIC and MEREC

Table 7. Some parameters of MARCOS and f(Ki) using SD [35]

Exp. No.	S_i	K_i -	K_i +	f(K_i -)	f(K_i +)	f(K_i)
AAI	0.1831	-	-	-	-	-
1.	0.5328	2.9098	0.5328	0.1548	0.8452	0.5181
2.	0.4141	2.2617	0.4142	0.1548	0.8452	0.4028
3.	0.4308	2.3530	0.4309	0.1548	0.8452	0.4190
4.	0.4238	2.3147	0.4239	0.1548	0.8452	0.4122
5.	0.3774	2.0610	0.3774	0.1548	0.8452	0.3670
6.	0.3499	1.9111	0.3500	0.1548	0.8452	0.3403
7.	0.3601	1.9669	0.3602	0.1548	0.8452	0.3502
8.	0.3937	2.1504	0.3938	0.1548	0.8452	0.3829
9.	0.3710	2.0264	0.3711	0.1548	0.8452	0.3608
10.	0.5727	3.1276	0.5727	0.1548	0.8452	0.5569
11.	0.5002	2.7316	0.5002	0.1548	0.8452	0.4864
12.	0.5234	2.8584	0.5234	0.1548	0.8452	0.5090
13.	0.4845	2.6463	0.4846	0.1548	0.8452	0.4712
14.	0.4079	2.2279	0.4080	0.1548	0.8452	0.3967
15.	0.4247	2.3196	0.4248	0.1548	0.8452	0.4130
16.	0.6440	3.5173	0.6441	0.1548	0.8452	0.6263
17.	0.4985	2.7228	0.4986	0.1548	0.8452	0.4848
18.	0.4329	2.3644	0.4330	0.1548	0.8452	0.4210
19.	0.3043	1.6620	0.3044	0.1548	0.8452	0.2960
20.	0.3388	1.8503	0.3388	0.1548	0.8452	0.3295
21.	0.3114	1.7006	0.3114	0.1548	0.8452	0.3028
22.	0.3264	1.7828	0.3265	0.1548	0.8452	0.3175
23.	0.3515	1.9194	0.3515	0.1548	0.8452	0.3418
24.	0.3593	1.9622	0.3593	0.1548	0.8452	0.3494
25.	0.3902	2.1312	0.3903	0.1548	0.8452	0.3795
26.	0.3251	1.7753	0.3251	0.1548	0.8452	0.3161
27.	0.2882	1.5741	0.2882	0.1548	0.8452	0.2803
AI	0.9990	-	-	-	-	-

Table 8. f(Ki) and ranks of SD, CRITIC and MEREC

Exp. No.	SD		CRITIC		MEREC	
	$f(K_i)$	Rank	$f(K_i)$	Rank	$f(K_i)$	Rank
1.	0.5181	3	0.5180	2	0.5890	**1***
2.	0.4028	12	0.3984	13	0.3940	4
3.	0.4190	9	0.4121	9	0.4070	3
4.	0.4122	11	0.4077	10	0.3705	6
5.	0.3670	16	0.3727	17	0.3558	7
6.	0.3403	21	0.3397	20	0.2929	12
7.	0.3502	18	0.3625	18	0.2951	11
8.	0.3829	14	0.4010	12	0.3205	10
9.	0.3608	17	0.3731	16	0.2907	13
10.	0.5569	2	0.5145	3	0.2744	15
11.	0.4864	5	0.4543	7	0.2300	19
12.	0.5090	4	0.4720	5	0.2690	18
13.	0.4712	7	0.4683	6	0.3246	8
14.	0.3967	13	0.3947	14	0.2779	14
15.	0.4130	10	0.4022	11	0.2707	17
16.	0.6263	**1***	0.6209	**1***	0.4790	2
17.	0.4848	6	0.4943	4	0.3859	5
18.	0.4210	8	0.4353	8	0.3232	9
19.	0.2960	26	0.2836	26	0.1525	25
20.	0.3295	22	0.3195	22	0.1398	26
21.	0.3028	25	0.2911	25	0.1334	27
22.	0.3175	23	0.3124	23	0.1933	21
23.	0.3418	20	0.3394	21	0.2246	20
24.	0.3494	19	0.3422	19	0.1579	23
25.	0.3795	15	0.3863	15	0.2734	16
26.	0.3161	24	0.3083	24	0.1761	22
27.	0.2803	27	0.2776	27	0.1539	24

4. RESULTS AND DISCUSSION

4.1. ANOVA of f(Ki)

Taguchi method and ANOVA were used to optimize $f(K_i)$ and assess the impact of machining parameters and their interactions on a set of objectives [38]. ANOVA was performed using Minitab-19 software. Table 9 displays the summarized ANOVA findings for the averages of $f(K_i)$ together with the F-ratio, P-value, and percentage contribution (% C). Figure 3 displays the pie chart of % C corresponding to SD, CRITIC, and MEREC. Based on P-values, the significance of a parameter is determined. It has been found that parameters A and C are significant at 5% and 10% confidence levels for SD and CRITIC respectively. Whereas parameters A, AxB and C are significant at 5% confidence level for MEREC. These results are found to be consistent with the work of [19]. All other parameters are insignificant as their P-values are higher. Parameter A has the highest % C, i.e., 61.57%, 61.79% and 56.46% for SD, CRITIC and MEREC respectively as shown in Figure 3. The % C of parameters towards $f(K_i)$ are arranged in descending order as follows,

For SD: A > A x B > C > B > D. MANUSCRIPT

For CRITIC: A > A x B > C > A x C > D.

For MEREC: A > A x B > C >D > B

Table 9. Summarized ANOVA for means - f(Ki)

Source	SD			CRITIC			MEREC		
	F-ratio	P-value	% C	F-ratio	P-value	% C	F-ratio	P-value	% C
A	29.30	0.001 #	61.57 I	26.36	0.001 #	61.79 I	37.25	0.000 #	56.46 I
B	2.34	0.177	4.92 IV	1.43	0.310	3.36 V	0.63	0.564	0.96 V
C	4.35	0.068 $	9.15 III	4.07	0.076 $	9.55 III	5.34	0.047 #	8.09 III
D	0.70	0.531	1.47 V	0.62	0.568	1.46	1.09	0.396	1.65 IV
A*B	2.38	0.164	9.99 II	2.27	0.176	10.66 II	8.30	0.013 #	25.17 II
A*C	1.00	0.477	4.19	0.75	0.591	3.53 IV	0.16	0.949	0.50
A*D	0.57	0.695	2.39	0.56	0.703	2.61	0.87	0.532	2.64
Error	--	--	6.30	- -	- -	7.03	--	--	4.55
Total			100			100			100
R^2-value	93.7%			93.0%			95.5%		

significant parameters at #5% and $10% confidence levels, I, II, III, IV,V ranks of parameters

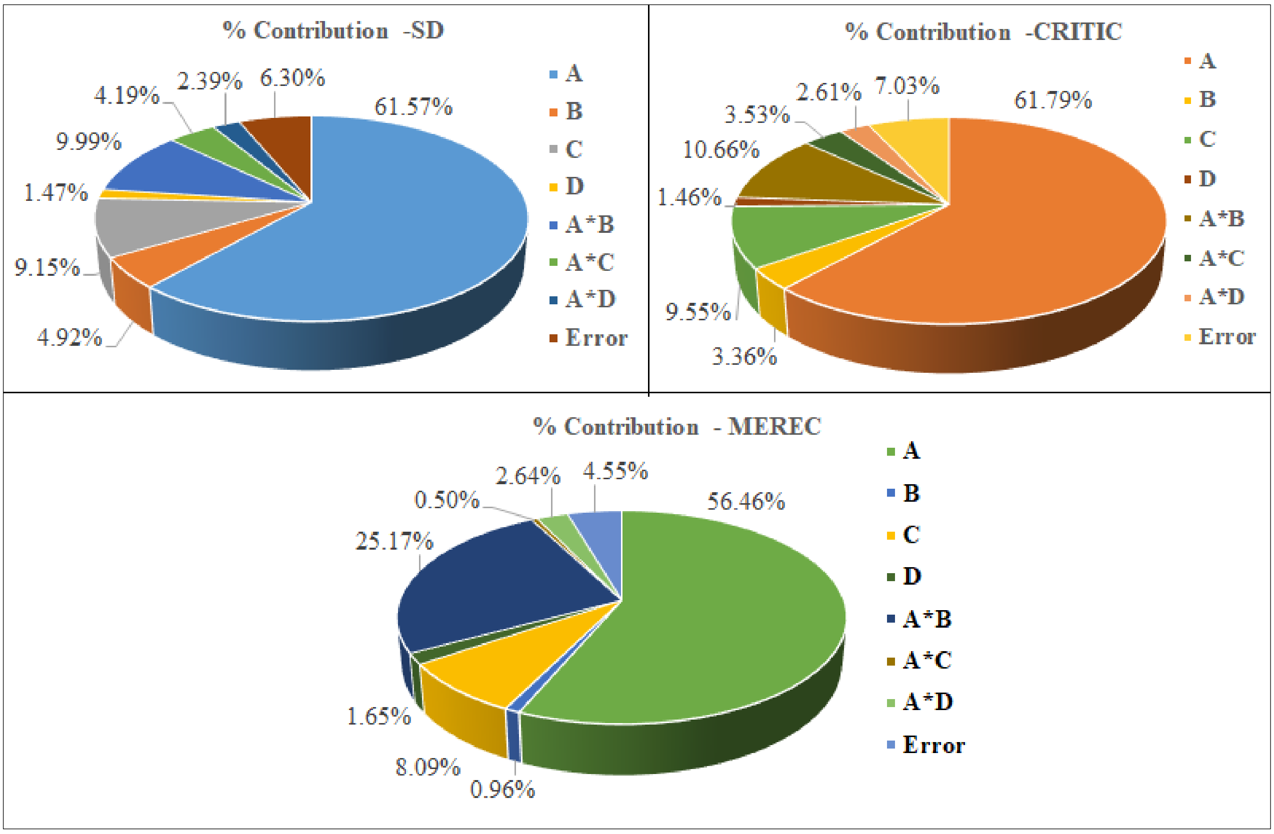

Fig. 3. Pie chart of % C of parameters

The main effects plot for means- f(Ki) are shown in Figures 4, 5 and 6 respectively. It is revealed from plots that electrode material is the most significant parameter as it has the highest influence on $f(K_i)$ with all weighing methods. The maximum values of $f(K_i)$ are obtained with brass electrode, followed by copper and EN8 in the case of SD and CRITIC. But, the maximum value of f(Ki) is obtained with copper electrode, followed by brass and EN8 in case of MEREC. There is not much variation of f(Ki) with an increase of peak current and pulse off time for all weighing methods in the present study and a similar trend is observed near the mean line. The next most influencing parameter on $f(K_i)$ is the pulse on time. $f(K_i)$ values are decreasing with an increase of pulse on time. In MARCOS, $f(K_i)$ is expected to be as maximum as possible. So, optimum parameters are identified as (A_2 B_1 C_1 D_3), (A_2 B_1 C_1 D_3) and (A_1 B_3 C_1 D_3) at maximum values of $f(K_i)$ from main effects plots, i.e., figures 4, 5 and 6 respectively. The optimum parameters are the same for SD and CRITIC in the present study as shown in Table 10.

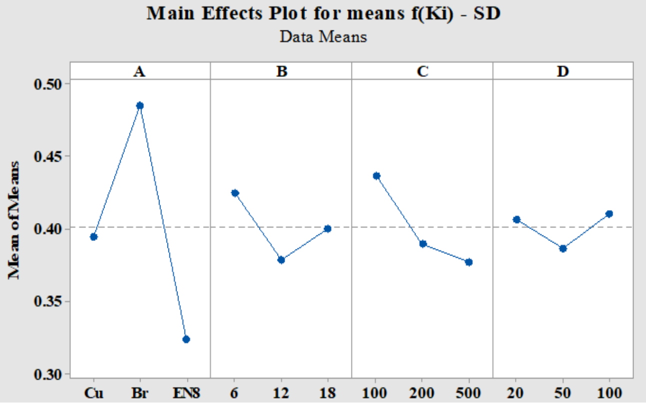

Fig. 4. Main effects plot of f(Ki) - SD

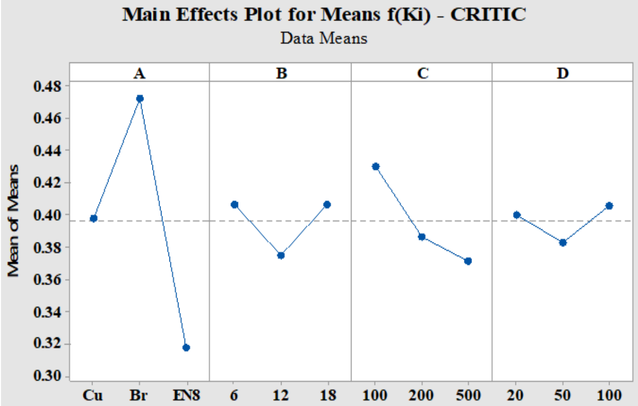

Fig. 5. Main effects plot of f(Ki) - CRITIC

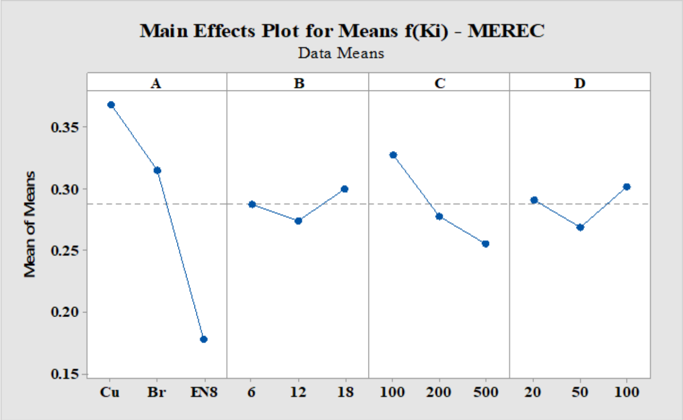

Fig. 6. Main effects plot of f(Ki) - MEREC

4.2 Comparison and confirmation of results

For comparison and confirmation of results, experiments were conducted twice at the optimum parameters and average values were used for analysis. The predicted $f(Ki)_{pred}$ values were calculated based on the additive model [12], i.e., equation (26) and are shown in Table 10. The predicted $f(Ki)_{pred}$ are close to experimental values as shown in Table 10.

$$f(K_i)_{pred} = f(K_i)_m + \sum_{p=1}^{q} \overline{f(K_i)} - f(K_i)_m \qquad (26)$$

Here, $f(Ki)_m$ = overall mean of f(Ki)

$\overline{f(K_i)}$ = mean of f(Ki) at optimum level of parameter (Table 4)

Further, the comparison was made between the $f(Ki)_{pred}$ using three weighing methods at optimum parameters and commonly used EDM parameters as shown in Table 11. Commonly used parameters A_1 B_1 C_2 D_2 were considered in the present study. It can be seen that percentage improvements in f(Ki) at optimum parameters are 37.21%, 32.30% and 10.68% for SD, CRITIC and MEREC respectively.

The percentage changes in objectives at optimum parameters and commonly used parameters are shown in Table 12. The objectives are ranked based on the % change. The rank order is the same for SD and CRITIC as they have the same optimum parameters, but different for MEREC. It is observed that all objectives except TWR improved positively for SD and CRITIC and all objectives except MRR deteriorated for MEREC. This may be due to variations in distribution of weights among objectives. In the case of SD and CRITIC, the weight differences are less as compared to MEREC (Figure 2). In MEREC, the MRR and TWR have weights of 0.270 and 0.459 respectively. This might have led to the deterioration of other objectives. Also electrode material has a dominant effect on the performance of EDM. Thus, it is revealed that MRR was improved positively and TWR deteriorated in all weighing methods. Other objectives SR, RLT and ROC improved positively in the cases of SD and CRITIC but deteriorated in the case of MEREC. Such kind of improvements in some objectives and deterioration in other objectives usually occur in multi-objective optimization problems [9, 21]. Further, rankings of alternatives according to SD, CRITIC and MERIC are shown in Table 4. The comparative graphs of $f(K_i)$ are shown in Figure

7. It is obvious that experiment No. 16 is the best solution provided by both SD and CRITIC and experiment No.1. is the best solution provided by MEREC.

Table 10. Predicted and experimental values of f(Ki) at optimum parameters [21]

Weighing Method	Optimum parameter levels	Predicted $f(K_i)_{pred}$	Experimental $f(K_i)_{exp}$	Percentage deviation
SD	A_2 B_1 C_1 D_3 Brass/6Amps/100µs/100µs	0.5527	0.5397	-2.35
CRITIC	A_2 B_1 C_1 D_3 Brass/6Amps/100µs/100µs	0.5271	0.5021	-4.74
MEREC	A_1 B_3 C_1 D_3 Copper/18Amps/100µs/100µs	0.4361	0.2951	-32.33

Table 11. Percentage improvements in f(Ki) at predicted optimum parameters

Weighing method	Commonly used parameters	Predicted Optimum parameters	% improvements in $f(K_i)$ over commonly used parameters
SD	0.4028	0.5527	37.21%
CRITIC	0.3984	0.5271	32.30%
MEREC	0.3940	0.4361	10.68%

Table 12. Results of confirmation experiments

Weighing method	Objectives	Commonly used parameters	Experimental value at optimum parameters	% change over commonly used parameters
SD	-	**A_1 B_1 C_2 D_2**	**A_2 B_1 C_1 D_3**	-
	MRR	18.401	34.521	87.60 **I**
	TWR	0.330	4.356	-1220.01**V**
	SR	4.060	3.313	18.40 **IV**
	RLT	40.597	22.91	43.58 **III**
	ROC	0.465	0.109	76.55 **II**
CRITIC	-	**A_1 B_1 C_2 D_2**	**A_2 B_1 C_1 D_3**	-
	MRR	18.401	34.521	87.60 **I**
	TWR	0.330	4.356	-1220.01**V**
	SR	4.060	3.313	18.40 **IV**
	RLT	40.597	22.91	43.58 **III**
	ROC	0.465	0.109	76.55 **II**
MEREC	-	**A_1 B_1 C_2 D_2**	**A_1 B_3 C_1 D_3**	-
	MRR	18.401	179.375	878.11**I**

	TWR	0.330	1.675	-407.57^{V}
	SR	4.060	5.782	-42.41^{III}
	RLT	40.597	58.627	-44.42^{IV}
	ROC	0.465	0.655	-40.86^{II}

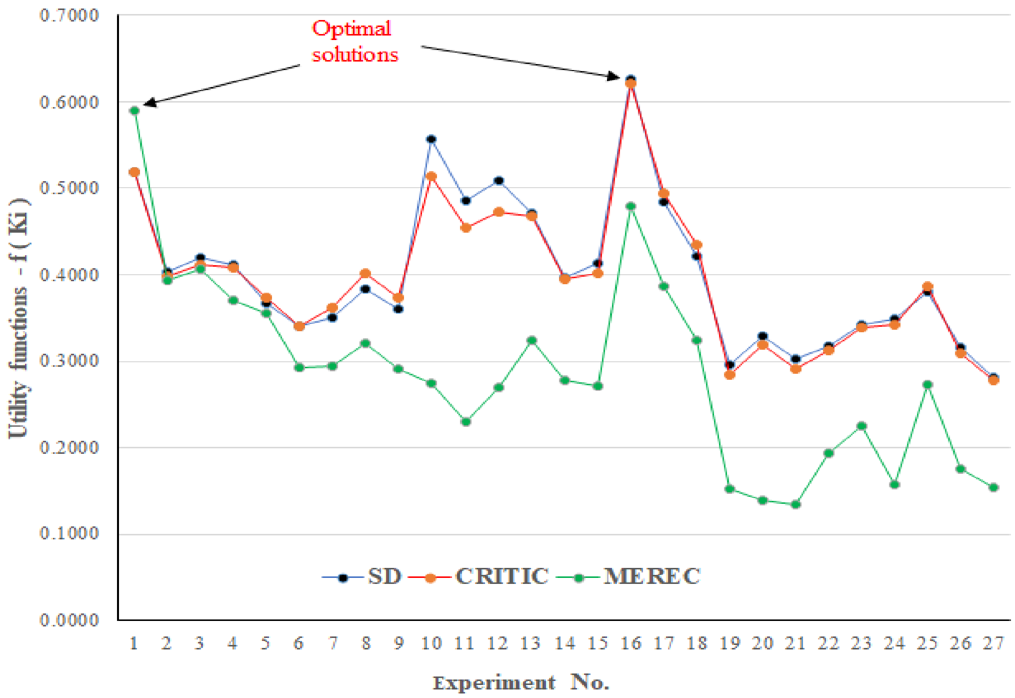

Fig. 7. Comparison of f(Ki) for SD, CRITIC and MERIC

5. CONCLUSIONS

In the present study, multi-objective optimization of machining parameters was carried out in the EDM of ZE41. A novel MARCOS algorithm and objective weights, i.e., SD, CRITIC and MEREC were utilized considering objectives such as MRR, TWR, SR, RLT and ROC. This methodology is a simple and structured technique. Also, it can be done with the aid of Excel and Minitab tools. Taguchi's L_{27} orthogonal array was employed to conduct experiments. ANOVA was performed on $f(K_i)$ to find out the most significant parameters.

1.The optimum parameter settings were obtained as (1) A_2 B_1 C_1 D_3 (Electrode material Brass, peak current – 6 Amps, pulse on time – 100 µs and pulse off time – 100 µs) for SD and CRITIC (2) A_1 B_3 C_1 D_3 (Electrode material – Copper, peak current – 18 Amps, pulse on time – 100 µs and pulse off time – 100 µs) for MEREC.

2.ANOVA showed that electrode material is the most significant parameter, followed by interaction between electrode material and peak current, and pulse on time for all weighing methods. Peak current and pulse off time were found to be insignificant parameters.

3.The percentage improvement in the $f(K_i)$ value at optimum parameters over commonly used parameters was 37.21%, 32.30% and 10.68% for SD, CRITIC and MEREC respectively.

4.Confirmation results indicated that MRR improved positively and TWR deteriorated for all weighing methods. All objectives except TWR improved positively for SD and CRITIC. All objectives except MRR deteriorated for MEREC. Hence, it can be concluded that SD and CRITIC are better than MEREC in terms of utility functions in this study.

5.These results are useful to industries in improving the objectives simultaneously. MARCOS can be employed for optimum parameter settings in other machining processes considering appropriate and different subjective, objective and comprehensive weighing methods.

Conflicts of Interest: There is no conflict of interest.

REFERENCES

1. Venkata Rao R., Kalyankar V. D., (2014), *Optimization of modern machining processes using advanced optimization techniques: a review,* Int. J Adv Manuf Tech, 73,1159–1188.
2. Edmundas K. Z., Govindan K., Jurgita A., Zenonas T., (2016), *Hybrid multiple criteria decision-making methods: a review of applications for sustainability issues,* Econ Res, 29(1), 857-887.
3. Garg R. K., Singh K. K., Sachdeva A., Sharma V.S., Ojha K., Sharanjith Singh., (2010), *Review of research work in sinking EDM and WEDM on metal matrix composite materials.* Int J Adv Manuf Tech, 50(5–8), 611–624.
4. Jahan M. P., (2015), *Surfaces in electrical discharge machining*, Electrical discharge machining (EDM) types, technologies and applications, pp. 123-150, Nova Science Publishers, New York.
5. Chakraborty S., Chakraborty Sh., (2022), *A scoping review on the applications of MCDM techniques for parametric optimization of machining processes,* Arch Comput Methods Eng, 29, 4165–4186.
6. Yakup C., Fatih T., (2020), *An in-depth review of theory of the TOPSIS method: An experimental analysis,* J Manag Anal, 7(2), 1 – 21.
7. Shukla A., Agarwal P., Rana R. S., Purohit R., (2017), *Applications of TOPSIS algorithm on various manufacturing processes: A Review,* Mater Today Proc, 4(4), 5320-5329.
8. Chakraborty S., Datta H. N., Chakraborty Sh., (2023), *Grey relational analysis-based optimization of machining processes: a comprehensive review,* Process Integr Optim Sustain, 7, 609 - 639.
9. Phan H. N. et al., (2022), *Multi-objective optimization of micro EDM using TOPSIS method with Tungsten carbide electrode,* Sadhana, 47(133), 1-12.
10. Sudhir Kumar., Ghoshal S. K., Arora P. K., Nagdeve L., (2021), *Multi-variable optimization in die-sinking EDM process of AISI420 stainless steel,* Mater Manuf Process, 36(5),572-582.
11. Dhiraj Kumar., Mondal S., (2021), *Multi-attribute optimization of EDM process parameters of al-2050 alloy using Taguchi based TOPSIS and GRA with different rotating tools,* International Journal of Modern Manufacturing Technologies, 8(1), 84-95.
12. Bikash R. M., Patro S. S., (2019), *Multi-objective optimization of machining parameters of EN-8 carbon steel in EDM process using GRA method,* International Journal of Modern Manufacturing Technologies, 9(2), 50-56.
13. Somasundaram M., Pradeep Kumar, J., (2022), *Multi response optimization of EDM process parameters for biodegradable AZ31 magnesium alloy using TOPSIS and grey relational analysis,* Sadhana, 47(136), 1-14.
14. Boumaza H., Belhadi S., Yallese M. A., Safi K., Haddad A., (2023), *Optimization of surface roughness, tool wear and material removal rate in turning of Inconel 718 with ceramic composite tools using MCDM methods based on Taguchi methodology,* Sadhana, 48(1), 1-14.
15. Suneesh S., Sivapragash M., (2021), *Multi-response optimisation of micro-milling performance while machining a novel magnesium alloy and its alumina composites,* Measurement, 168, 1-23.
16. Gopal P. M., Soorya Prakash K., (2018), *Minimization of cutting force, temperature and surface roughness through GRA, TOPSIS and Taguchi techniques in end milling of Mg hybrid MMC,* Measurement, 116, 178-192.
17. Rahul N., Kumar R., Singh T., Ranchan C., Patnaik A., Brijesh G., (2018), *Experimental investigation and optimization of cobalt bonded tungsten carbide composite by hybrid AHP-TOPSIS approach,* Alex Eng J, 57, 3419-3428.
18. Shastri R. K., Mohanty C. P., (2021), *Sustainable electrical discharge machining of nimonic C263 superalloy,* Arab J Sci Eng, 46, 7273-7293.
19. Alagarsamy S. V., Raveendran P., Ravichandran M., (2021), *Investigation of material removal rate and tool wear rate in spark erosion machining of AL-FE-SI alloy composite using Taguchi coupled TOPSIS approach,* Silicon, 13, 2529–2543.
20. Wang D., Zhao J., (2016), *Design optimization of mechanical properties of ceramic tool material during turning of ultra-high-strength steel 300M with AHP and CRITIC method,* Int J Adv Manuf Tech, 84, 2381–2390.
21. Raman Kumar, Singh B. P., Singh S., (2017), *Multi objective optimization using different methods of assigning weights to energy consumption responses, surface roughness and material removal rate during rough turning operation,* J Clean Prod, 164, 45-57.
22. Ricardo V. B. B., Dzulinski A. C., Everton L. M., Junior A. B., (2021), *Comparison of EDM and laser trepanation micro-drilling processes using multiple-criteria decision analysis,* Int J Adv Manuf Tech, 116, 2599–2612.

23. Kumar S., Patnaik L., Shafi S. M., Venkatesh V. S. S., Maity S. R., (2023), *Wear parameter optimization for CrN/TiAlSiN coating using novel BWM integrated TODIM decision-making approach,* Int J Interact Des M, 17, 579–601.
24. Das P. P., Chakraborty S., (2022), *SWARA-CoCoSo method-based parametric optimization of green dry milling processes,* J Eng App Sci, 69(35), 1-14.
25. Dragan S. P., Snezana P. T., Tanja P., (2018), *New hybrid multi-criteria decision-making DEMATEL-MAIRCA model: sustainable selection of a location for the development of multimodal logistics centre*, Econ Res, 31(1), 1641–1665.
26. Jagdish K., Ray A., (2015), *Multi-objective optimization of green EDM: an integrated theory,* Journal of Institute of Engineers India - Series C, 96(1), 41–47.
27. Shrinivas Balraj U., Gopalakrishna A., (2014), *Multi-objective optimization of EDM process parameters using Taguchi method, principal component analysis and grey relational analysis*, Int J Manuf Mater ME, 4(2), 29-46.
28. Rajendra Prasad S., Ravindranath K., Devakumar M. L. S., (2018), *Experimental investigation and parametric optimization in abrasive jet machining on nickel 233 alloy using WASPAS and MOORA*, Cogent Eng, 5(1497830), 1-12.
29. Nafisa A. S., Zaman P. B., Dhar N. R., (2022), *Multi-response optimization of hard turning parameters: a comparison between different hybrid Taguchi-based MCDM methods,* Int J Interact Des M, 16, 1779–1795.
30. Venkata Reddy V., Anantharam K., Srikanth K., Belachew G. T., (2021), *Turning Process Parameters optimization of Al7075 Hybrid MMC's using Standard deviation method coupled with VIKOR*, International Journal of Mechanical Engineering, 6(1), 11-15.
31. Trung, D. D., Thinh, H. X., (2021), *A multi-criteria decision-making in turning process using the MAIRCA, EAMR, MARCOS and TOPSIS methods: A comparative study,* Adv Produc Engineer Manag, 16, 443–456.
32. Tariq Ahmad et. al., (2023), *Fabrication and machinability study of Zn-Al-TiC composite using wire EDM with different dielectric media*, 9(3), 1340-1355, Adv Mater Process Te, DOI:10.1080/2374068X.2022.2116878.
33. Keshavarz Ghorabaee M., Amiri M., Zavadskas E. K., Turskis Z., Antucheviciene J., (2021), *Determination of objective weights using a new method based on the removal effects of criteria (MEREC),* Symmetry, 13/4, 525.
34. Huy-Anh B., Tran N., T., Nguyen D. L., (2023), M*ulti-criteria decision-making in the powder-mixed electrical discharge machining process based on the COCOSO, SPOTIS algorithms and the weighting methods*, International Journal of Modern Manufacturing Technologies, 15/1, 69-79.
35. Stevic Z., Pamucar D., Puska A., Chatterjee P., (2020), *Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement Alternatives and Ranking according to Compromise Solution (MARCOS)*, Comput Ind Eng, 140, 1-33.
36. Trung D. D., (2022), *Multi-criteria decision-making under the MARCOS method and the weighting methods: applied to milling, grinding and turning processes*, Manuf Review, 5, 3.
37. Tiago C., Higa C. F., Torres R. D., Laurindo C. A. H., Jose Mario, Lohrengel A., Amorim F. L. (2019), *Materials used for sinking EDM electrodes: a review,* J Braz Soc Mech Sci Eng, 41, 14.
38. Ross P. J., *Orthogonal arrays*, Taguchi Techniques for Quality Engineering: Loss Function, Orthogonal Experiments, Parameter and Tolerance Design, pp. 22-50, McGraw-Hill, New York, USA (2006).
39. Diakoulaki D., Mavrotas G., Papayannakis L., (1995), *Determining objective weights in multiple criteria problems: the CRITIC method,* Comput Oper Res, 22, 763–770.

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