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Application of MABAC, MOORA, MAIRCA and Entropy Methods in Multi-Criteria Decision Making for EDM of 90CrSi Using Graphite Electrodes

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Abstract—This paper reports the findings of a study aimed at optimizing the electrical discharge machining (EDM) process for cylindrical surface parts composed of 90CrSi using graphite electrodes. This study's innovation is in determining the best EDM parameters for cutting cylindrical surfaces using three types of graphite electrodes: HK0, HK15, and HK20. Prior studies on EDM with graphite electrodes have exclusively focused on the machining of hollow, concave components, including die cavities, molds, or holes. In this work, three multi-criteria decision-making (MCDM) methods have been used for accomplishing this: Multi-Attributive Border Approximation Area Comparison (MABAC), Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA), and Multi-Attributive Ideal-Real Comparative Analysis (MAIRCA). Furthermore, the Entropy method was employed to figure out the weight of evaluation criteria. The research focused on three principal targets: surface roughness (SR), electrode wear rate (EWR), and material removal rate (MRR). Additionally, five process variables have been investigated: servo voltage (SV), pulse current (IP), pulse-on duration (T_{on}), pulse-off duration (T_{off}), and type of graphite (TOG). The Taguchi technique employing an L18 ($6^1 + 3^4$) experimental design, in conjunction with Minitab R19 software, was implemented for experimental planning and result analysis. The results successfully handled the MCDM issue and suggested best input settings for the EDM process, enhancing machining performance for cylindrical surfaces using graphite electrodes.

Keywords—EDM, MCDM, MABAC, MOORA, MAIRCA, Entropy, Surface Roughness, Electrode wear rate, Material removal rate, Graphite electrode.

I. INTRODUCTION

An advanced machining technique is electrical discharge machining (EDM). It serves to produce complicated shapes or remove materials from the surfaces of mechanical components made of materials that are challenging to cut. This machining technique has been widely applied in a number of industries, such as mold and die manufacturing, aerospace, and automotive, regardless of the physical characteristics of the materials being machined—as long as they are conductivity-containing. This is the reason that many scientists find it interesting to investigate the EDM process.

Numerous investigations have been conducted thus far to explore EDM processes. The impact of IP and T_{on} on MRR EWR when EDM Ti-6Al-4 V (Ti64) alloy was investigated in [1]. The results of the experiment shown that, although the influence of T_{on} was not very significant, the MRR increased as IP and T_{on} decreased. The highest MRR (3.2379 mm^3/min) was discovered at IP = 25 (A), T_{on} = 150 (μs), whereas the lowest EWR (0.0082 mm^3/min) was noted at IP = 5 (A), T_{on} = 200 (μs). The investigators in [2] explored the optimization of the relative wear ratio (RWR) for EDM titanium alloy 685. The aim of the work is to improve the MRR while reducing the RWR. The tool face is an exact replica of the machined surface. This work optimizes the RWR. A regression model to find RWR was also constructed. Advanced optimization techniques, like the Jaya Algorithm, teaching-learning-based optimization, and response optimizers, are employed to enhance RWR. This study optimized parameters for IP, T_{on}, T_{off}, and SV to enhance RWR. The effect of EDM process variables on the surface roughness of AISI P20 was evaluated in [3]. The research showed that IP and T_{on} influenced the SR of both the electrode and the workpiece. The SR developed with the augmentation of both parameters' levels. The surface

quality improved by reducing IP, decreasing T_{on}, and extending T_{off}.

In [4], MRR, EWR, and surface integrity factors for Ti–6Al–4V utilizing EDM have been studied. Three input parameters were used for the study: SV, IP, and T_{on}. The experimental findings indicate that IP and T_{on} significantly influence the surface integrity characteristics of machined materials. The fluctuations in pulse energy substantially influence the density of pits, micro holes, and cracks on the work surface. The average thickness and microhardness of the recast layer increase with pulse energy, despite an enhancement in material removal efficiency. Researchers in [5] examined the influence of EDM input parameters on SR. A regression equation accurately predicting SR based on power, pulse time, and spark time was derived from the data analysis. The research conducted in [6] analyzed the impact on various input parameters on the surface quality, MRR, and EWR in the WC-Co machining process. The design of experiments (DOE) method has been used in the study for creating mathematical models that determined the optimal machining parameters for the finishing steps.

To accurately establish the MRR and thermal stresses in AISI 316L and AISI D2 steels, a novel finite element (FE) model was developed in [7]. A numerical simulation of the EDM process was conducted using a dynamic coupled thermo-mechanical analysis under the plane-strain assumption. The discharge radius function suitable for each grade of steel was determined by integrating experimental data from prior research with numerically anticipated MRR discharge current diagrams. The results of this research show that the optimal heat input size functions for determining the MRR reflect the effect of discharge current. A cooling analysis was employed to predict thermal stresses. RSM, Gray Relational Analysis (GRA), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) have been used in [8] to investigate the effects of process factors on response characteristics during manufacturing of D2 steel. The study was mainly concentrated on the input parameters of EDM, including IP, T_{on}, T_{off}, and SV. The output characteristics examined were MRR, EWR, and radial overcut or gap (G). An examination into the influence of key input variables on the EWR during the EDM process was conducted, [9]. The research aimed to enhance the characteristics associated with the machining of cylindrical components made of 90CrSi steel. The input values for EDM that have been examined involve SV, IP, T_{on}, and T_{off}. An investigation was conducted to discover the impact of the input elements on the EWR. The most effective input configurations were determined by analyzing the signal-to-noise ratio to minimize the associated width reduction.

Currently, optimization issues are utilized throughout various domains. I. K. The authors in [10] developed a study that explores the diagnosis of gas turbine blade damage in non-stationary settings. A novel model has been included in the study for the precise calculation of parameters in crack detecting systems utilizing capsules filled with ionizing chemicals. The findings can be applied to enhance damage detection, hence augmenting the efficiency and safety of gas turbine engines. A dynamic model of the physicochemical processes in copper concentrate electromelting, including a priori information to characterize essential state variables (material flow, energy, charge, matte, and slag composition) was proposed in [11]. This approach facilitates automation in metallurgy, mechanical engineering, and manufacturing. Classical approaches were used due to the complexity of the procedure... A Multi-Criteria Decision-Making (MCDM) approach to determine the ideal dressing mode for grinding Hardox 500 has been conducted, [12]. The Simple Additive Weighting (SAW) technique and Entropy were employed to ascertain criteria weights in the study. The primary criteria were material removal rate (MRR) and surface roughness (RS), in addition to five dressing factors. Sixteen L16 tests were performed. The optimal input parameters for grinding Hardox 500 were identified from the findings.

Methods for MCDM are helpful for optimizing problems by balancing various criteria, particularly in situations where conflicting factors like cost and quality are present. Techniques like AHP, MOORA, TOPSIS, MAIRCA, or MABAC facilitate precise, independent, and clear decision-making. MCDM finds extensive application across engineering, economics, medicine, and various other domains to enhance processes, enhance performance, and efficiently allocate resources. For example, within the framework of energy policy [13], the process of determining the optimal airport [14], identifying the most suitable factors for a helical gearbox [15], or deciding renewable energy sources [16].

This article presents the results of a multi-criteria decision-making analysis performed on EDM cylindrical parts made from 90CrSi. The study concentrates on the utilization of electrodes made from numerous kinds of graphite materials. Additionally, three objectives were examined: minimum SR, minimum EWR, and maximum MRR. Additionally, three distinct MCDM techniques, namely MABAC, MOORA, and MAIRCA, had been used to deal with the MCDM issue, while the Entropy method used to determine the criteria weights. The study's findings indicated the best input EDM factors that can simultaneously attain the minimum SR, minimum EWR, and maximum MRR.

II. METHODOLOGY

A. Method for solving MCDM

MABAC method

In 2015, Pamucar and Cirovic proposed the MABAC method. Listed below are the steps to implement this strategy, [17]:

Step 1: Create the initial decision-making matrix:

$$X = \begin{bmatrix} r_{11} & \cdots & r_{1j} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r_{1} & \cdots & r_{ij} & \cdots & r_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mj} & \cdots & r_{mn} \end{bmatrix}_{m\times n} \quad (1)$$

Where, *m* is the number of options; *n* is the number of criteria.

Step 2: Calculate the normalized values r_{ij} by:

$$r_{ij}^{*} = \frac{r_{ij} - r_i^{-}}{r_i^{+} - r_i^{-}} \quad (2)$$

$$r_{ij}^{*} = \frac{r_{ij} - r_i^{+}}{r_i^{-} - r_i^{+}} \quad (3)$$

In which $i = 1, 2, ..., m$ *and* $j = 1, 2, ..., n$. Equation (2) is used for criteria MRR, and (3) is used for creation SR and EWR. Also, $r_i^{+} = max(r_1, r_2, \dots, r_m)$ and $r_i^{-} = min(r_1, r_2, \dots, r_m)$.

Step 3: Find the weighted matrix elements by:

$$v_{ij} = w_j + w_j \times r_{ij}^{*} \quad (4)$$

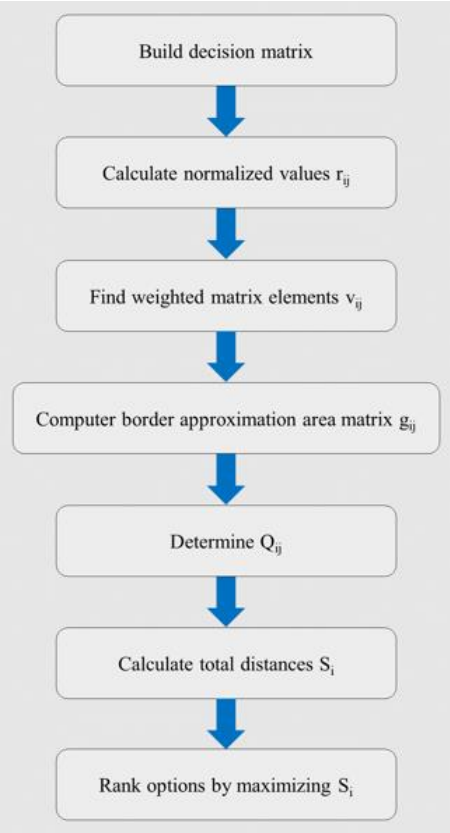

Fig. 1. Flowchart of MABAC process

Step 4: Calculate the border approximation area matrix:

$$g_j = \left(\prod_{i=1}^{m} v_{ij}\right)^{1/m} \quad (5)$$

In which $j = 1, 2, ..., n$.

Step 5: Determine the distance between the options and the border approximation area by:

$$q_{ij} = v_{ij} - g_i \quad (6)$$

Where $i = 1, 2, ...,$ m and $j = 1, 2, ..., n$.

Step 6: Compute the total distances of each option from the approximate border area:

$$S_i = \sum_{j=1}^{n} q_{ij} \quad (7)$$

Where $i = 1, 2, ...,$ m and $j = 1, 2, ..., n$.
Step 7: Rank the options by maximizing S_i.

Figure 1 describes the flow chart of the MABAC method.

MOORA method

The MOORA approach was employed to address the MCDM issue in this study. To implement this technique, the subsequent steps should be followed, [18]:

Step 1: Build the first decision-making matrix:

$$X = \begin{bmatrix} r_{11} & \cdots & r_{1j} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r_1 & \cdots & r_{ij} & \cdots & r_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mj} & \cdots & r_{mn} \end{bmatrix} \quad (8)$$

In which, *m* is the number of the option and *n* is the number of criteria.

Step 2: Calculate the normalized matrix by:

$$n_{ij} = \frac{r_{ij}}{max r_{ij}} \quad (9)$$

$$n_{ij} = \frac{min r_{ij}}{r_{ij}} \quad (10)$$

Equation (9) is used to calculate SR and EWR, while (10) is used to find MRR.

Step 3: Determine $\left[X_{ij}\right]_{m \times n}$:

$$X_{ij} = \frac{y_{ij}}{\sqrt{\sum_{i=1}^{m} y_{ij}^2}} \quad (11)$$

Step 4: Compute the decision-making matrices aftenormalizing the weights by:

$$W_{ij} = w_j \times y_{ij} \quad (12)$$

Step 5: Calculate P_i and R_i by:

$$P_i = \frac{1}{|B|} \sum_{j \in B} W_{ij} \quad (13)$$

$$R_i = \frac{1}{|NB|} \sum_{j \in NB} W_{ij} \quad (14)$$

where B and NB represent the criteria number as large as better and the criterion number as small as better, correspondingly.

Step 6: Determine Q_i by:

$$Q_i = P_i - R_i \quad (15)$$

Step 7: Rank the options by maximizing Q_i.

The flow chart of the MOORA process was presented in Figure 2.

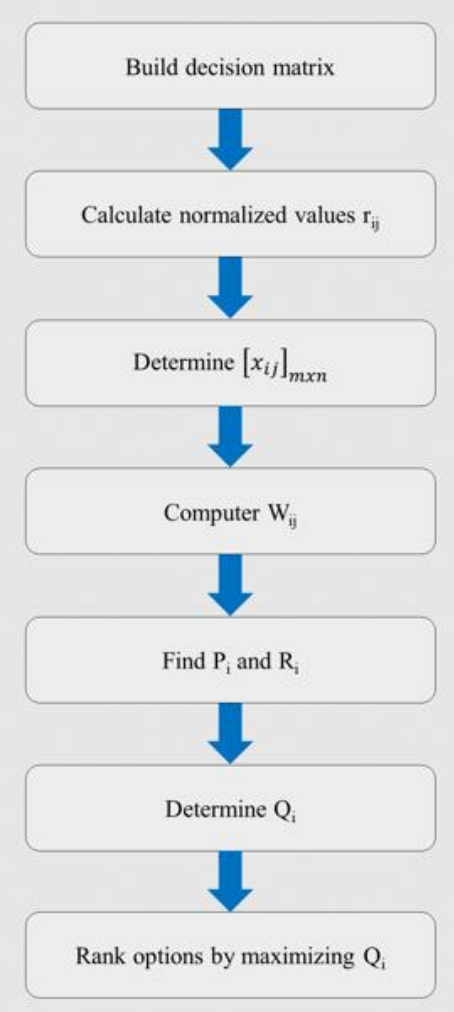

Fig. 2. Flowchart of MOORA process

MAIRCA method

In this work, the MAIRCA technique is applied to solve the problem of MCDM. The following steps are essential to use this method, [19]:

Step 1: Build the initial

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ x_{21} & \cdots & x_{2n} \\ \vdots & \cdots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \quad (16)$$

In which, x_{mn} denotes the result of criterion *n* in variant *m*.

Step 2: Calculate choices based on different selection P_{A_j} by:

$$P_{A_j} = \frac{1}{m} \quad , j = 1, 2, \ldots, n \quad (17)$$

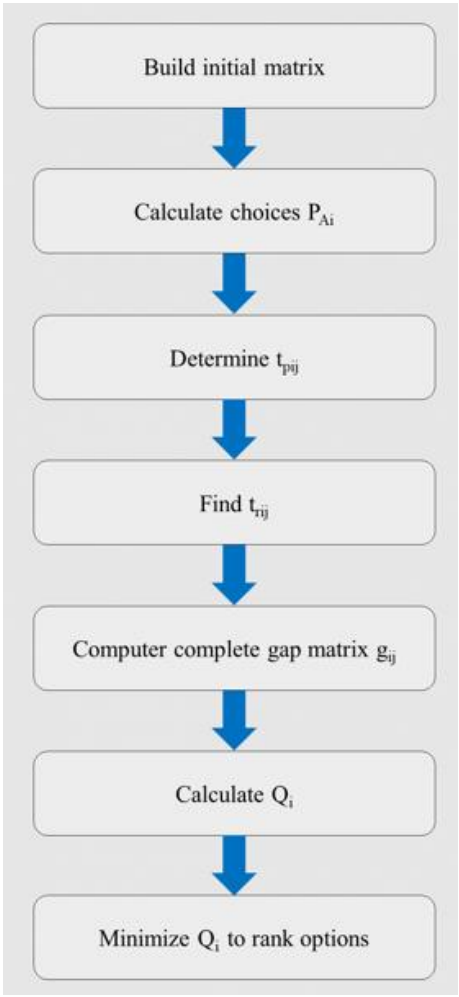

Fig. 3. Flowchart of MAIRCA process

Step 3: Find the elements t_{pij} by:

$$t_{p_{ij}} = P_{A_j} \cdot w_j \quad , i = 1, 2, \ldots, m; j = 1, 2, \ldots, n \quad (18)$$

Where w_j is the weight of the j^{th} criterion.

Step 4: Calculate t_{rij} by:

+) For MRR objective:

$$t_{r_{ij}} = t_{p_{ij}} \cdot \left(\frac{x_{ij} - x_i^-}{x_i^+ - x_i^-}\right) \quad (19)$$

+) For SR and EWR objective:

$$t_{r_{ij}} = t_{p_{ij}} \cdot \left(\frac{x_{ij} - x_i^+}{x_i^- - x_i^+}\right) \quad (20)$$

Step 5: Compute the complete gap matrix g_{ij} by:

$$g_{ij} = t_{p_{ij}} - t_{r_{ij}} \quad (21)$$

Step 6: Determine the criterion functions' ultimate values (Q_i):

$$Q_i = \sum_{i=1}^{m} g_{ij} \quad (22)$$

- Rank the option's order by minimizing Q_i.
Figure 3 shows the flow chart of the MAIRCA technique.

B. Method to calculate criation weights

This study used the Entropy approach to determine the weights of the criteria. The implementation procedure for the ENTROPY approach is detailed in reference, [20].

Step 1: Determine the indicator's normalized values by:

$$p_{ij} = \frac{x_{ij}}{m + \sum_{i=1}^{m} x_{ij}^2} \quad (23)$$

Step 2: Find the Entropy for each indicator by:

$$me_j = -\sum_{i=1}^{m}[p_{ij} \times ln(p_{ij})] - (1 - \sum_{i=1}^{m} p_{ij}) \times ln(1 - \sum_{i=1}^{m} p_{ij}) \quad (24)$$

Step 3: Calculate the weight of each indicator by:

$$w_j = \frac{1 - me_j}{\sum_{j=1}^{m}(1 - me_j)} \quad (25)$$

III. EXPERIMENTAL WORK

In this work, five process factors including SV, IP, T_{on}, T_{off}, and TOG were selected. Their involvement in the investigation is related to their vital role as key elements in the EDM process. The input factors and their levels are shown in Table 1 (Appendix). The experiment was conducted, and data analysis was executed utilizing the Taguchi method with Minitab R19 software. The Taguchi method represents a robust tool for enhancing quality, effectively decreasing both testing time and costs, while simultaneously increasing the efficiency and reliability of a process or product. Additionally, it is beneficial to investigate various factors and their interrelationships, as this can promote creativity and innovation. The experiment utilized the L18 ($6^1 + 3^4$) design. The experimental setup, depicted in Figure 4, included the Sodick A30 EDM machine, a Mitutoyo 178-923-2A surface roughness tester, samples made from 90CrSi tool steel, graphite electrodes, and the Diel MS 7000 dielectric solution. The procedure for the experiment was carried out as follows: The duration for processing each sample has been collected throughout the experiment. The mass of the electrodes and samples were measured prior to and following the performance of the experiment. The SR for each sample was measured following each test run. The EWR and MRR were calculated using the supplied data in line with the defined formulas:

- To find EWR:

$$EWR = \sum_{i=1}^{n} \frac{m_{ebi} - m_{eai}}{t_{si}} \quad (26)$$

- To determine MRR:

$$MRR = \sum_{i=1}^{n} \frac{m_{pbi} - m_{pai}}{t_{si}} \quad (27)$$

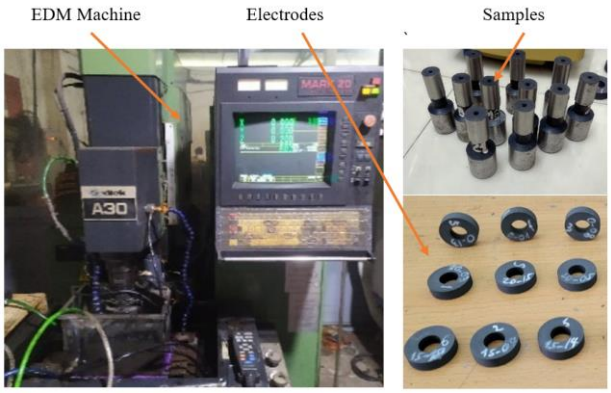

Fig. 4. Experimental setup

In which, m_{ebi} and m_{eai} denote the mass of electrode i before and after processing (mg); m_{sbi} and m_{sai} denote the mass of sample i before and after machining (mg); t_{si} is the machining time (min.); n is the number of electrodes (n=3). Table 2 (Appendix) shows the experimental plan and the output experimental results (SR, EWR and MRR).

IV. EXPERIMENTAL WORK

After the experiment finishes the SR, EWR, and MRR values of the outcome will be applied as input variables for dealing with the MCDM problem. The criteria weights for the MCDM problem were determined using the Entropy technique, as detailed in Section 2.2. The values p_{ij} are normalized according to Equation (23). The entropy value for each indicator me_j was calculated using Equation (24). Estimate the weight of the criteria, W_j, using Equation (25). The calculated weights for Ra, EWR, and MRR were 0.3729, 0.4447, and 0.1824, respectively. Section 2.1 provides guidance on the efficient application of the MABAC, MOORA, and MAIRCA methods to address the MCDM problem. Below are the detailed calculations:

The stages for carrying out MCDM using the MABAC technique are detailed in Section 2.1.1: The initial matrix is generated in accordance with Equation (1). Subsequently, Equations (2), pertaining to the MRR objective, and (3), associated with the SR and EWR objectives, will be employed to calculate the normalized values of r_{ij}*. The normalized weighted values, denoted as v_{ij}, are subsequently calculated utilizing formula (4). The matrix representing the border approximation area is computed utilizing Equation (5). The computation of the distance between the alternatives and the boundary approximation area q_{ij} is executed utilizing formula

(6). Ultimately, the comprehensive distances between each alternative and the projected border area S_i are ascertained utilizing formula (7). In order to ascertain the ranking of the alternatives, S_i is subjected to refinement. Table 5 (Appendix) presents a variety of computed parameters in conjunction with the ranking of alternatives derived from the MABAC method. Based on the data presented in Table 5 (Appendix), it was observed that option 11 is the most beneficial. This is because it has the highest value for the S_i ($S_i = 0.1775$).

The procedure for MCDM employing the MOORA technique is detailed in Section 2.1.2. Apply equations (9) for the SR and EWR objectives, and equation (10) for the MRR objective to calculate the normalized matrix. Continue to calculate the normalized decision-making matrix utilizing equation (11). After that, determine the decision-making matrices by applying equation (12). Proceed to calculate P_i utilizing Equation (13) for MRR and R_i by applying Equation (14) for SR and EWR objectives. The estimation of Q_i is performed using the formula (15). Finally, arrange the options in order, arranging the one with the highest Q_i at the top as the most ideal choice. Table 4 (Appendix) presents the outcomes of various calculated parameters along with alternative rankings. Analysis of Table 4 (Appendix) indicates that option 11 stands out as the most favorable choice. This is attributed to the maximum value for the Q_i ($Q_i = -0.0874$).

Section 2.1.3 outlines simple guidelines for the appropriate use of the MAIRCA technique to address the MCDM effectively. Upon establishing the initial matrix, the priority, denoted as criterion P_{Aj}, can be determined through the application of equation (17). In addition, the parameter t_{pij} is calculated according to Equation (18), and the importance of the criterion's weight is clearly detailed in Section 2.2. After that, the values of t_{rij} are computed utilizing equations (19) for the MRR objective and (20) for the SR and EWR objectives, while the values of g_{ij} are ascertained through equation (21). The calculation of the criteria functions Q_i is ultimately derived from equation (22). The outcomes of the parameter calculation and the rankings of options are detailed in Table 5 (Appendix), utilizing the MAIRCA methodology. Analysis of Table 5 (Appendix) indicates that option 11 stands out as the most suitable choice. This has been attributed to the minimal value for the Q_i ($Q_i = 0.0222$).

Figure 5 (Appendix) presents the ranking of alternatives based on different MCDM methods, as obtained from the data in Appendix in Table 3, Table 4 and Table 5. All three MCDM methods indicate that option 11 is the optimal choice. Based on the analysis and Table 2 (Appendix), the best input parameters for achieving the minimum SR, minimum EWR, and maximum MRR simultaneously are: IP = 9.5 (A); SV = 5 (V); T_{on} = 8 (μs); T_{off} = 8 (μs); electrode HK20.

V. CONCLUSIONS

This paper presents the findings of a MCDM analysis aimed at identifying the optimal input parameters for the electrical discharge machining of cylindrical components fabricated from 90CrSi tool steel, utilizing electrodes composed of three distinct varieties of graphite. The study was designed with three primary objectives: to minimize SR, to reduce EWR, and to maximize MRR. The analysis covered five process factors: SV, IP, T_{on}, T_{off}, and TOG. Three varieties of graphite were employed as electrode materials: HK0, HK15, and HK20. The experiment was conducted applying the Taguchi method utilizing an L18 configuration ($6^1 \times 3^4$), and the results were subsequently analyzed using Minitab R19 software. The MCDM task has been effectively addressed, and the optimal input parameters have been recommended. The study results showed that the optimal parameter combination to simultaneously accomplish minimum SR, minimum EWR and maximum MRR was: IP = 9.5 (A); SV = 5 (V); T_{on} = 8 (μs); T_{off} = 8 (μs); electrode HK20. Additionally, it is essential to note that the MABAC, MOORA, and MAIRCA methods are applicable for resolving MCDM issues within the EDM process.

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DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

The authors wrote, reviewed and edited the content as needed and they have not utilised artificial intelligence (AI) tools. The authors take full responsibility for the content of the publication.

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Contribution of Individual Authors to the Creation of a Scientific Article (GhosEWRiting Policy)

The concept of this study was introduced by Le Thi Phuong Thao and subsequently deliberated upon and endorsed by every author. Each author contributed to the conception, resolution, and analysis of the MCDM issues. Le Thi Phuong Thao prepared the paper with the collaboration of the co-authors. All authors have reviewed and consented to the final version of the manuscript.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare.

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APPENDIX

Table 1. Input factors

No.	Input factors	Unit	Level					
			1	2	3	4	5	6
1	IP	A	3.5	5.5	7.5	9.5	11.5	13.5
2	SV	V	4	5	6	-	-	-
3	T_{on}	µs	8	12	16	-	-	-
4	T_{off}	µs	8	12	16	-	-	-
5	TOG	-	HK0	HK15	HK20	-	-	-

Table 2. Experimental plan and output results

No.	IP (A)	SV (V)	T_{on} (µs)	T_{off} (µs)	TOG	Ra (µm)	EWR (mg/min.)	MRR (mg/min.)
1	3.5	4	8	8	HK0	3.917	2.035	21.354
2	3.5	5	12	12	HK15	4.093	0.797	25.569
3	3.5	6	16	16	HK20	4.704	0.647	26.413
4	5.5	4	8	12	HK15	4.217	1.204	55.745
5	5.5	5	12	16	HK20	3.948	1.018	64.712
6	5.5	6	16	8	HK0	4.443	3.788	115.398
7	7.5	4	12	8	HK20	3.814	1.689	99.835
8	7.5	5	16	12	HK0	2.744	5.57	137.401
9	7.5	6	8	16	HK15	3.142	2.486	99.131
10	9.5	4	16	16	HK15	3.772	1.051	31.361
11	9.5	5	8	8	HK20	2.618	0.954	32.611
12	9.5	6	12	12	HK0	2.050	2.446	46.825
13	11.5	4	12	16	HK0	3.524	2.991	84.004
14	11.5	5	16	8	HK15	3.908	1.842	64.374
15	11.5	6	8	12	HK20	4.087	0.956	60.897
16	13.5	4	16	12	HK20	6.354	1.945	95.996
17	13.5	5	8	16	HK0	3.688	3.503	114.831
18	13.5	6	12	8	HK15	5.453	2.723	93.703

Table 3. Calculated results and ranking of options in MABAC method

No.	g_{ij}			q_{ij}			S_i	Rank
	Ra	EWR	MRR	Ra	EWR	MRR		
1	0.5777	0.7492	0.2539	0.0064	0.0149	-0.0715	-0.0503	14
2	0.5777	0.7492	0.2539	-0.0089	0.1267	-0.0649	0.0529	8
3	0.5777	0.7492	0.2539	-0.0618	0.1403	-0.0636	0.0148	11
4	0.5777	0.7492	0.2539	-0.0196	0.0900	-0.0175	0.0528	9
5	0.5777	0.7492	0.2539	0.0037	0.1068	-0.0034	0.1070	4
6	0.5777	0.7492	0.2539	-0.0392	-0.1435	0.0762	-0.1064	16
7	0.5777	0.7492	0.2539	0.0152	0.0461	0.0518	0.1132	3
8	0.5777	0.7492	0.2539	0.1079	-0.3045	0.1108	-0.0857	15
9	0.5777	0.7492	0.2539	0.0735	-0.0259	0.0507	0.0983	5
10	0.5777	0.7492	0.2539	0.0189	0.1038	-0.0558	0.0669	7
11	0.5777	0.7492	0.2539	0.1189	0.1125	-0.0539	0.1775	1
12	0.5777	0.7492	0.2539	0.1681	-0.0222	-0.0315	0.1143	2
13	0.5777	0.7492	0.2539	0.0404	-0.0715	0.0269	-0.0042	12
14	0.5777	0.7492	0.2539	0.0071	0.0323	-0.0039	0.0355	10
15	0.5777	0.7492	0.2539	-0.0084	0.1124	-0.0094	0.0946	6
16	0.5777	0.7492	0.2539	-0.2048	0.0230	0.0458	-0.1360	18
17	0.5777	0.7492	0.2539	0.0262	-0.1177	0.0753	-0.0162	13
18	0.5777	0.7492	0.2539	-0.1267	-0.0473	0.0421	-0.1318	17

Table 4. Calculated results and ranking of options in MOORA method

No.	W_{ij}			R_i	P_i	Q_i	Rank
	Ra	EWR	MRR				
1	0.3729	0.4447	0.1824	0.1895	0.01302	-0.1764	13
2	0.3729	0.4447	0.1824	0.1346	0.01559	-0.1190	5
3	0.3729	0.4447	0.1824	0.1419	0.016105	-0.1258	8
4	0.3729	0.4447	0.1824	0.1569	0.033989	-0.1230	7
5	0.3729	0.4447	0.1824	0.1417	0.039457	-0.1023	2
6	0.3729	0.4447	0.1824	0.2854	0.070362	-0.2150	17
7	0.3729	0.4447	0.1824	0.1706	0.060873	-0.1097	4
8	0.3729	0.4447	0.1824	0.3302	0.083778	-0.2464	18
9	0.3729	0.4447	0.1824	0.1926	0.060443	-0.1322	9
10	0.3729	0.4447	0.1824	0.1391	0.019122	-0.1200	6
11	0.3729	0.4447	0.1824	0.1073	0.019884	-0.0874	1
12	0.3729	0.4447	0.1824	0.1650	0.028551	-0.1364	10
13	0.3729	0.4447	0.1824	0.2257	0.05122	-0.1745	12
14	0.3729	0.4447	0.1824	0.1801	0.039251	-0.1408	11
15	0.3729	0.4447	0.1824	0.1421	0.037131	-0.1049	3
16	0.3729	0.4447	0.1824	0.2427	0.058532	-0.1842	15
17	0.3729	0.4447	0.1824	0.2540	0.070016	-0.1840	14
18	0.3729	0.4447	0.1824	0.2585	0.057134	-0.2014	16

Table 5. Calculated results and ranking of options in MAIRCA method

No.	t_{rij}			g_{ij}			S_i	Rank
	Ra	EWR	MRR	Ra	EWR	MRR		
1	0.0117	0.1191	0.0000	0.0090	0.0468	0.0101	0.0659	10
2	0.0109	0.1608	0.0004	0.0098	0.0051	0.0098	0.0246	3
3	0.0079	0.1658	0.0004	0.0128	0.0000	0.0097	0.0225	2
4	0.0103	0.1471	0.0030	0.0104	0.0188	0.0071	0.0363	7
5	0.0116	0.1533	0.0038	0.0091	0.0125	0.0063	0.0280	5
6	0.0092	0.0600	0.0082	0.0115	0.1058	0.0019	0.1192	17
7	0.0122	0.1307	0.0069	0.0085	0.0351	0.0033	0.0469	8
8	0.0174	0.0000	0.0101	0.0033	0.1658	0.0000	0.1692	18
9	0.0155	0.1039	0.0068	0.0053	0.0620	0.0033	0.0705	13
10	0.0124	0.1522	0.0009	0.0083	0.0136	0.0093	0.0312	6
11	0.0180	0.1555	0.0010	0.0027	0.0103	0.0091	0.0222	1
12	0.0207	0.1052	0.0022	0.0000	0.0606	0.0079	0.0685	12
13	0.0136	0.0869	0.0055	0.0071	0.0790	0.0047	0.0907	15
14	0.0118	0.1256	0.0038	0.0089	0.0403	0.0064	0.0556	9
15	0.0109	0.1554	0.0035	0.0098	0.0104	0.0067	0.0269	4
16	0.0000	0.1221	0.0065	0.0207	0.0437	0.0036	0.0681	11
17	0.0128	0.0696	0.0082	0.0079	0.0962	0.0020	0.1061	16
18	0.0043	0.0959	0.0063	0.0164	0.0699	0.0038	0.0901	14

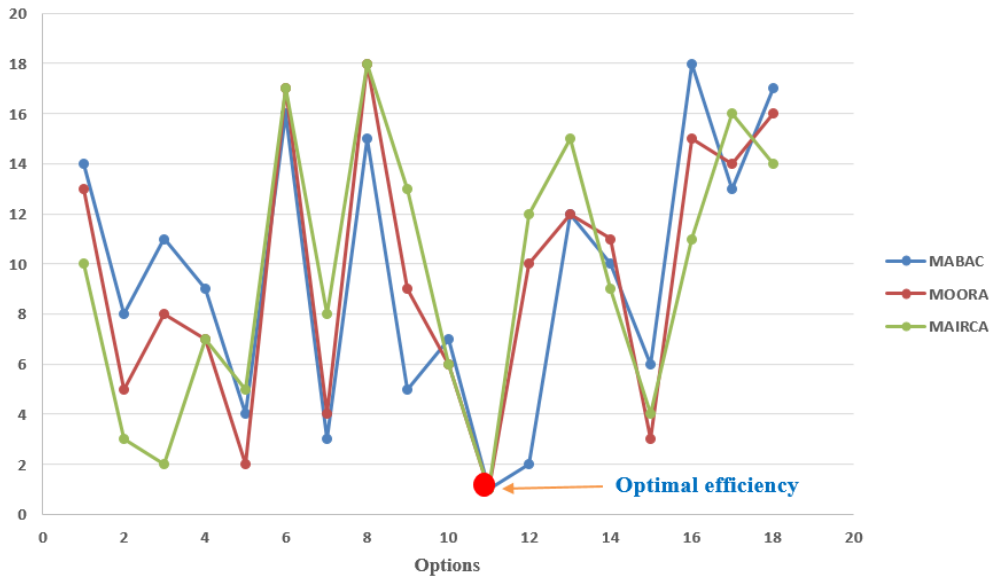

Fig. 5. Ranking of alternatives by different MCDM's methods