Sustainable Production, Instrumentation and Engineering Sciences
https://doi.org/10.57223/spies.2023.1.1.04
No. 1| 2023

Vidyapati Kumar[1*], Abhishek Mohata[2], Ankita Mistri[3], Marian Bartoszuk[4]
[1] Department of Mechanical Engineering, Indian Institute of Technology, Kharagpur West Bengal, India
[2] Department of Mechanical Engineering, Jalpaiguri Government Engineering College, West Bengal, India
[3] Department of Mechanical Engineering, Indian Institute of Technology, Dhanbad, Jharkhand, India
[4]Department of Manufacturing Engineering and Materials Science, Opole University of Technology, 45-758 Opole, Poland
*Corresponding author: vidyapatikumar.me@gmail.com

Application of SWARA-CoCoSo-based approach for tool selection of an electrical discharge machining process

KEYWORDS

Tool selection; MCDM; SWARA method; CoCoSo; EDM process

ABSTRACT

Electrical discharge machining (EDM) is a non-traditional machining process widely used in manufacturing to create complex geometries on hard-to-machine materials. The tool material used in EDM plays a crucial role in determining the machining performance and final surface finish of the workpiece. In this research, we aimed to optimize the tool selection for creating circular holes on SG iron (grade 450/12) using EDM. To this end, we employed a step-wise weight assessment ratio analysis (SWARA) based combined compromise solution (CoCoSo) approach to evaluate the performance of different tool materials under various machining conditions. The machining conditions considered in this study included peak current (I), pulse-on time (Ton), and inter-electrode gap (IEG). The results of our study showed that the CoCoSo approach is an effective method for tool selection in EDM, and it can be used to identify the optimal tool material and machining conditions for creating circular holes on SG iron. The final appraisal scores obtained from the ranking of tool materials indicated that copper tools scored highest (2.4767, ranking 1), followed by copper tungsten (2.3615, ranking 2), while brass scored lowest (1.6606, ranking 3). Furthermore, Spearman's rank correlations for different integrated MCDM techniques were performed, which demonstrated the efficacy of this technique. It has been demonstrated that implementing the SWARA-CoCoSo method can effectively optimize the EDM process with regard to sustainable machining practices.

1. Introduction

Numerous non-traditional machining (NTM) technologies have developed as plausible alternatives for the current manufacturing sectors to fulfil the demands of creating complicated form functionalities on multiple complex, sophisticated engineering components [1]. These technologies provide great dimensional precision and texture polish with minimal tool wear and residual stress development. Various energies in their direct forms are used to remove work material without direct contact between the tool and the work material [2]. Electrical discharge machining (EDM) is an unconventional machining method that has been developed over the past few decades to produce difficult-to-cut materials. It is also used to alter the material's surface characteristics through the EDM process. Conventional techniques for material removal, including turning, milling, shaping, grinding, and drilling, all involve applying pressure to the workpiece with a cutting tool to remove extraneous material in the form of chips [3]. Shear action and the loss of material are both produced due to the plastic deformation induced within the workpiece [4]. In NTM methodologies, instead of employing sharp cutting tools, the material is eliminated using one or more of the following forms of energy: mechanical, thermal, electrical, or chemical energy, or a hybrid of these. In other NTM procedures, the tool does not come into any kind of contact with the work material at all, and the material of the tool does not even have to be harder than the material being worked on. The material that is removed from the surface of the workpiece using NTM procedures is done so in the form of fine particles [5]. This results in improved surface uniformity and geometric precision. Welding, machining, additive manufacturing, joining, and other procedures have all been used at some point in producing tools and other components [6]. From this perspective, it is worth emphasizing that diverse work materials are required for various engineering applications, therefore it is critical to understand and examine materials machined using the EDM process. Despite Joseph Preistly establishing the background of the EDM operation in 1770, it wasn't until two Soviet scientists, the Lazarenkos, were able to create a machining technique that was employed as the foundation for the current EDM approach that they were successful. This procedure leverages electrical power to spark an electrical current between an electrode and a work material, and electro-discharge erosion is mainly employed to remove material. This electric spark generates a tremendous amount of heat, with temperatures ranging from 8000°

to 12000°C, which can only impact the workpiece surface when adequately regulated and limited. The metal removal mechanism applies a pulsing (on/off) electrical charge to the work material, causing controlled erosion of tiny metal components from the work material via the electrode. Substance removal is therefore accomplished via the material's fast vapourization and melting.

2. Literature review

This section summarises the research work done in the last decade in the domain of EDM using different process parameters, responses, and MCDM/Optimization methodologies on diverse work materials. Mandal et al. [7] utilized pulse on time (Ton), pulse off time (Toff), and peak current as process parameters for machining C40 steel work material and measured the responses such as material removal rate (MRR), tool wear rate (TWR), and used the artificial neural network (ANN) in conjunction with NSGA-II for parametric optimization of the machining parameters. Dewangan and Biswas [8] employed pulse on time (Ton), working time (WT), lift time (LT), peak current, and inter-electrode gap (IEG) as process parameters for machining of the AISI P20 tool steel work material and measured the responses such as material removal rate (MRR), tool wear rate (TWR), further used grey relation analysis methodology for parametric optimization of the machining parameters. Dewangan et al. [9] adopted pulse on time (Ton), working time (WT), lift time (LT), and peak current as process parameters for machining AISI P20 tool steel work material and measured the responses such as material removal rate (MRR), tool wear rate (TWR), and used grey fuzzy logic methodology for parametric optimization of the machining parameters. Golshan et al. [10] deployed the NSGA-II methodologies to optimize the process parameters such as pulse on time, gap voltage, peak current, and percent of volume fraction of SiC while milling an Al/SiC composite and measuring the output responses such as MRR and surface roughness (SR). Furthermore, Jagdish and Ray [11] machined the AISI D2 tool steel work material using the Ton, I, dielectric level, and flushing pressure as process parameters and measured the output responses Process time (PT), Process energy (PE), Aerosol concentration (CA), Dielectric consumption (DC), and finally performed the parametric optimization employing grey relational analysis. Majumder [12]–[15] used a genetic algorithm, fuzzy-based particle swarm optimization (PSO), desirability-based particle swarm optimization, genetic algorithm, simulated annealing, PSO, and ANN to optimize the input parameters while machining various work materials such as mild steel and stainless steel. Ming et al. [16] implemented a genetic algorithm in conjunction with a desirability function to optimize I, Ton, Toff, and V using MRR and SR as responses and SiC/Al composites as the workpiece. Moghaddam and Kolahan [17] adopted simulated annealing methods to optimize the parameters I, Ton, Toff, V, and DF in AISI 2312 hot-worked steel and measured the output responses as RR, TWR, and SR. Mohanty et al. [18] utilized Vikor-index-based optimization to optimize I, Ton, and V on the work material of high carbon steel while considering output responses MRR, TWR, SR, and radial overcut (ROC). Kumar et al. [19] addressed its parametric optimization grey relational analysis on the D3 tool steel material by considering different surface roughness characteristics as the responses, using I, Ton Toff as the process parameters. Niamat et al. [20] used the desirability function technique to use the same process parameters as Kumar et al. [19] for parametric optimization on the AISI L3 tool steel. Sharma et al. [21] applied grey fuzzy logic techniques to optimize Ton, I, and IEG on an SG iron (pearlitic 450/12 grade) workpiece using MRR and overcut as input responses. Furthermore, Kumar et al. [22] evaluated the machining of SG iron (pearlitic 450/12 grade) workpieces utilizing teaching learning-based optimization using V, I, cycle time (CT), and rotational tool speed as input responses. Satija et al. [23] investigated the potential of copper tungsten tools in identifying the most significant process parameters for machining, with MRR, TWR, and SR as output responses. Khoshaim et al. [24] explored the feasibility of using different tool electrode materials, including copper, brass, and tungsten carbide, with an iso-energy pulse generator, and found that brass electrodes can produce larger craters on the machined surface of titanium alloy specimens due to their lower melting points. Ceritbinmez et al. [25] studied the drilling and formation of holes using various tool materials, such as copper and brass electrodes, with input parameters such as current, pulse on time, and pulse off time, and investigated output responses like MRR, TWR, etc. Several MCDM techniques [26], [27] have been implemented in various manufacturing sectors in this regard.

In the field of electrical discharge machining (EDM), extensive research has been conducted over the past decade to optimize the process parameters and responses for various work materials using different metaheuristic and multi-criteria decision-making (MCDM) methodologies. However, most of these studies have neglected the crucial role of tool materials in determining the machining performance and final surface finish of the workpiece. Therefore, there is a significant gap in the literature regarding the optimal selection of tool materials for EDM. In this context, this research aims to address this gap by focusing on the optimization of tool selection for creating circular holes on SG iron (grade 450/12) using EDM. The study employs a step-wise weight assessment ratio analysis (SWARA) based combined compromise solution (CoCoSo) approach to evaluate the performance of different tool materials under various machining conditions. The considered machining conditions include peak current (I), pulse-on time (Ton), and inter-electrode gap (IEG). The novelty of this research lies in the application of the SWARA-CoCoSo method for tool selection in EDM, which has not been explored in previous studies. The results of the study demonstrate that the approach is effective in identifying the optimal tool material and machining conditions for creating circular holes on SG iron. Furthermore, the study highlights the importance of considering tool materials in the EDM process optimization to achieve sustainable machining practices. In present times, every sector of industry strives to produce objects in the most efficient manner possible while minimizing negative environmental impact. This optimization should also be applied to EDM processes, and it is for this reason that the authors wish to explore this work. A holistic approach to producing and consuming material goods is essential in the current era, and this reinforces the relevance of the present research. The exploration of sustainable EDM practices not only benefits the industry but also aligns with the growing societal concern for sustainable manufacturing practices. Hence, this research will contribute to the knowledge of sustainable EDM practices and assist the industry in adopting more sustainable processes.

3. Methodology

3.1. Step-wise Weight Assessment Ratio Analysis (SWARA) method

Kersuliene et al. [28] devised and suggested the Step-wise Weight Assessment Ratio Analysis (SWARA) approach. SWARA is an easy weighting method compared to other MCDM weight-calculating methods [29]. The steps involved in the criteria weight calculation by SWARA method are discussed below:

Step 1: The criteria are arranged in descending order based on their importance.

Step 2: The respondent expresses the relevance of criteria j with respect to the preceding criterion (j-1), starting with the second criterion. Kersuliene et al. [28] refer to this S_j ratio as the relative significance of the average value.

Step 3: Determination of k_j:

$$k_j = \begin{cases} 1, & j = 1 \\ s_j + 1, & j > 1 \end{cases} \tag{1}$$

Step 4: Determination of q_j:

$$q_j = \begin{cases} 1, & j = 1 \\ \frac{k_{j-1}}{k_j}, & j > 1 \end{cases} \tag{2}$$

Step 5: The following formula is used to establish the relative weights of the assessment criteria:

$$w_j = \frac{q_j}{\sum_{k=1}^{n} q_j} \tag{3}$$

Where the relative weight of *j*-th criterion is denoted by w_j and the number of criteria is denoted by *n*.

3.2. Combined Compromised Solution (CoCoSo) method

CoCoSo is one of the recent MCDM methods proposed by Yazdani et al. [30]. This approach successfully sorts or diverts alternatives because it uses simple additive weighting and an exponentially weighted product model. The procedural steps employed in the CoCoSo method are as follows:

Step 1: Development of decision matrix in the first phase using the structure shown below:

$$D = (d_{ij})_{mxn} = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ d_{m1} & d_{m2} & \cdots & d_{mn} \end{bmatrix} \tag{4}$$

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

Step 2: The initial decision matrix is normalized based on the compromised normalization equation [31]:

$$x_{ij} = \frac{d_{ij} - \min_i d_{ij}}{\max_i d_{ij} - \min_i d_{ij}}, \text{ for benefit criteria} \tag{5}$$

$$x_{ij} = \frac{\max_i d_{ij} - d_{ij}}{\max_i d_{ij} - \min_i d_{ij}}, \text{ for non-benifit criteria} \tag{6}$$

Step 3: The weighted comparability sequence *(S_i)* of each alternative and power weight of the comparability sequence *(P_i)* for each alternative is calculated utilizing equations (7) and (8), respectively:

$$S_i = \sum_{j=1}^{n} w_j x_{ij} \tag{7}$$

$$P_i = \prod_{j=1}^{n} (x_{ij})^{w_j} \tag{8}$$

Step 4: Relative weight of each alternative is calculated using three aggregation approaches as provided through equations (9)-(11):

$$k_{ia} = \frac{S_i + P_i}{\sum_{i=1}^{m} (P_i + S_i)} \tag{9}$$

$$k_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i} \tag{10}$$

$$k_{ic} = \frac{\lambda(S_I) + (1-\lambda)(P_i)}{(\lambda \max_i S_i + (1-\lambda) \max_i P_i} \tag{11}$$

Equation (9) exhibits the average of the weighted sum measure *(Si)* and weighted power measure *(Pi)*, while equation (7) embodies a sum of S_i and P_i. Equation (11) provides the balanced compromise of (S_i) and (P_i) scores. In equation (11), the expert decision maker selects the value of λ (usually λ = 0.5).

Step 5: The order in which the alternatives are ranked is determined by the value of k_i which is computes using equation (12):

$$k_i = (k_{ia} k_{ib} k_{ic})^{\frac{1}{3}} + \frac{1}{3}(k_{ia} + k_{ib} + k_{ic}) \tag{12}$$

The alternative having the higher value of k_i is of higher significance.

4. Experimental Details

Experiments are being conducted using an EDM (electrical discharge machining) setup to produce circular holes in pearlitic SG iron (grade 450/12). The process variables, such as peak current, pulse-on duration, and inter-electrode spacing, are kept constant. The Taiwan Oscar-S 430 EDM setup offers a travel range of [X-400 Y-300 Z-300] mm and a precision of 0.02 mm/300 mm. Pearlitic SG iron was chosen as the material for this EDM operation due to its various beneficial properties, including good wear and corrosion resistance, superior castability and machinability, reasonable strength, low cost, and suitability for hydraulic applications compared to steel. It also has a higher fluidity than steel, allowing for the creation of intricate shapes, and requires less heat treatment, resulting in better dimensional stability compared to malleable castings. This material is often used in producing hydraulic pump bodies, pump enclosures, pump casings, and pump hubs for diesel engine cooling systems. Tables 1 and 2 show the mechanical properties of pearlitic SG iron (grade 450/12) and the chemical composition of pearlitic ductile iron, respectively.

Table 1. Mechanical Characteristics of Pearlitic SG Iron (450/12 Grade)

Properties	Measurement Value
Ultimate Tensile Strength	450 N/mm^2
Yield Point Stress	310 N/mm^2
Elongation	12%
Brinell Hardness Number	197 BHN
Density	6.95 gm/cm^2
Wear resistance (relative)	Excellent

Table 2. Chemical Composition of Pearlitic Ductile Iron

Element	%
Carbon (C)	3.365
Silicon (Si)	2.393
Manganese (Mn)	0.238
Phosphorus (P)	0.072
Sulphur (S)	<0.150
Chromiun (Cr)	0.007
Molybdenum (Mo)	<0.010
Copper (Cu)	0.37
Magnesium (Mg)	0.085
Titanium (Ti)	0.032
Zinc (Zn)	0.027
Iron (Fe)	90.75
Others	2.661

In this experiment, an EDM machine was used to conduct experiments with a constant current of 32 A, pulse-on time of 30 µs, and inter-electrode spacing of 0.011 mm. The EDM machine was set up as shown in Figure 1. The dielectric fluid used throughout the machining process was Castrol SE 180 EDM fluid, which was chosen for its low smell, long-lasting stability, low viscosity, high flash point, reliable performance, and safe usage. The specimen size was 15 x 40 mm and the machined component is exhibited in Figure 2. To measure the material removal rate (MRR) and tool wear rate (TWR), an electronic weighing balance (A&D GR-202 type) was used. Surface roughness (SR) was measured using a Hommel Werke Turbo Wave V7.20 roughness tester, and coordinate measuring machine (CMM) software (GEOMET universal CMM) was used to measure the circularity error (CE) using a ZEISS O-INSPECT 442 CMM machine.

Table 3. Experimental details

Process Parameters	Tool	MRR (mm^3/min)	SR (µm)	TWR (mm^3/min)	CE (mm)
I=32 A	Cu	5.263	8.27	0.33707	0.1495
T_{on}=30 µs	CuW	3.0263	7.4	0.11428	0.1932
IEG=0.011 mm	Brass	0.789	5.1	0.3529	0.1795

Figure 1. Electric Discharge Machining Setup

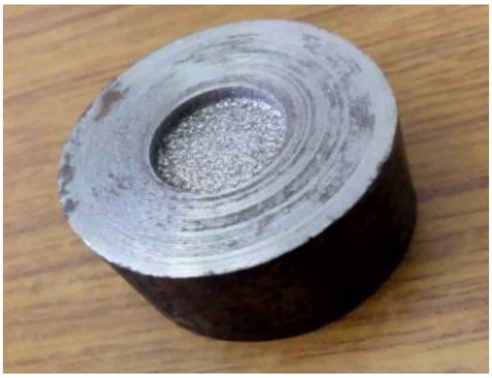

Figure 2. Machined Component

The SWARA-CoCoSo approach for the EDM process is a systematic method of selecting the optimal tool (alternative) based on multiple criteria as illustrated in Figure 3. The first step in this approach is to identify the critical process parameters and quality characteristics that are essential to the EDM process. This step involves selecting the parameters that have a significant impact on the process and identifying the quality characteristics that need to be optimized. The second step involves selecting the alternatives (Cu, CuW, Brass) and criteria (MRR, SR, TWR, CE) that will be used to evaluate each alternative. The alternatives represent the different materials that can be used for the EDM process, while the criteria represent the factors that must be considered when selecting the optimal alternative.

Each criterion must be carefully selected to ensure that it represents a critical factor that impacts the EDM process's quality and efficiency. The third step involves conducting experiments to evaluate each alternative's performance under different conditions. Feasible parametric settings of process parameters are chosen, and experimental trial runs are performed for different tools (alternatives) while recording the response values (criteria). This step is crucial in providing quantitative data that can be used to construct the initial decision matrix. In the fourth step, the initial decision matrix is constructed using the SWARA technique. The SWARA technique is a multi-criteria decision-making method that involves pairwise comparison of criteria to determine their relative importance. The weights for each criterion are calculated using this technique, and the initial decision matrix is constructed using the response values (criteria) obtained from the experimental trial runs. Finally, in the fifth step, MCDM methods such as CoCoSo, MABAC, and TOPSIS are used to select the optimal tool (alternative) based on the initial decision matrix and criterion weights. These methods use mathematical calculations to evaluate each alternative based on the criteria and criterion weights, and the optimal tool is selected based on the results obtained. The flowchart illustrated in Figure 3 depicts the entire process visually, making it easier to understand and implement. The SWARA-CoCoSo approach is a reliable and efficient method for selecting the best tool (alternative) for the EDM process based on multiple criteria, providing a scie-ntific basis for decision-making.

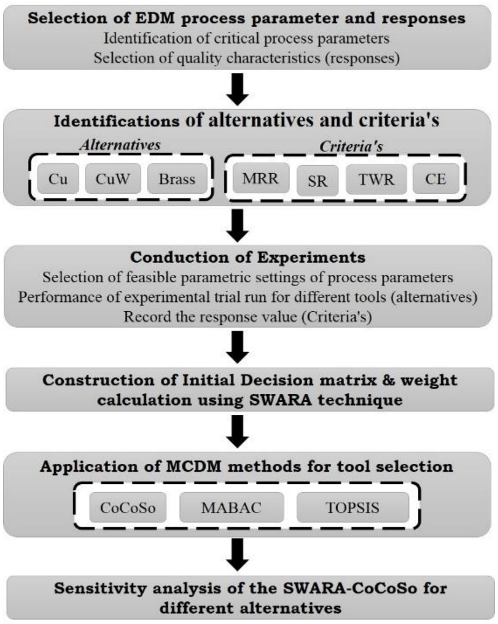

Figure 3. SWARA-CoCoSo approach for the tool selection of EDM Process

5. Results & Discussion

In this part, the study of tool selection of an EDM process is conducted on the data obtained experimentally. MRR is the only beneficial criterion and SR, TWR, and CE are non-beneficial criteria. The weights of several criteria were analyzed using the SWARA approach after brainstorming with experts and considering their essential input. The results are reported in Table 4.

Table 4. Weight calculation through SWARA

Criteria	Comparative Importance of Average (s_j)	Coefficient (k_j)	Recalculated Weight (q_j)	Relative Weight (w_j)
MRR	-	1	1	0.3251
SR	0.2	1.2	0.8333	0.2710
TWR	0.15	1.15	0.7246	0.2356
CE	0.4	1.4	0.5176	0.1683

After calculating the criteria weights, the problem is solved using the CoCoSo method. Equations (5)-(11) are used to compute the normalized decision matrix, weighted comparability sequence, power weight of comparability sequence, and an overall score of the alternatives once the decision matrix is formed. The final rank of the alternatives is obtained according to the decreasing order of the values of *k* as shown in Table 5. The data provided enabled the estimation of values for three distinct appraisal scores, which were subsequently combined to generate the final appraisal scores for all the alternatives considered for tool selection. The resulting rankings in Table 5 reveal Cu as the highest-ranked material, with the highest appraisal score, followed by CuW. Conversely, Brass received the lowest preference. A visual representation of the ranking positions for these alternative tool materials is provided in Figure 4.The ranking of the tool material selection problem is also verified by comparing the performance of the integrated SWARA-CoCoSo technique with some of the renowned MCDM techniques like TOPSIS and MABAC. The same results are shown in Table 5; it is evident that the copper tool remains the best alternative.

Table 5. Calculated Score values by CoCoSo Method And Rank Comparison

Tool	S_i	P_i	k_{ia}	k_{ib}	k_{ic}	k	CoCoSo	MABAC	TOPSIS
Cu	0.5091	2.5277	0.3722	2.9594	1.0000	2.4767	1	1	1
CuW	0.4726	2.5027	0.3647	2.8329	0.9238	2.3615	2	2	2
Brass	0.3237	1.8227	0.2631	2.0000	0.6359	1.6606	3	3	3

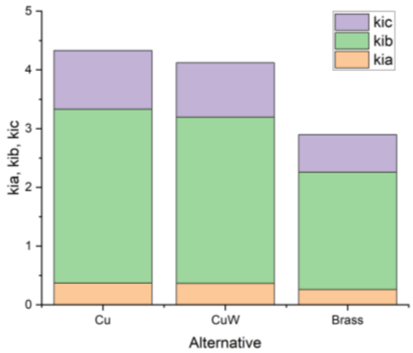

Figure 4. Ranking of tools based on their appraisal scores

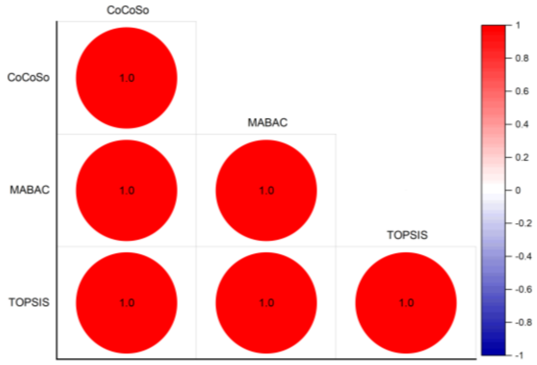

Figure 5. Spearman's rank correlations for different integrated MCDM techniques

Furthermore, in this particular context, the study employed Spearman's correlation analysis, visually represented in Figure 4, as a statistical tool to determine the magnitude and direction of the relationship among three MCDM methods. Spearman's correlation analysis is a non-parametric measure of correlation that does not make any assumptions about the distribution of the data points and relies on the rank order of the data. The resulting correlation coefficient ranges between -1 and +1, where a value of -1 represents a perfect negative correlation, +1 represents a perfect positive correlation, and 0 indicates no correlation. As depicted in Figure 5, the correlation coefficient for the applied MCDM methods is +1, signifying a perfect positive correlation.

5.1. Influence of λ value on CoCoSo Ranking

The sensitivity analysis is performed by changing the values of λ. While applying the CoCoSo method, the value of λ is expected to be 0.5. This value of λ can vary between 0 to 1. The assumption of λ value depends solely on the decision maker. It may so happen that upon changing the λ value, the ranking of the alternatives may change. Thus, to validate the stability of ranking by the given model, the importance of λ has been varied from 0.1 to 1, and the corresponding alternative ranking has been evaluated as shown in Figure 6.

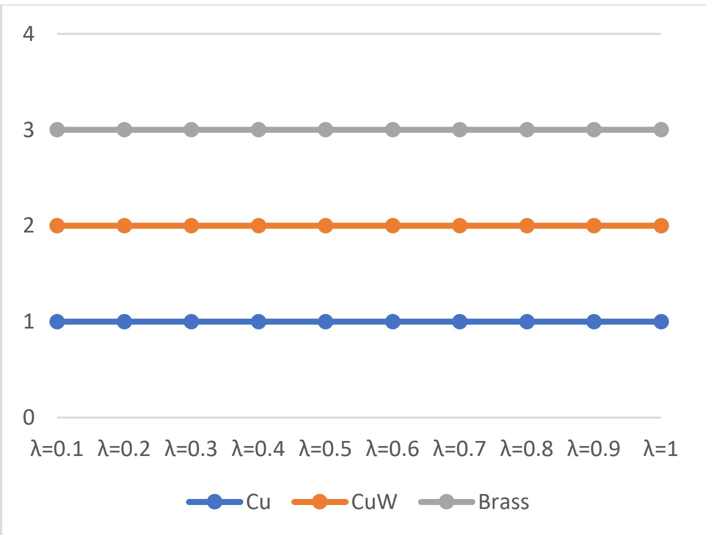

Figure 6. Sensitivity analysis of tool selection by changing the λ value

6. Conclusion

Based on the research and analysis, it was found that the copper electrode has the highest MRR, followed by copper tungsten and brass electrodes, respectively. Optimizing tools, EDM can significantly enhance the sustainability and efficiency of the machining process. This can be achieved by selecting the appropriate tool for the task at hand, maintaining it properly, ensuring it is appropriately balanced, and optimizing its geometry and design. The right tool selection can help reduce tool wear and prolong tool life, while proper maintenance can extend the tool's lifespan and reduce the need for frequent tool changes. Balancing the tool can minimize vibration and improve the accuracy and precision of the machining process while optimizing its geometry and design can enhance its performance and extend its life. The SR has been found to be the minimum for brass electrodes for the considered material and process parameters. The SR for the copper electrode is the highest, and that of the copper tungsten electrode lies between copper and brass electrodes. The TWR is maximum for brass electrodes and is minimum for copper tungsten electrodes. The value of CE is highest for copper tungsten electrodes and is lowest for the copper electrode. After applying the MCDM techniques, it has been found that the maximum weightage is given to MRR, followed by SR, TWR and CE. The copper electrode is best suited for electric discharge machining, and the brass tool is the worst among the three considered tool materials which has been identified with its appraisal scores and the derived ranking. Furthermore, the spearman's rank correlations for different integrated MCDM techniques which signified the perfect positive correlation between them.

From the sensitivity analysis performed by changing the values of λ, no change has been observed in the ranking of the tools by the integrated SWARA-CoCoSo technique. For low-dimensional MCDM issues, the suggested approach is highly resilient since it is unaffected by changes in the appropriate tuning parameter value. In addition, when compared to other subjective criterion weighting methodologies, the SWARA method performs similarly. As a result, this integrated method may be regarded as a suitable tool for ranking options for real-time manufacturing-related situations in a group decision-making context, considering expert viewpoints. Thus, it can be concluded that copper is the best tool material for electric discharge machining of pearlitic SG iron (450/12 grade) and that decision-makers may utilize the SWARA-CoCoSo technique in making the best decision in any conflicting environment as it has proved its robustness. In conclusion, the integrated method proposed in this context is an effective tool for ranking options in real-time manufacturing situations where group decision-making is necessary. This method considers expert opinions and other important factors such as cost, performance, and availability, making it a comprehensive and valuable choice for decision-making. This method can lead to numerous benefits, including reduced wear on electrodes, lower material consumption, improved production efficiency, cost savings, and alignment with sustainable production trends. Overall, it is a suitable tool for optimizing tool material selection in manufacturing settings.

References

[1] K.H. Ho and S. T. Newman, "State of the art electrical discharge machining (EDM)," *Int. J. Mach. Tools Manuf.*, vol. 43, no. 13, pp. 1287–1300, 2003, doi: 10.1016/S0890-6955(03)00162-7.

[2] S. Chakraborty and V. Kumar, "Development of an intelligent decision model for non-traditional machining processes," *Decis. Mak. Appl. Manag. Eng.*, vol. 4, no. 1, pp. 194–214, 2021, doi: 10.31181/dmame2104194c.

[3] S. Chakraborty, P. P. Das, and V. Kumar, "Application of grey-fuzzy logic technique for parametric optimization of non-traditional machining processes," *Grey Syst. Theory Appl.*, vol. 8, no. 1, pp. 46–68, 2018, doi: 10.1108/gs-08-2017-0028.

[4] J. E. Abu Qudeiri, A. H. I. Mourad, A. Ziout, M. H. Abidi, and A. Elkaseer, "Electric discharge machining of titanium and its alloys: review," *International Journal of Advanced Manufacturing Technology*, vol. 96, no. 1–4. pp. 1319–1339, 2018, doi: 10.1007/s00170-018-1574-0.

[5] V. KUMAR, P. P. DAS, and S. CHAKRABORTY, "Grey-fuzzy method-based parametric analysis of abrasive water jet machining on GFRP composites," *Sādhanā*, vol. 45, no. 1, p. 106, Dec. 2020, doi: 10.1007/s12046-020-01355-9.

[6] P. Kumar, L. N. Pattanaik, and R. K. Singh, "Simultaneous parametric optimization of micro-EDM drilling of brass C360 using Taguchi based grey relation analysis," *Eng. Rev.*, vol. 41, no. 1, pp. 14–24, 2021, doi: 10.30765/er.1377.

[7] D. Mandal, S. K. Pal, and P. Saha, "Modeling of electrical discharge machining process using back propagation neural network and multi-objective optimization using non-dominating sorting genetic algorithm-II," *J. Mater. Process. Technol.*, vol. 186, no. 1–3, pp. 154–162, 2007, doi: 10.1016/j.jmatprotec.2006.12.030.

[8] S. Dewangan and C. K. Biswas, "Optimisation of machining parameters using grey relation analysis for EDM with impulse flushing," *Int. J. Mechatronics Manuf. Syst.*, vol. 6, no. 2, pp. 144–158, 2013, doi: 10.1504/IJMMS.2013.053826.

[9] S. Dewangan, S. Gangopadhyay, and C. K. Biswas, "Multi-response optimization of surface integrity characteristics of EDM process using grey-fuzzy logic-based hybrid approach," *Eng. Sci. Technol. an Int. J.*, vol. 18, no. 3, pp. 361–368, 2015, doi: 10.1016/j.jestch.2015.01.009.

[10] A. Golshan, S. Gohari, and A. Ayob, "Multi-objective optimisation of electrical discharge machining of metal matrix composite Al/SiC using non-dominated sorting genetic algorithm," *Int. J. Mechatronics Manuf. Syst.*, vol. 5, no. 5–6, pp. 385–398, 2012, doi: 10.1504/IJMMS.2012.049972.

[11] Jagadish and A. Ray, "Multi-Objective Optimization of Green EDM: An Integrated Theory," *J. Inst. Eng. Ser. C*, vol. 96, no. 1, pp. 41–47, 2015, doi: 10.1007/s40032-014-0142-0.

[12] A. Majumder, "Process parameter optimization during EDM of AISI 316 LN stainless steel by using fuzzy based multi-objective PSO," *J. Mech. Sci. Technol.*, vol. 27, no. 7, pp. 2143–2151, 2013, doi: 10.1007/s12206-013-0524-x.

[13] A. Majumder, P. K. Das, A. Majumder, and M. Debnath, "An approach to optimize the EDM process parameters using desirability-based multi-objective PSO," *Prod. Manuf. Res.*, vol. 2, no. 1, pp. 228–240, 2014, doi: 10.1080/21693277.2014.902341.

[14] A. Majumder, "Parametric Optimization of Electric Discharge Machining by GA-based Response Surface Methodology," *J. Manuf. Sci. Prod.*, vol. 12, no. 1, pp. 25–30, 2012, doi: 10.1515/jmsp-2011-0016.

[15] A. Majumder, "Comparative study of three evolutionary algorithms coupled with neural network model for optimization of electric discharge machining process parameters," *Proc. Inst. Mech. Eng. Part B J. Eng. Manuf.*, vol. 229, no. 9, pp. 1504–1516, 2015, doi: 10.1177/0954405414538960.

[16] N. M. Liu, J. T. Horng, and K. T. Chiang, "The method of grey-fuzzy logic for optimizing multi-response problems during the manufacturing process: A case study of the light guide plate printing process," *Int. J. Adv. Manuf. Technol.*, vol. 41, no. 1–2, pp. 200–210, 2009, doi: 10.1007/s00170-008-1448-y.

[17] M. Azadi Moghaddam and F. Kolahan, "Optimization of EDM process parameters using statistical analysis and simulated annealing algorithm," *Int. J. Eng. Trans. A Basics*, vol. 28, no. 1, pp. 157–166, 2015, doi: 10.5829/idosi.ije.2015.28.01a.20.

[18] U. Kumar Mohanty, J. Rana, and A. Sharma, "Multi-objective optimization of electro-discharge machining (EDM) parameter for sustainable machining," in *Materials Today: Proceedings*, 2017, vol. 4, no. 8, pp. 9147–9157, doi: 10.1016/j.matpr.2017.07.271.

[19] V. Kumar and S. Chakraborty, "Analysis of the Surface Roughness Characteristics of EDMed Components Using GRA Method," 2022, pp. 461–478.

[20] M. Niamat, S. Sarfraz, W. Ahmad, E. Shehab, and K. Salonitis, "Parametric modelling and multi-objective optimization of electro discharge machining process parameters for sustainable production," *Energies*, vol. 13, no. 1, 2019, doi: 10.3390/en13010038.

[21] A. Sharma, V. Kumar, A. Babbar, V. Dhawan, K. Kotecha, and C. Prakash, "Experimental Investigation and Optimization of Electric Discharge Machining Process Parameters Using Grey-Fuzzy-Based Hybrid Techniques," *Materials (Basel).*, vol. 14, no. 19, p. 5820, Oct. 2021, doi: 10.3390/ma14195820.

[22] V. Kumar, S. Diyaley, and S. Chakraborty, "Teaching-learning-based parametric optimization of an electrical discharge machining process," *Facta Univ. Ser. Mech. Eng.*, vol. 18, no. 2, pp. 281–300, 2020, doi: 10.22190/FUME200218028K.

[23] D. Satija, P. Bhute, V. Gohil, and D. B. Meshram, "A study in electrical discharge machining using copper tungsten electrode," *Mater. Today Proc.*, no. xxxx, pp. 1–5, 2023, doi: 10.1016/j.matpr.2023.01.043.

[24] A. B. Khoshaim, T. Muthuramalingam, E. B. Moustafa, and A. Elsheikh, "Influences of tool electrodes on machinability of titanium α- β alloy with ISO energy pulse generator in EDM process," *Alexandria Eng. J.*, vol. 63, pp. 465–474, 2023, doi: 10.1016/j.aej.2022.07.059.

[25] Ferhat CERİTBİNMEZ Elif Simay GÖKKAYA Erdoğan KANCA, "MRR, EWR and KERF Analysis in Cold Work Tool Steel Machining in EDM Method by Copper and Brass Electrode," vol. 6, no. 1, pp. 35–51, 2023.

[26] A. Mohata, N. Mukhopadhyay, and V. Kumar, "CRITIC-COPRAS-Based Selection of Commercially Viable Alternative Fuel CRITIC-COPRAS-Based Selection of Commercially Viable Alternative Fuel," no. February, pp. 51–69, 2023, doi: 10.1007/978-981-19-6107-6.

[27] S. Das, B. Sarkar, and V. Kumar, "RIM-Based Performance Evaluation of DLC Coating Under Conflicting RIM-Based Performance Evaluation of DLC Coating Under Conflicting," no. February, pp. 303–320, 2023, doi: 10.1007/978-981-19-6107-6.

[28] V. Keršuliene, E. K. Zavadskas, and Z. Turskis, "Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (Swara)," *J. Bus. Econ. Manag.*, vol. 11, no. 2, pp. 243–258, Jan. 2010, doi: 10.3846/jbem.2010.12.

[29] V. Kumar, K. Kalita, P. Chatterjee, E. K. Zavadskas, and S. Chakraborty, "A SWARA-CoCoSo-Based Approach for Spray Painting Robot Selection," *Informatica*, vol. 0, no. 0, pp. 1–20, Dec. 2021, doi: 10.15388/21-INFOR466.

[30] M. Yazdani, P. Zarate, E. Kazimieras Zavadskas, and Z. Turskis, "A combined compromise solution (CoCoSo) method for multi-criteria decision-making problems," *Manag. Decis.*, vol. 57, no. 9, pp. 2501–2519, Jan. 2018, doi: 10.1108/MD-05-2017-0458.

[31] M. ZELENY, "Compromise programming," *Mult. Criteria Decis. Mak.*, 1973.