Development of entropy embedded COPRAS-ARAS hybrid MCDM model for optimizing EDM parameters while machining high carbon chromium steel plate

Shankha Shubhra Goswami¹, Dhiren Kumar Behera¹, Soupayan Mitra², C Ahamed Saleel³, Baha Saleh⁴, Abdul Razak⁵, Abdulrajak Buradi⁶ and Abiot Ketema⁷

Abstract
The purpose of this paper is to discuss the optimization of electrical discharge machining (EDM) parameters in a green production environment. The primary goal of this work is to create a novel hybrid multi-criteria decision making (MCDM) model that combines COPRAS and ARAS to determine the best input EDM parameters for machining high carbon chromium tool steel plate. To carry out the selection process, a total of nine tests were carried out using four input parameters, including dielectric level, peak current, flushing pressure, and pulse duration at three different levels of magnitude, and the readings of the respective five output parameters were measured. The weights of these five criterions are evaluated using entropy, while COPRAS-ARAS hybrid model is implemented to choose the best alternative experiment among these nine availabilities. Experiment 5 is found to be the best choice, with the machining parameters 261 μs pulse length, 0.3 kg/cm² flushing pressure, 4.5 A current, and 80 mm dielectric level being the optimal input values. The primary result demonstrates that the developed hybrid model is sufficiently accurate and provides the best choice when compared to six existing MCDM tools. Finally, sensitivity analysis is used to justify the hybrid model's stability and consistency.

Keywords
EDM, green manufacturing, MCDM, hybrid model, COPRAS, ARAS

Date received: 10 June 2022; accepted: 12 September 2022

Handling Editor: Chenhui Liang

¹Department of Mechanical Engineering, Indira Gandhi Institute of Technology, Sarang, India
²Department of Mechanical Engineering, Jalpaiguri Government Engineering College, Jalpaiguri, India
³Department of Mechanical Engineering, College of Engineering, King Khalid University, Alha, Saudi Arabia
⁴Mechanical Engineering Department, College of Engineering, Taif University, Taif, Saudi Arabia
⁵Department of Mechanical Engineering, P. A. College of Engineering (Affiliated to Visvesvaraya Technological University, Belagavi), Mangaluru, India
⁶Department of Mechanical Engineering, Nitte Meenakshi Institute of Technology, Bengaluru, India
⁷Department of Biosystems Engineering, Institute of Technology, Hawassa University, Ethiopia, Hawassa

Corresponding author:
Abiot Ketema, Department of Biosystems Engineering, Institute of Technology, Hawassa University, P.O.B. 05, Ethiopia, Hawassa.
Email: ketemaabiot80@gmail.com

Shankha Shubhra Goswami, Department of Mechanical Engineering, Indira Gandhi Institute of Technology, Sarang, Odisha 759146, India.
Email: sg.mech.official@gmail.com

Abdul Razak, Department of Mechanical Engineering, P. A. College of Engineering (Affiliated to Visvesvaraya Technological University, Belagavi), Mangaluru, Karnataka 574153, India.
Email: arkmch9@gmail.com
Introduction

With the world’s rapid growth and technological advancements, traditional machining operations are becoming obsolete and being replaced by various non-traditional machining (NTM) processes in various sectors. Despite its high capital cost, NTM has numerous significant advantages like, the ability to achieve high precision and smooth surface finish, no thermal distortion and heat affected zone (HAZ) occurs, the ability to machine a wide range of materials, including composites, ceramics, high strength alloy steel, complex and intricate profiles can be easily generated, tool wear and chip generation are almost absent. NTM has gained widespread acceptance in the manufacturing sector as a result of its appealing and desirable characteristics.

EDM is one of the popular and widely used NTM process in industry for producing complex shapes and cutting extremely hard materials to close tolerances that are nearly impossible to achieve with conventional machining, but at the same time it is also considered hazardous to the environment that should not be overlooked.1 During its operation, EDM emits aerosols and toxic gases that are extremely harmful and can have a negative impact on one’s health. Furthermore, it emits a large amount of solid and liquid wastes in the form of dielectric sludge and deionizing resins, which are then dumped into nearby rivers or bare land, thus contaminating the environment and causing pollution. These hazardous substances pose a great risk toward mankind, especially to the operators. It is also true that the volume of toxic waste generated by EDM is highly dependent on the input process parameters. Hence, it is possible to control the environmental pollution and to implement the green concept by optimizing the EDM process parameters. Green manufacturing is a progressive conception that aims to improve the efficiency of any manufacturing process, while significantly reducing the environmental impacts and resource consumption.1

The authors were inspired by the following reasons that they came up with an idea of optimizing the EDM input parameters in order to achieve green EDM. Optimization of green EDM parameters necessitates the consideration of a number of critical factors for example, technical, economic, environmental aspects, and managing all these multiple parameters at a time is very difficult. Therefore, dealing with these kinds of multiple criteria problems requires the implementation of some robust technique like MCDM.

Over the last few decades, MCDM has become an important decision-making tool in number of diverse areas including manufacturing,1 trade, economic,2 health and education,3,4 domestic5,6 etc. Several researchers are actively focusing on this field to update different MCDM strategies and to fill up the gaps that occur in previous approaches. Some researchers have already developed several recent groundbreaking MCDM frameworks for more precise and effective decision-making. Day-by-day MCDM approaches are gaining more popularity owing to their intrinsic capacity to evaluate various alternatives, while at the same time, conventional MCDM techniques are becoming outmoded. To evaluate some complicated decision-making problems, a single MCDM method is not adequate to render effective decisions.7 Therefore, two or more MCDM tools need to be combined together to create a hybrid paradigm for efficient decision-making, and now researchers are mainly focusing on hybrid MCDM models to execute any decision-making problems. The fundamental benefit of any hybrid approach is the consolidation of the advantages of each MCDM into a single system. On the other hand, while focus is given on the industrial aspect, the processing process employed by the business depends strongly on the final product it produces. Chakraborty and Zavadskas8 stated that “Manufacturing can be defined as the application of mechanical, physical and chemical processes to modify the geometry, properties and/or appearance of a given input material while making a new finished part/product.” In the current context, production entails a number of similar tasks, such as product creation, inventory procurement, method preparation, system selection, repair preparing and reporting, quality control, stock management and promotion. The design of production methods and optimum method parameters plays a crucial role in maintaining good product efficiency, lowering processing expenses, minimizing lead times and inventory rates and increasing the overall profitability of manufacturing organizations.8,9 In the industrial sector, decision makers (DM) often face a problem of evaluating broad range of alternatives and choosing the strongest based on a series of competing parameters. This should be remembered that, when selecting the most suitable choice, there is not necessarily a clear definitive preference factor, but a vast range of factors must be taken into consideration by the decision-makers. There is also a need for certain easy, structured and rational approaches or statistical techniques to direct decision-makers in evaluating a variety of competing selection parameters and their interrelationships. Therefore, efforts must be expanded to define certain parameters that determine the best alternative option for a given question, utilizing simple and rational approaches, to exclude unsuitable alternatives, and to choose the most acceptable one to improve current selection procedures.8

This current research work particularly focuses on developing of such an easy and logical hybrid COPRAS-ARAS model, and its ability to solve a MCDM problem is demonstrated through the selection of optimum EDM process parameters. The following optimization problem is adopted from a previous article
by Sivapirakasam et al.\textsuperscript{1} published in a reputed journal “Expert Systems with Applications.” Sivapirakasam et al.\textsuperscript{1} solved the following EDM parameters selection problem using Taguchi embedded with fuzzy-TOPSIS method while machining high carbon chromium tool steel plate on the basis of five output performance parameters (criterions) namely, aerosol concentration (AC), relative tool wear ratio (RTWR), dielectric consumption (DC), process time (PT), and process energy (PE). Sivapirakasam et al.\textsuperscript{1} considered four input parameters with three different levels of magnitude as displayed in Tables 1 and 9 experiments were conducted by combining different levels of four input parameters. The four input parameters and their respective five measured output parameters for nine experiments are given in Table 2. The authors discovered some substantial errors in the previous study conducted by Sivapirakasam et al.\textsuperscript{1} which is the fundamental reason for reconsidering the same MCDM issue. The authors argued that the prior optimization study is inconsistent and biased as a result of using the fuzzy concept in decision-making. As we all know, the fuzzy idea is generally utilized to make uncertain or hazy judgments, that is, when actual or complete knowledge is unavailable. The decision-makers will then have to communicate their own ideas and verdicts verbally in linguistic terms. The expert’s opinions may disagree from one another, resulting in unfair or partial decisions. As a result, fuzzy-based findings are always accompanied with imprecision and ambiguity.\textsuperscript{10} Similarly, TOPSIS is an antiquated tool with two major flaws that is, rank reversal and inconsistency in assessment during additional features. Furthermore, TOPSIS is a time-consuming process that necessitates some complex steps for its mathematical computations. TOPSIS assesses the performance of alternatives using Euclidean distance, which does not support the correlation between the attributes.\textsuperscript{10} Due to these severe drawbacks, the authors felt forced to replace the research gaps with more advanced and potential MCDM tools. The hybrid MCDM model presented in this article has the following benefits.

- It is completely independent of the expert’s ideas and judgments. Entropy method is an objective weight estimation tool that doesn’t allow the interference of decision makers. Hence, it is less biased.
- This hybrid system has the ability to distinguish the beneficial and cost criteria separately, that helps in considering the effect of positive and negative ideal solutions.
- It is very simple, straightforward and easy to understand process. The time requirement for calculation is also less compared to other tools.
- It is highly robust, with a very low chance of rank reversal.
- This hybrid model is more advanced, accurate and has greater stability.

The same EDM parameters optimization problem is again reconsidered in this present article and re-evaluated using Entropy integrated COPRAS-ARAS hybrid MCDM method. The relative importance’s (weights) of the criteria are determined using entropy method and the best alternative is proposed using COPRAS-ARAS hybrid model. The main objective of this research work is to propose the best input EDM parameters by choosing the favorable experiment among nine alternatives in order to optimize the

### Table 1. Input parameters and their three levels of magnitude.

| Parameters               | Unit | Level 1 | Level 2 | Level 3 |
|--------------------------|------|---------|---------|---------|
| Dielectric level (DL)    | mm   | 40      | 60      | 80      |
| Peak current (PC)        | A    | 2       | 4.5     | 7       |
| Flushing pressure (FP)   | kg/cm\(^2\) | 0.3 | 0.5     | 0.7     |
| Pulse duration (PD)      | μs   | 2       | 261     | 520     |

Source: Sivapirakasam et al. (2011).

### Table 2. Input and output parameters of nine experiments.

| Sl. No. | Input parameters | Output parameters |
|---------|------------------|-------------------|
|         | PC   | PD  | DL  | FP  | PT (s) | RTWR | PE (Watt) | AC (mg/m\(^3\)) | DC (cm\(^3\)) |
| Exp. 1  | 2    | 2   | 40  | 0.3 | 0.7258 | 0.3899 | 54.433    | 0.82      | 0.0665   |
| Exp. 2  | 2    | 261 | 60  | 0.5 | 1.5357 | 0.0055 | 115.178   | 0.77      | 0.0981   |
| Exp. 3  | 2    | 520 | 80  | 0.7 | 1.6393 | 0.0051 | 122.951   | 0.64      | 0.0865   |
| Exp. 4  | 4.5  | 2   | 60  | 0.7 | 0.4705 | 0.3496 | 57.612    | 1.22      | 0.051    |
| Exp. 5  | 4.5  | 261 | 80  | 0.3 | 0.3415 | 0.0041 | 66.516    | 1.98      | 0.0394   |
| Exp. 6  | 4.5  | 520 | 40  | 0.5 | 0.3942 | 0.0049 | 106.362   | 2.4       | 0.0497   |
| Exp. 7  | 7    | 2   | 80  | 0.5 | 0.4062 | 0.3452 | 62.4884   | 4.12      | 0.0351   |
| Exp. 8  | 7    | 261 | 40  | 0.7 | 0.2381 | 0.0065 | 69.469    | 5.05      | 0.0434   |
| Exp. 9  | 7    | 520 | 60  | 0.3 | 0.2646 | 0.0076 | 60.469    | 5.05      | 0.0434   |

Source: Sivapirakasam et al. (2011).
output. At the same time, the potential and the efficiency of the newly developed hybrid model is also proven by comparing the present outcomes with the past researchers results. Further, the final outcome result from this hybrid model is vindicated by applying six other popular MCDM tools that is WSM, WPM, WASPAS, COPRAS, ARAS, PROMETHEE, and the robustness of the hybrid model is also validated through sensitivity analysis. The rest of the article is organized as follows, extensive review of literature followed by materials and methods, result and discussion, finally, conclusion reached from this study.

Development of COPRAS-ARAS hybrid MCDM model

As previously said, the hybrid MCDM concept is the combination of two or more tools to reflect the advantages of one tool over another. In this article, COPRAS and ARAS are integrated to create a robust hybrid system by weighing the benefits of both tools at the same time. Let us first look at the advantages and disadvantages of ARAS and COPRAS. To begin with the advantages of ARAS MCDM, it ranks a finite number of alternatives in relation to an ideal alternative by evaluating the proportionate utility ratio, which significantly improves the decision-making process. Furthermore, in the ARAS approach, the utility degree idea is directly proportional to the major criteria weights analyzed in a study that is used to determine the complicated comparative efficacy of a viable alternative. The main disadvantage of the ARAS technique is that it cannot handle the cost and benefit criteria individually. For ARAS functioning, all cost criteria should be turned into advantageous criteria first by obtaining the reciprocal values. However, the COPRAS MCDM compensates the limitations of ARAS MCDM. COPRAS have the capacity to consider maximum and minimum criteria individually, which aids in forecasting the influence of ideal and anti-ideal solutions on alternative selection. Moreover, the relative importance in COPRAS allows you to prioritize the ideal solution that maximizes the benefit while minimizing the cost criteria, whereas the negative ideal solution maximizes the cost while minimizing the benefit criteria. In addition, both the tools are free from rank reversals and can generate more accurate results than old conventional tools like SAW, TOPSIS, VIKOR, AHP, etc. As a result, the benefits are so compelling that when both these technologies are united, it is possible to create a more powerful hybrid system while simultaneously overcoming some of the significant downsides. These factors motivate the authors to adopt COPRAS and ARAS because of their major advantages over other MCDM and to begin developing a fresh hybrid model for the first time. Each of the favorable phases from COPRAS and ARAS are combined in this hybrid model as follows.

Step 1: The formation of a decision matrix as illustrated in Table 3, is the standard first and foremost step for most of the MCDM concerns (including COPRAS and ARAS), with the exception of subjective weighting tools such as AHP, SWARA, BWM, etc.

Step 2: Create an ideal alternative (in this example, Exp. 0) by taking the minimum values of the cost criterion (non-beneficial) and the maximum values of the beneficial criteria into account. This crucial step is primarily inspired by ARAS. Since, all five criteria considered here are minimum in nature, Exp. 0 is developed by taking the lowest values of each of the five criteria as shown in Table 3.

Step 3: Normalization is done using equation (2) and shown in Table 6. Both COPRAS and ARAS method employs linear normalization, therefore, the same procedure is followed here as well. It should
be noted that the conversion of the minimum criteria into maximum criteria is not conducted here like ARAS to reflect the advantage of COPRAS MCDM.

**Step 4:** Compute the weighted values using equation (7), which is the universal step for both techniques.

**Step 5:** Calculate the relative significances of the alternatives using equation (8). This is the COPRAS stage that impact of positive and negative ideal solution on the alternative rating.

**Step 6:** Finally, using equation (11) calculate the quantitative utility degree of the options shown in Table 7. The alternative with the highest quantitative utility degree is ranked first, and similarly decreasing values can form a ranking order. This metric compares the performance of the chosen alternatives to the ideal one in percentage terms. The quantitative utility in COPRAS measures the performance of the alternatives in comparison to the most superior one (i.e. maximum), whereas the utility degree in ARAS measures the performance of the alternatives in comparison to the ideal one. Technically, there is no distinction between the two, but evaluating from the ideal alternative also determines the performance and quality of the superior alternative in terms of the best optimum one, but in the case of COPRAS, the superior alternative has a proportionate ratio of one, making it impossible to determine the performance of the best alternative. Therefore, the utility degree concept is adopted from ARAS to make the decision analysis more accurate. Flowchart shown in Figure 1 depicts the hybrid model's step-by-step evolution.

**Green EDM MCDM model**

EDM is a thermal NTM procedure that removes material by local melting and vaporization of small areas on the workpiece surface. The material is removed through controlled material erosion, which is accomplished through the use of repeating electrical sparks between the tool and the work piece while immersed in a dielectric solution. There are different types of dielectric fluid that are used in EDM like, kerosene, paraffin oil, deionized water etc. which acts as a semiconductor between the workpiece and electrode to facilitate a controlled and stable spark gap ionization condition. The dielectric medium also acts a flushing agent that wash and carried away the molten eroded debris from the spark gap area with the help of flushing pressure. The input of this EDM process includes workpiece and tool material, dielectric, electrical energy and the process parameters for example dielectric level, peak current, flushing pressure, pulse duration, etc. while the output includes relative tool wear rate, dielectric consumption, material removal rate (MRR), gaseous emissions, eroded tool and work material debris, noise and heat. In this present research work, both the manufacturing and environmental aspects are taken into consideration to enhance the concept of green EDM which is clearly depicted in Figure 2. Among the five output parameters, two responses that is process time and relative tool wear ratio are the manufacturing elements, whereas the rest three responses that is dielectric consumption, aerosol concentration, and process energy falls under the category of environmental aspects. All the five output responses are elaborately discussed in...
the upcoming sub-sections. Figure 3 clearly illustrates the relationship between the input and output parameters of green EDM.

**Process time**

Time for material removal is one of the important parameters in EDM process, since it determines both the MRR and the cost of production. This factor is therefore subject to non-beneficial criteria whose lower value is desired.

**Relative tool wear ratio**

High energy intensity and extremely high temperature generated due to the applied potential differences at the spark gap causes the work piece to melt, and at the same time, it also causes the tool material to wear out and erode. This electrode wear directly affects the cost of production. The amount of erosion that occurred at the tool interface with respect to the workpiece is referred to as the relative wear ratio of the tool. This factor is also a non-beneficial criterion whose lower value is desired.

**Process energy**

Electrical energy consumption during EDM process has an indirect impact on the environment as more waste is generated during the generation of more electricity. Hence, process energy is considered as an important factor in this green EDM optimization problem. This energy is determined by discharge gap voltage, discharge current and the duration of current flow. Lower the value of process energy better is the criteria.

**Aerosol concentration**

The concentration of aerosol is considered to be one of the important environmental factors in this problem. Industrial exposure of toxic aerosols generated by the EDM process may include metallic residues and toxic reactive products of dielectric material that may contaminate the soil and water if not properly dumped. In addition, during the machining process, evolution of harmful gases can also pollute the operator’s breathing zone. Therefore, the concentration of aerosols should be minimized.

**Dielectric consumption**

According to Yeo et al., three paths are mainly responsible for the wastage of dielectric fluid during the EDM process.

1. Dielectric fluid coating on the workpiece.
2. Dielectric fluid coating on the removed materials from both the workpiece and tool.
3. Diffusion of the dielectric vapor into surroundings.

Dielectric consumption has both environmental and economic impacts. It is therefore considered to be one of the factors in this present study, whose minimum value is anticipated. Dielectric waste in the form of liquid and gas pollute the atmosphere as well as cause harm to the operator. Its minimum consumption is therefore cost-effective and can reduce environmental hazards.1

Review of literature

For the last few years, MCDM serves as an effective tool in solving numerous decision-making challenges in wide variety of areas and several researchers have already implemented different MCDM tools for choosing the right option for example material handling equipment selection,14,15 material selection,16,17 cutting parameters selection,18,19 cutting fluid selection20 etc. related to industry. In recent times, several hybrid MCDM models have been also developed and applied in broad areas by many researchers. Few examples of effective optimization of cutting parameters by various MCDM strategies and industrial applications involving entropy, ARAS21 and COPRAS22 techniques are addressed in the following literatures.

Jagdish and Ray23 solved a process parameters optimization problem of green EDM using an integrated MCDM approach of entropy and GRA, which was also validated by Taguchi-VIKOR and Fuzzy-TOPSIS methodology. Thirumalai and Senthilkumar24 proposed a new TOPSIS based MCDM concept for choosing the optimum cutting parameters during machining Inconel 718 using a carbide cutting tool on the basis of six objective factors against three input variables that is feed, cutting speed and depth of cut. Parida and Routara25 used TOPSIS method for the optimization of process parameters in turning of glass fiber reinforced polymer composites. Wang et al.26 integrated green EDM theory with the traditional EDM process to establish a new evaluation method by combining DEMATEL and ANP MCDM techniques. Jagdish and Ray27 developed a combined hybrid model of GRA and PCA to optimize the green EDM process parameters.

Singaravel and Selvaraj28 determined the optimum machining parameters for EN25 steel turning operation with coated carbide tools using combined TOPSIS and AHP methods. Khan and Maity28 investigated the implementation of a novel MCDM method known as VIKOR analysis coupled with the Taguchi methodology for optimizing cutting variables during turning of commercially pure grade 2 titanium utilizing uncoated carbide inserts. Meena et al.29 optimized the cutting parameters like frequency, current, and pulse on time during EDM of micro holes on Cp titanium. Modanloo et al.30 applied MOORA and TOPSIS methods to select the optimal process parameters for sheet hydroforming process. Chakraborty and Banik14 used AHP technique for designing a material handling equipment selection model under specific environment. Saha and Majumder31 performed a machining parameters optimization analysis considering gray-COPRAS hybrid MCDM approach during turning of ASTM A36 mild steel.

Das and Chakraborty32 optimized four green EDM input parameters like flushing pressure, pulse duration, dielectric level, and peak current using DEMATEL and SIR method to minimize the toxic and harmful emissions. Prakash and Krishnaiah33 optimized the process parameters using VIKOR and AHP for turning AISI 1040 steel with coated tools. Balasubramaniyan and Selvaraj34 integrated Taguchi with TOPSIS method to evaluate the optimal process parameters for the EN25 steel turning procedure utilizing coated carbide tools. Tang and Du35 solved the EDM parameters optimization problem by combining GRA with Taguchi method during machining Ti-6Al-4V. Majumder and Saha36 applied hybrid MCDM approaches of MOORA-PCA and TOPSIS-PCA for optimizing turning of ASTM A588. Mohapatra and Sahoo37 optimized the output parameters MRR and kerf width using TOPSIS method during gear cutting in wire EDM. Singaravel et al.18 applied the ARAS approach for deciding optimum process parameters and suitable coated instrument for turning steel AISI 4340.

Kumar et al.39 optimized the EDM cutting parameters using MCDM model of AHP-ARAS during machining AA7050-B4C composite. Martin and Deepak16 selected the suitable material for engineering components design using ARAS technique. Pathapalli et al.38 applied MOORA and WASPAS method to optimize the machining parameters for cutting metal matrix composites comprises of titanium carbide as reinforcement and aluminum 6063 as matrix. Sharma et al.39 reduced the tool wear and maximized MRR with the help of PROMETHEE MCDM by adjusting EDM input parameters for example pulse off time, pulse on time, current, and gap voltage while machining combustor material using copper cadmium as an electrode. Temuquin et al.40 developed a fuzzy based decision model to select the optimum non-traditional machining process among seven NTM alternatives while cutting carbon steel plate of width 10mm. Goswami and Behera41 implemented entropy-ARAS MCDM technique for the selection of best engineering materials among a group of seven alternatives by considering six conflicting criteria. Tang and Guo41 combined Taguchi and GRA method to optimize four EDM input
parameters that is pulse interval, pulse width, gap voltage, and peak discharge current while investigating S-03 stainless steel. Sharsar et al. established two MCDM models combining entropy-TOPSIS and entropy-ARAS to select the optimal experimental setup for EDM process.

It is evident from the above-mentioned literatures that ARAS and COPRAS are very rarely used MCDM tools for optimizing cutting parameters. Most of the time, researchers have only considered turning operations for the optimization purposes. There are also other machining operations such as, shaping, milling, broaching, etc. which are completely ignored. While several researchers have started refining input parameters for non-traditional machining such as EDM or wire EDM, relatively few research projects have been undertaken under the green manufacturing climate to date. This new work tries to fill the recognized research gaps by attempting to construct a hybrid MCDM model that integrates ARAS and COPRAS, which has never been done previously. This research report has three main goals. First, the optimum green EDM machining parameters were chosen, then a novel hybrid MCDM model was created, and finally, the output results were validated using six different MCDM approaches that had never been utilized together before for EDM cutting parameter optimization. Overall, the novelty of this study lies in the selection of optimal green EDM input parameters using a newly developed hybrid system of entropy embedded COPRAS-ARAS.

Materials and methods

This section includes the step-wise calculation details of entropy and COPRAS-ARAS hybrid technique. The following sub-sections 3.1 and 3.2 shows the assessment of criteria weights by entropy method and the estimation of the best alternative by hybrid method respectively. The complete green EDM optimization process is illustrated using a flowchart shown in Figure 4.

Entropy

Entropy is an objective weighting method used to calculate the criteria weights without taking DM’s opinion into consideration. This method is fully independent of DM’s interference and doesn’t require any pair-wise comparison matrix. Therefore, this objective weighting method is free from inconsistency and doesn’t require checking of consistency. Hence, entropy method is more advantageous than other subjective weighting methods like AHP, BWM, SWARA, etc. It automatically calculates the criteria weights based on the performance score (decision) matrix shown by equation (1). The steps of Entropy are described as follows.

**Step 1:** A \((m \times n)\) decision or evaluation matrix is formed according to equation (1). Where, “\(m\)” is the alternative count and “\(n\)” is the criteria count. Table 3 shows the decision matrix as proposed by Sivapirakasam et al. 1

\[
D(m \times n) = \begin{bmatrix}
    d_{11} & d_{12} & \ldots & d_{1n} \\
    d_{21} & d_{22} & \ldots & d_{2n} \\
    \vdots & \vdots & \ddots & \vdots \\
    d_{m1} & d_{m2} & \ldots & d_{mn}
\end{bmatrix}
\]

Where, \(i = 1, 2, \ldots, m; j = 1, 2, \ldots, n\). “\(d_{ij}\)” is the evaluation score of the \(i\)th alternative and \(j\)th criteria.
Step 2: Now, normalization is done using equations (2) and (3) according to the category of criteria. It must be noted that all the criteria considered in this present analysis are non-beneficial (minimum) in nature whose lower values are desired as indicated in Table 3, hence the normalization operation is executed using equation (3) and depicted in Table 4.

For beneficial criteria

\[
N_{ij} = \frac{d_{ij}}{\sum_{i=1}^{m} d_{ij}}
\]  
(2)

For non-beneficial criteria,

\[
N_{ij} = \frac{\left( \frac{1}{d_{ij}} \right)}{\sum_{i=1}^{m} \left( \frac{1}{d_{ij}} \right)}
\]  
(3)

“Nij” is the normalized values of the ith alternative and jth criteria.

Step 3: The entropy “ej” for every criterion is determined using equation (4) and displayed in Table 5.

\[
e_j = -K \sum_{i=1}^{m} N_{ij} \ln(N_{ij})
\]  
(4)

In above equation (4), “K” is a constant. The value of K = \(\frac{1}{\ln(m)}\) that ensures \(0 \leq e_j \leq 1\). In this case, \(m = 9\), therefore, the value of \(K = 0.45512\).

Step 4: Determine the degree of divergence “Zj” for each criterion using equation (5) and the same are depicted in Table 5.

\[
Z_j = |1 - e_j|
\]  
(5)

Step 5: Finally, calculate the criteria weightages “wj” using equation (6).

\[
w_j = \frac{Z_j}{\sum_{j=1}^{n} Z_j}
\]  
(6)

“wj” is the weight of the jth criteria. Table 5 shows the final criteria weightages.
COPRAS-ARAS hybrid MCDM model

COmplex PRoportional ASsessment (COPRAS) was first applied by Zavadskas et al.\textsuperscript{22} to assess building life cycles. It evaluates the effect of advantageous and non-beneficial factors individually to establish the relative significance of the alternatives. On the other hand, the Additive Ratio ASsessment (ARAS) technique assesses the utility degree of each alternative in comparison to the ideal best choice.\textsuperscript{21} Zavadskas and Turskis\textsuperscript{21} created ARAS in 2010 to evaluate the microclimate in office environments. In this hybrid model, the quantitative utility and degree of utility concept of both COPRAS and ARAS techniques are combined to reflect the benefits of the two individual MCDM. This method begins with the formation of an evaluation matrix ($m_i \times n_j$) according to equation (1) which is already shown in Table 3. It must be noted, an ideal (optimal) alternative has to be considered in this technique which is denoted by Exp. 0 in Table 3 and the analysis should be carried out along with this in addition to nine other actual alternatives.\textsuperscript{46–49} This ideal alternative is created by taking the best values of each criteria that is as all the criteria considered in this analysis are non-beneficial in nature, the ideal alternative Exp. 0 is formed by taking the minimum values of each criteria as depicted in Table 3.

Now moving toward the next step that is normalization of the decision matrix using equation (2). This hybrid technique also follows linear normalization as the previous entropy method, but the main difference is that, in this case the conversion of the non-beneficial into beneficial criteria is not required. Table 6 shows the normalized matrix and their respective normalized values.

Now the weighted values ($C_{ij}$) and the relative significances ($R_i$) of each alternative are evaluated using equations (7) and (8) respectively and shown in Table 7.

\begin{equation}
C_{ij} = N_{ij} \times w_j
\end{equation}

\begin{equation}
R_i = S_{+i} + \frac{S_{-\min} \sum_{i=1}^{m} S_{-i}}{S_{+i} \sum_{i=1}^{m} (S_{-\min} / S_{-i})} = S_{+i} + \frac{\sum_{i=1}^{m} S_{-i}}{S_{-i} \sum_{i=1}^{m} (1 / S_{-i})}
\end{equation}

In equation (8), “$S_{+i}$” and “$S_{-i}$” can be determined using equations (9) and (10) that represents the weighted values summation of the maximizing and minimizing criteria. “$S_{-\min}$” is the least among the $S_{-i}$ values.

\begin{equation}
S_{+i} = \sum_{j=1}^{n} C_{+ij} \rightarrow \sum_{i=1}^{m} S_{+i} = \sum_{i=1}^{m} \sum_{j=1}^{n} C_{+ij}
\end{equation}

\begin{equation}
S_{-i} = \sum_{j=1}^{n} C_{-ij} \rightarrow \sum_{i=1}^{m} S_{-i} = \sum_{i=1}^{m} \sum_{j=1}^{n} C_{-ij}
\end{equation}

“$C_{+ij}$” and “$C_{-ij}$” are the weighted values of the maximizing and minimizing criteria respectively.

Finally, quantitative utility degree (QU$_i$) of each alternative is determined using equation (11) and the rankings are proposed in Table 7.

\begin{equation}
QU_i = \frac{R_i}{R_0} \times 100\%
\end{equation}

“$R_0$” is the relative significances of the ideal experiment (Exp. 0) as indicated in Table 7.

Result and discussion

The ranking of the alternatives is done according to the decreasing quantitative utility values and shown in Table 7. Now, this proposed ranking is validated using two approaches. Firstly, the same problem is executed by applying six other solo MCDM tools namely, WSM, WPM, WASPAS, COPRAS, ARAS, and PROMETHEE utilizing the same entropy criteria weights and secondly, sensitivity analysis is performed which are included in the following sub-sections.
Validation using six other MCDM techniques

The alternative rankings obtained by implementing six different MCDM tools are provided in Table 8. Table 8 reveals that all the applied approaches indicate experiment no. 5 is the best option among these nine alternatives. Although the rankings proposed by different MCDM tools doesn’t exactly matches with each other, but all the methods offer the same performance alternative 5 as the highest. Even, Sivapirakasam et al. proposed that experiment 5 is the optimal alternative by analyzing through fuzzy-TOPSIS which exactly matches with the present outcomes. Experiments 1 and 7 compete with each other for occupying the worst position, but higher percentage of MCDM tools indicates that experiment 7 is the worst alternative between them which is also justified from the final ranking by Borda voting rule as depicted in Table 8.

Spearman rank correlation co-efficient (CC) is also determined and displayed in Table 9 to validate and compare the rankings obtained from different techniques. The CC values in Table 9 clearly represents that the newly developed hybrid model holds a good interrelationship with the other methods and all the CC values are above 0.8, which can be considered as high. Therefore, from the first validation analysis it can be decided that the output provided by the COPRAS-ARAS hybrid model is quite genuine and accurate.

Sensitivity analysis

Sensitivity analysis is performed to verify the findings and to explain the precision and variance of the judgment outcomes. A sensitivity analysis may allow the decision-makers to show the implications of their process by making any improvements to the primary model. Sensitivity analysis is executed to determine the variances in the final output ranking due to changes in the input data or criteria weights. According to Zavadskas et al., the final ratings are primarily influenced by two parameters, one is the input performance values and the other one is the criteria weights. However, the performance data for a specific problem remains consistent, therefore the criteria weights can be varied to investigate the stability of a MCDM system. To meet the needs, weight replacement strategy is performed here. For example, the letters ABC can be rearranged in total six possible combinations that is ABC, ACB, BAC, BCA, CAB, CBA. Likewise, a number of 120 distinct combinations may be created from these five weights and alternate rankings are derived from each case to track the differences in performance results which are clearly portrayed in Table 10. Sub-group 12 represents the criteria weights w1 and w2 will remain in the first and second position respectively, while the rest three weights that is, w3, w4, and w5 will make different combinations among

Table 7. Alternative ranking by COPRAS-ARAS hybrid model.

| Exp. No. | PT   | RTWR | PE   | AC   | DC  | Ri   | QU   | % Rank |
|----------|------|------|------|------|-----|------|------|--------|
| 0        | 0.00680 | 0.00170 | 0.00319 | 0.00779 | 0.00423 | 0.27196 | 1     | 100    |
| 1        | 0.02072 | 0.16194 | 0.00319 | 0.00999 | 0.00847 | 0.03156 | 1     | 11.605 |
| 2        | 0.04384 | 0.00228 | 0.00674 | 0.00938 | 0.01250 | 0.08627 | 1     | 31.722 |
| 3        | 0.04680 | 0.00212 | 0.00719 | 0.00779 | 0.01102 | 0.08606 | 1     | 31.643 |
| 4        | 0.01343 | 0.14520 | 0.00465 | 0.01486 | 0.00650 | 0.03492 | 1     | 12.842 |
| 5        | 0.00975 | 0.000120 | 0.00337 | 0.002594 | 0.00423 | 0.14331 | 1     | 52.695 |
| 6        | 0.00125 | 0.00204 | 0.00389 | 0.02411 | 0.05020 | 0.15992 | 1     | 51.192 |
| 7        | 0.01160 | 0.14337 | 0.00624 | 0.02923 | 0.06630 | 0.03277 | 1     | 12.050 |
| 8        | 0.00680 | 0.00270 | 0.00366 | 0.05018 | 0.00447 | 0.09510 | 1     | 34.969 |
| 9        | 0.00755 | 0.00316 | 0.00406 | 0.06150 | 0.00553 | 0.07882 | 1     | 28.982 |

Table 8. Alternative ranking by six other MCDM tools.

| Exp. No. | Hybrid model | WSM | WPM | WASPAS | COPRAS | ARAS | PROMETHEE | Final ranking by Borda voting rule |
|----------|--------------|-----|-----|--------|--------|------|-----------|-----------------------------------|
| Exp. 1   | 9            | 7   | 8   | 7      | 9      | 7    | 8         | 8                                 |
| Exp. 2   | 4            | 4   | 4   | 4      | 4      | 4    | 6         | 5                                 |
| Exp. 3   | 5            | 2   | 3   | 3      | 5      | 2    | 5         | 3                                 |
| Exp. 4   | 7            | 8   | 7   | 8      | 7      | 8    | 7         | 7                                 |
| Exp. 5   | 1            | 1   | 1   | 1      | 1      | 1    | 1         | 1                                 |
| Exp. 6   | 2            | 3   | 2   | 2      | 2      | 3    | 2         | 2                                 |
| Exp. 7   | 8            | 9   | 9   | 9      | 8      | 9    | 9         | 9                                 |
| Exp. 8   | 3            | 5   | 5   | 5      | 3      | 5    | 3         | 4                                 |
| Exp. 9   | 6            | 6   | 6   | 6      | 6      | 6    | 6         | 6                                 |

Source: Author's own elaboration.
them by shifting their positions. The six possible combinations for sub-group 12 can be done as follows: w1w2w3w4w5, w1w2w3w5w4, w1w2w4w3w5, w1w2w4w5w3, w1w2w5w3w4, w1w2w5w4w3. Similarly, for sub-group 13 the criteria weights w1 and w3 will be in the first and second position, while the rest three weights w2, w4, and w5 will make combination as follows: w1w3w2w4w5, w1w3w2w5w4, w1w3w4w2w5, w1w3w4w5w2, w1w3w5w2w4, w1w3w5w4w2. Likewise, the combinations for rest of the sub-groups can be obtained. As a result, there will be six possible combinations for each of the 20 sub-groups and the variations in the alternative rankings are observed for all the 120 weights combinations.

The total 120 arrangements are divided into five groups and each group are further divided into four sub-groups. Sub-group 12 represents 6 possible arrangements of 5 criteria weights as follows: w1w2w3w4w5, w1w2w3w5w4, w1w2w4w3w5, w1w2w4w5w3, w1w2w5w3w4, w1w2w5w4w3. Similarly, for sub-group 13 the criteria weights w1 and w3 will be in the first and second position, while the rest three weights w2, w4, and w5 will make combination as follows: w1w3w2w4w5, w1w3w2w5w4, w1w3w4w2w5, w1w3w4w5w2, w1w3w5w2w4, w1w3w5w4w2. Likewise, there will six combinations in each and every sub-group, which means, 24 combinations in each group and overall, there will 120 combinations. It is evident from Table 10 that 104 different weights arrangements out of 120 recommended experiment 5 as the best option, which is adequate to conclude that Exp. 5 is the best choice within the community of nine alternatives. More specifically, 86.67% of the test is in favor of experiment 5. However, it is very difficult to infer the worst alternative from such figures in Table 10, since 26 tests suggest experiment 7 as the worst option, whereas 34 tests imply experiment 1 as the worst choice. Although a greater number of tests show experiment 1 to be the worst alternative, some of them even award experiment first, second, third, fourth, or fifth position. Also, experiment 1 was considered to be the best by two study tests as can be seen in Table 10. Table 10 also shows that, in comparison to the last position, experiment 1 is often moved to better positions such as first, third, fourth, fifth, etc. through a variety of trials. At the other side, if focus is given to experiment 7, it can be observed that the most highest position achieved by experiment 7 is fifth among these 120 trial combinations. As a consequence, it may be inferred that experiment 1 is marginally stronger than experiment 7 if judgment is made on the overall basis. So, it is better to stick to the final result provided by Borda voting rule shown in Table 8. Therefore, the final ranking of the alternatives can be proposed as follows.

Exp. 5 > Exp. 6 > Exp. 3 > Exp. 8 > Exp. 2 > Exp. 9 > Exp. 4 > Exp. 1 > Exp. 7

This green EDM parameter selection problem is solved by several researchers in the past using number of optimization techniques for example Taguchi embedded with fuzzy-TOPSIS, entropy-GRA, combination of gray relational analysis (GRA) with principle component analysis (PCA), Taguchi-VIKOR model etc. The earlier proposed rankings are displayed in Table 11 and Figure 5 shows the graphical comparisons of the previous results with the present analysis. The alterations in the final ranking for 120 different weight combinations are also demonstrated graphically in Figure 6.

It is evident from Table 11 that all the analysis performed by the previous researchers recommended experiment 5 had the optimum machining parameters among the nine alternative experiments and the outcome from this present analysis correlates precisely with the past findings. The proposed methodology is therefore validated and can be used for optimization problems dealing with green manufacturing. However, the ranking orders suggested by different researchers are different, but the alternative ranking obtained from this study is more robust because there is a good Spearman rank correlation between the final ranking and the other MCDM techniques shown in Table 9.

Table 9. Spearman rank correlation co-efficient.

| Source: Author’s own elaboration. | Hybrid model | WSM | WPM | WASPAS | COPRAS | ARAS | PROMETHEE | Final ranking |
|-----------------------------------|--------------|-----|-----|--------|--------|------|-----------|--------------|
| Hybrid model                      |              |     |     |        |        |      |           |              |
| WSM                               | 0.83333      | 0.91667 | 0.88333 | 1 | 0.83333 | 0.91667 | 0.93333 |              |
| WPM                               |              | 0.96667 | 0.98333 | 0.83333 | 1 | 0.8 | 0.95 |              |
| WASPAS                            |              | 0.98333 | 0.91667 | 0.96667 | 0.86667 | 0.98333 |              |
| COPRAS                            |              | 0.88333 | 0.98333 | 0.96667 | 0.85 | 0.96667 |              |
| ARAS                              |              |        |        | 0.83333 | 0.91667 | 0.93333 |              |
| PROMETHEE                         |              |        |        |        | 0.8 | 0.95 |              |
| Final ranking                     |              |        |        |        |        | 0.91667 |              |

Conclusion

The current research proposed a new hybrid MCDM model for solving an EDM process parameters selection problem. An empirical framework for multi-criteria decision-making has been created and ranking were performed on the basis of the criteria weights gained.
### Table 10. Ranking performance test for different weights combination.

|       | Group 1 | Sub-group 12 | Sub-group 13 | Group 1 | Sub-group 14 | Sub-group 15 | Group 2 | Sub-group 21 | Sub-group 23 | Group 3 | Sub-group 31 | Sub-group 32 | Group 3 | Sub-group 34 | Sub-group 35 | Group 4 | Sub-group 41 | Sub-group 42 | Group 4 | Sub-group 43 | Sub-group 45 | Group 5 | Sub-group 51 | Sub-group 52 | Group 5 | Sub-group 53 | Sub-group 54 |
|-------|---------|--------------|--------------|---------|--------------|--------------|---------|--------------|--------------|---------|--------------|--------------|---------|--------------|--------------|---------|--------------|--------------|---------|--------------|--------------|---------|--------------|--------------|
| Exp. 1| 9 9 9 9 9 9 9 3 5 1 7 4 6 | Exp. 1| 8 8 7 9 7 9 9 6 3 4 7 3 7 | Exp. 2| 4 6 5 5 6 4 8 5 9 7 9 9 | Exp. 1| 5 5 4 6 4 6 8 8 6 9 5 9 | Exp. 2| 5 5 4 6 4 6 8 8 6 9 5 9 | Exp. 3| 5 5 6 6 5 5 9 9 6 8 5 8 | Exp. 3| 6 6 3 5 3 5 9 9 5 8 6 8 | Exp. 4| 7 7 7 7 7 7 4 6 4 5 3 4 | Exp. 4| 7 7 6 7 6 7 5 5 3 4 4 5 | Exp. 5| 1 1 1 1 1 1 2 1 1 | Exp. 5| 1 1 2 1 2 1 1 1 1 1 1 1 | Exp. 6| 2 2 3 2 3 2 2 3 3 2 2 2 | Exp. 6| 3 2 1 3 1 3 3 2 2 2 2 3 | Exp. 7| 8 8 8 8 8 8 7 7 6 6 5 7 | Exp. 7| 7 9 9 9 8 9 8 7 7 5 7 6 | Exp. 8| 3 3 2 3 2 3 5 2 8 2 8 3 | Exp. 8| 2 3 5 2 5 2 2 4 8 3 8 2 | Exp. 9| 6 4 4 4 4 4 6 6 4 9 4 9 7 | Exp. 9| 4 4 8 4 8 4 4 6 9 6 9 4 |
| Exp. 2| 8 8 8 8 8 8 8 8 8 8 8 8 | Exp. 2| 7 7 7 7 7 7 7 8 8 8 8 8 | Exp. 2| 7 7 7 7 7 7 7 8 8 8 8 8 | Exp. 2| 2 6 5 5 6 4 6 9 8 8 9 6 | Exp. 3| 9 9 9 9 9 9 9 9 9 9 9 9 | Exp. 3| 9 9 8 8 8 8 9 9 9 9 9 9 | Exp. 4| 5 6 5 5 6 5 4 5 4 5 4 4 | Exp. 4| 5 5 5 6 5 6 5 4 5 4 5 5 | Exp. 5| 1 1 2 1 2 1 1 1 1 | Exp. 5| 2 1 1 1 2 2 1 1 1 1 | Exp. 6| 2 3 4 3 4 2 2 3 2 2 3 2 | Exp. 6| 4 3 2 3 2 4 3 2 2 2 2 4 | Exp. 7| 6 5 6 6 5 6 7 6 6 6 5 7 | Exp. 7| 6 6 6 6 5 6 5 7 6 7 6 7 | Exp. 8| 3 3 1 2 1 3 3 2 3 2 3 3 | Exp. 8| 1 2 3 2 3 1 1 3 3 3 3 3 | Exp. 9| 4 4 3 4 3 4 3 4 5 4 5 4 | Exp. 9| 3 4 4 4 4 3 4 5 4 5 4 3 | Group 4 | Sub-group 41 | Sub-group 42 | Group 4 | Sub-group 43 | Sub-group 45 | Group 5 | Sub-group 51 | Sub-group 52 | Group 5 | Sub-group 53 | Sub-group 54 |
| Exp. 3| 8 8 8 8 8 8 8 8 8 8 8 8 | Exp. 3| 6 5 6 6 5 6 4 5 6 5 | Exp. 3| 5 5 5 5 5 5 5 5 4 3 | Exp. 3| 1 5 6 6 5 1 4 8 7 7 8 4 | Exp. 4| 8 8 6 6 5 7 7 7 7 7 7 7 | Exp. 4| 7 7 8 8 7 6 5 4 5 5 4 5 | Exp. 5| 1 1 1 1 1 1 1 1 1 1 | Exp. 5| 4 1 1 1 1 3 1 1 1 1 1 | Exp. 6| 2 2 2 2 2 2 2 2 2 2 2 2 | Exp. 6| 3 2 2 2 2 2 2 2 2 2 2 2 | Exp. 7| 9 9 9 8 8 8 9 9 8 8 8 8 | Exp. 7| 9 8 9 9 8 9 7 7 9 9 7 7 | Exp. 8| 3 3 7 3 6 3 5 3 3 3 3 3 | Exp. 8| 5 3 3 3 3 5 8 3 3 4 3 8 | Exp. 9| 6 4 8 4 9 5 6 4 6 4 6 6 | Exp. 9| 8 4 4 4 4 8 9 6 6 6 5 9 | Group 4 | Sub-group 41 | Sub-group 42 | Group 4 | Sub-group 43 | Sub-group 45 | Group 5 | Sub-group 51 | Sub-group 52 | Group 5 | Sub-group 53 | Sub-group 54 |
| Exp. 4| 6 6 7 8 7 8 9 9 9 9 9 9 | Exp. 4| 6 9 7 9 7 9 7 3 5 4 3 6 3 | Exp. 5| 1 1 2 1 2 1 1 1 1 | Exp. 5| 1 1 1 1 1 1 1 1 1 1 1 1 | Exp. 6| 3 3 1 3 1 3 3 2 2 2 2 3 | Exp. 6| 2 3 2 3 2 2 2 2 2 2 2 2 | Exp. 7| 8 8 8 6 9 6 8 8 8 8 8 8 | Exp. 7| 6 6 7 7 6 5 7 6 7 7 6 6 | Exp. 8| 2 2 6 2 6 2 2 3 3 3 3 2 | Exp. 8| 8 2 3 2 3 8 8 2 3 2 3 8 | Exp. 9| 4 4 9 4 8 4 4 4 4 4 4 | Exp. 9| 9 4 6 4 5 9 9 4 5 4 4 9 | Group 5 | Sub-group 51 | Sub-group 52 | Group 5 | Sub-group 53 | Sub-group 54 | Group 5 | Sub-group 51 | Sub-group 52 | Group 5 | Sub-group 53 | Sub-group 54 |

Source: Author's own elaboration.
from entropy method. From this whole analysis, it can be concluded that Exp. No. 5 is the best choice and its respective input parameters that is 261 µs pulse duration, 0.3 kg/cm² flushing pressure, 4.5 A current, and 80 mm dielectric level 4.5 are the optimum machining values while machining high carbon chromium tool steel plate for the green EDM process. It can also be concluded that the findings of the newly established COPRAS-ARAS hybrid MCDM model is very true and reliable, which is also confirmed by other MCDM methods and sensitivity analysis. As a consequence, this hybrid model has the potential to solve MCDM problems and its development will make a major impact to the decision-making field.

**Limitation**

MCDM issues are strongly contingent on the weighting parameters and, if any adjustments have arisen in the weights, the production outcomes may be changed as already observed during sensitivity analysis operation. Many related objective weighted approaches, such as CRITIC, MEREC may also produce specific parameters weights that eventually alter the final ranking. In addition to these, the use of subjective weighting tools such as AHP, BWM, SWARA may contribute biased judgments, as such approaches include a relative matrix of comparison among the parameters that are entirely based on the opinion of the decision-maker and thus rely on the estimation and judgment of the decision-maker.

**Future scope**

Such research can be further expanded in the future by incorporating other MCDM methods such as VIKOR, MABAC, CODAS, MACBETH, ELECTRE, etc. by including greater number of parameters and alternatives to make the selection process more efficient and reliable, while at the same time, the findings can also be

---

**Table 11. Comparisons of different proposed rankings.**

| Exp. No. | Present ranking | Combined Taguchi and FTOPSIS | Entropy-GRA | Combined GRA and PCA | Taguchi-VIKOR |
|----------|-----------------|-------------------------------|-------------|----------------------|---------------|
| Exp. 1   | 8               | 5                             | 5           | 5                    | 6             |
| Exp. 2   | 5               | 9                             | 7           | 9                    | 9             |
| Exp. 3   | 3               | 8                             | 6           | 8                    | 8             |
| Exp. 4   | 7               | 3                             | 8           | 6                    | 5             |
| Exp. 5   | 1               | 1                             | 1           | 1                    | 1             |
| Exp. 6   | 2               | 2                             | 3           | 3                    | 2             |
| Exp. 7   | 9               | 6                             | 9           | 7                    | 7             |
| Exp. 8   | 4               | 4                             | 2           | 2                    | 3             |
| Exp. 9   | 6               | 7                             | 4           | 4                    | 4             |

Source: Sivapirakasam et al. (2011), Yadav and Patel (2013), Jagdish and Ray (2015, 2016).

---

**Figure 5.** Graphical representation of various researcher’s proposed rankings.

Source: Author’s own elaboration; Created using Microsoft word 2010 chart option.
correlated with the present outcomes. Other MCDM methods can also be combined together to create several different hybrid versions. Eventually, this recently established COPRAS-ARAS hybrid paradigm can also be used to render successful decisions in a broad variety of sectors, such as finance, health and education, transport and logistics, etc., that may confirm their decision-making ability in certain fields.

Declaration of conflicting interests
The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding
The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: The authors extend their appreciation to the Deanship of Scientific Research at King Khalid University, Saudi Arabia for funding this work through Research Group Program under Grant No: R.G.P.2/248/43. The author B. Saleh is grateful to the Taif University Researchers Supporting Project number (TURSP-2020/49), Taif University, Taif, Saudi Arabia for the financial support.

ORCID iD
Abdul Razak https://orcid.org/0000-0001-7985-2502

Data availability statement
The relevant data are already present in the article.

References
1. Sivapirakasam SP, Mathew J and Surianarayanan M. Multi-attribute decision making for green electrical discharge machining. Expert Syst Appl 2011; 38: 8370–8374.
2. Zavadskas EK and Turskis Z. Multiple Criteria Decision Making (MCDM) methods in Economics: an overview / Daugiaiaksliai Sprendimų priėmimo Metodai Ekonomikoje: Apžvalga. Technol Econ Dev Econ 2011; 17: 397–427.

3. Karmaker CL and Saha M. Teachers’ recruitment process via MCDM methods: a case study in Bangladesh. Manage Sci Lett 2015; 5: 749–766.

4. Stević Z, Pamučar D, Puška A, et al. Sustainable supplier selection in healthcare industries using a new MCDM method: measurement of alternatives and ranking according to compromise solution (MARCOS). Comput Ind Eng 2020; 140: 106231.

5. Adali EA and Isik AT. Air conditioner selection problem with COPRAS and ARAS methods. Manaw J Soc Stud 2016; 5: 124–138.

6. Goswami SS. Outranking methods: Promethee I and Promethee II. Found Manage 2020; 12: 93–110.

7. Karande P, Zavadskas EK and Chakraborty S. A study on the ranking performance of some MCDM methods for industrial robot selection problems. Int J Ind Eng Comput 2016; 7: 399–422.

8. Chakraborty S and Zavadskas EK. Applications of WASPAS method in manufacturing decision making. Informatica 2014; 25: 1–20.

9. Rao RV. Decision making in the manufacturing environment: using graph theory and fuzzy multiple attribute decision making methods. 3rd ed. London: Springer, 2007. https://www.springer.com/gp/book/9781846288180 (accessed 15 March 2022).

10. Goswami SS, Behera DK, Afzal A, et al. Analysis of a robot selection problem using two newly developed hybrid MCDM models of TOPSIS-ARAS and COPRAS-ARAS. Symmetry 2021; 13: 1331.

11. Jagadish and Ray A. Optimization of process parameters of green electrical discharge machining using principal component analysis (PCA). Int J Adv Manuf Technol 2016; 87: 1299–1311.

12. Pfleuger B. Familiar with your EDM fluid: Fluid choice and maintenance affect part quality, reduce DC arcing. Canadian Metal Working, 2013. https://www.canadianmetalworking.com/canadianindustrialmachinery/article/metal working/familiar-with-your-edm-fluid (accessed 10 September 2020).

13. Yeo SH, Tan HC and New AK. Assessment of waste streams in electric-discharge machining for environmental impact analysis. Proc IMechE, Part B: J Engineering Manufacture 1998; 212: 393–401.

14. Chakraborty S and Banik D. Design of a material handling equipment selection model using analytic hierarchy process. Int J Adv Manuf Technol 2006; 28: 1237–1245.

15. Banerjee K, Bairagi B and Sarkar B. Multiple criteria analysis based robot selection for material handling: A de novo approach. In: Castillo O, Jana D, Giri D, et al. (eds) Recent advances in intelligent information systems and applied mathematics, studies in computational intelligence, international conference on information technology and applied mathematics. Cham: Springer, 2020, pp.538–548.

16. Martin N and Deepak FX. Application of new additive ratio assessment (NARAS) method in selection of material for optimal design of engineering components. Mater Today Proc 2019; 11: 1049–1053.

17. Goswami SS and Behera DK. Implementation of ENTROPY-ARAS decision making methodology in the selection of best engineering materials. Mater Today Proc 2021; 38: 2256–2262.

18. Singaravel B, Shankar DP and Prasanna L. Application of MCDM method for the selection of optimum process parameters in turning process. Mater Today Proc 2018; 5: 13464–13471.

19. Kumar A, Hussain SAI and Rai RN. Optimization by AHP-ARAS of EDM process parameters on machining AA7050-10%B4C composite. In: Shanker K, Shankar R and Sindhwani R (eds) Advances in industrial and production engineering, Lecture Notes in Mechanical Engineering. Singapore: Springer, 2019, pp.285–296.

20. Prasad K and Chakraborty S. Application of the modified similarity-based method for cutting fluid selection. Decis Sci Lett 2018; 7: 273–286.

21. Zavadskas EK and Turskis Z. A new additive ratio assessment (ARAS) method in multicriteria decision-making. Technol Econ Dev Econ 2010; 16: 159–172.

22. Zavadskas EK, Kaklauskas A and Kvederytė N. Multivariate design and multiple criteria analysis of building life cycle. Informatica 2001; 12: 169–188.

23. Jagadish and Ray A. Multi-objective optimization of Green EDM: an integrated theory. J Inst Eng (India) Ser C 2015; 96: 41–47.

24. Thirumalai R and Senthilkumar JS. Multi-criteria decision making in the selection of machining parameters for Inconel 718. J Mech Sci Technol 2013; 27: 1109–1116.

25. Parida AK and Routara BC. Multiresponse optimization of process parameters in turning of GFRP using TOPSIS method. Int Sch Res Notices 2014; 2014: 905828.

26. Wang X, Chen L, Dan B, et al. Evaluation of EDM process for green manufacturing. Int J Adv Manuf Technol 2018; 94: 633–641.

27. Singaravel B and Selvaraj T. Optimization of machining parameters in turning operation using combined TOPSIS and AHP method. Tech Gazet 2015; 22: 1475–1480.

28. Khan A and Maity K. A novel MCDM approach for simultaneous optimization of some correlated machining parameters in turning of CP-titanium grade 2. Int J Eng Res Afr 2016; 22: 94–111.

29. Meena VK, Azad MS, Singh S, et al. Micro-EDM multiple parameter optimization for Cp titanium. Int J Adv Manuf Technol 2017; 89: 897–904.

30. Modanloo V, Doniavi A and Hasanzadeh R. Application of multi criteria decision making methods to select sheet hydroforming process parameters. Decis Sci Lett 2016; 5: 349–360.

31. Saha A and Majumder H. Multi criteria selection of optimal machining parameter in turning operation using comprehensive grey complex proportional assessment method for ASTM A36. Int J Eng Res Afr 2016; 23: 24–32.

32. Das PP and Chakraborty S. Parametric analysis of a green electrical discharge machining process using DEMATEL and SIR methods. OPSEARCH 2020; 57: 513–540.

33. Prakash DB and Krishnaiah G. Optimization of process parameters using AHP and VIKOR when turning AISI 1040 steel with coated tools. Int J Mech Eng Technol 2017; 8: 241–248.
34. Balasubramaniyan S and Selvaraj T. Application of integrated Taguchi and TOPSIS method for optimization of process parameters for dimensional accuracy in turning of EN25 steel. J Chin Inst Eng 2017; 40: 267–274.
35. Tang L and Du YT. Experimental study on green electrical discharge machining in tap water of Ti–6Al–4V and parameters optimization. Int J Adv Manuf Technol 2014; 70: 469–475.
36. Majumder H and Saha A. Application of MCDM based hybrid optimization tool during turning of ASTM A588. Decis Sci Lett 2018; 7: 143–156.
37. Mohapatra KD and Sahoo SK. A multi objective optimization of gear cutting in WEDM of Inconel 718 using TOPSIS method. Decis Sci Lett 2018; 7: 157–170.
38. Pathapalli VR, Basam VR, Gudimetta SK, et al. Optimization of machining parameters using WASPAS and MOORA. World J Eng 2019; 17: 237–246.
39. Sharma V, Misra JP and Singhal P. Optimization of process parameters on combustor material using Taguchi & MCDM method in electro-discharge machining (EDM). Mater Today Proc 2019; 18: 2672–2678.
40. Temuçin T, Tozan H, Vayyay, et al. A fuzzy based decision model for nontraditional machining process selection. Int J Adv Manuf Technol 2014; 70: 2275–2282.
41. Tang L and Guo XF. Electrical discharge precision machining parameters optimization investigation on S-03 special stainless steel. Int J Adv Manuf Technol 2014; 70: 1369–1376.
42. Sharsar R, Ghosh S, Mandal MC, et al. Optimum experimental setup of EDM using entropy coupled MCDM techniques. In: Tyagi M, Sachdeva A and Sharma V (eds) Optimization Methods in engineering, Lecture Notes on Multidisciplinary Industrial Engineering. Singapore: Springer, 2020, pp. 549–566.
43. Yazdani M, Zarate P, Kazimieras Zavadskas E, et al. A combined compromise solution (CoCoSo) method for multi-criteria decision-making problems. Manage Decis 2019; 57: 2501–2519.
44. Zavadskas EK, Zakarevicius A and Antucheviciene J. Evaluation of ranking accuracy in multicriteria decisions. Inform 2006; 17: 601–618.
45. Yadav SK and Patel SK. Optimization of green electro-discharge machining using VIKOR. MTech Theses, Department of Mechanical Engineering, National Institute of Technology Rourkela, India, 2013. http://ethesis.nitrk.ac.in/5445/1/211ME2203.pdf
46. Afzal A, Aabid A, Khan A, et al. Response surface analysis, clustering, and random forest regression of pressure in suddenly expanded high-speed aerodynamic flows. Aerosp Sci Technol 2020; 107: 106318.
47. Fayaz H, Afzal A, Mohammed Samee AD, et al. Optimization of Thermal and Structural Design in Lithium - Ion Batteries to Obtain energy efficient battery thermal management system ( BTMS ): a critical review. Arch Comput Methods Eng 2022; 29: 129–194.
48. Samuel OD, Okwu MO, Oyejide OJ, et al. Optimizing Biodiesel production from abundant waste oils through empirical method and Grey Wolf Optimizer. Fuel 2020; 281: 118701.
49. Samuel OD, Adekojo Waheed M, Taheri-Garavand A, et al. Prandtl number of optimum biodiesel from food industrial waste oil and diesel fuel blend for diesel engine. Fuel 2021; 285: 119049.
50. Afzal A, Samee ADM, Jilte RD, et al. Battery thermal management: an optimization Study of parallelized conjugate numerical analysis using cuckoo search and artificial bee colony algorithm. Int J Heat Mass Transf 2021; 166: 120798.
51. Afzal A. Optimization of thermal management in modern electric vehicle battery cells employing genetic algorithm. J Heat Transf 2021; 143: 1–12.
52. Afzal A, Khan SA and Ahamed Saleel C. Role of ultrasonication duration and surfactant on characteristics of ZnO and CuO nanofluids. Mater Res Express 2019; 6: 1150d8.
53. Afzal A, Mokashi I, Khan SA, et al. Optimization and analysis of maximum temperature in a battery pack affected by low to high Prandtl number coolants using response surface methodology and particle swarm optimization algorithm. Numer Heat Transf A Appl 2021; 79: 406–435.
54. Chandrashekar A, Chaluvuraju BV, Afzal A, et al. Mechanical and corrosion studies of friction stir welded nano Al2O3 reinforced Al-Mg matrix composites: RSM-ANN Modelling Approach. Symmetry 2021; 13: 537.
55. Samylingam L, Asfiattahi N, Sa'dur R, et al. Solar energy materials and solar cells thermal and energy performance improvement of hybrid PV/T system by using olein palm oil with mxene as a new class of heat transfer fluid. Sol Energy Mater Sol Cells 2020; 218: 110754.
56. Zayer Kabeh K and Haghjigh Khoshkho R. Economic feasibility of small-scale gas to liquid technology in reducing flaring in Iran and case study of implementing the technology at the third South pars refinery. Energy Equip Syst 2021; 9: 317–330.
57. Arabhaighighi A and Moghimi M. Thermo-economic analysis and optimization of a novel combination of the solar tower power plant, stirling engine, reverse osmosis desalination, and proton exchange membrane electrolyzer. Energy Equip Syst 2021; 9: 331–349.
58. Hajabdollahi M, Shafiey Dehaj M and Hajabdollahi H. Investigation of optimization algorithms and their operating parameters in different types of heat exchangers. Energy Equip Syst 2021; 9: 351–370.
59. Shadidi B and Najafi G. Impact of covid-19 on biofuels global market and their utilization necessity during pandemic. Energy Equip Syst 2021; 9: 371–382.
60. Dehghanzadeh Baghfi M, Sefid M, Shamsoddini R, et al. Investigation of the effect of Debye length change on electroosmotic flow with using constant density weakly compressible smoothed particle hydrodynamics method. Energy Equip Syst 2021; 9: 383–395.