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PARAMETRIC OPTIMIZATION OF ABRASIVE WATER JET MACHINING PROCESS USING COPRAS AND VIKOR METHODS

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Abstract:

Abrasive Waterjet Machining (AWJM) is one of the widely used non-traditional machining process to cut the hard materials like aluminium metal matrix composites (AMMCs) and the materials which are very difficult to machine using conventional machining due to their high hardness and tendency to cause tool wear. Present work two popular multi criteria decision making (MCDM) techniques Complex Proportional Assessment (COPRAS) AND VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) Methods have been used to optimize the AWJM machining process

parameters for the machining of AMMCs. Both equal weight and standard deviation methods are used to find the weight of three response parameters like material removal rate, surface roughness and kerf width. From the results it is observed that there is a strong correlation between the weight calculation and the MCDM techniques which shows the robustness of the techniques. It is also noticed that machining with highest traverse speed and with out silicon carbide (SiC) is giving good response paramètres. However machining with low traverse speed is giving worst response parameters.

Key Word: AWJM, MCDM, COPRAS, VIKOR

1 INTRODUCTION

Machining is the use of power tools to remove extra material from a workpiece. There are different kinds of machining like turning, milling, facing, and grinding. Various factors such as the speed of work completion, amount of material removed, the size of the tool you use, and the angle of the tool are really important to get the desired results [Ghadai 2024]. An inventive and adaptable non-traditional machining technique, abrasive water jet machining (AWJM) is well-known for its remarkable precision and low heat effects while cutting, shaping, and processing a variety of materials [Cárach 2018]. Controlling the quality of the machining is one of the major challenges in AWJM [Valicek 2009]. When dealing with difficult-to-machine or composite materials, AWJM is a better option than traditional machining methods since it uses a high-pressure water jet combined with abrasive particles [Srivastava 2017, Ghadai 2024]. The roughness/waviness are one of the important factor while machining through AWJM [Valicek 2007]. Reduced heat-affected zones, improved surface smoothness, and less mechanical stress on workpieces are among of its operating benefits, which make it perfect for intricate cutting jobs in sectors like

automotive and aerospace. However, in order to effectively utilize AWJM's capabilities, it is essential to comprehend and adjust process parameters including traverse speed, abrasive flow rate, jet pressure, and standoff distance. The interaction of these variables and the various performance standards required to assess the efficiency of the machining process, including surface roughness, material removal rate, and kerf width, can make the optimization process complicated. Multi-Criteria Decision-Making (MCDM) approaches are invaluable in this situation. Making better decisions in manufacturing processes is made possible by MCDM approaches, which allow for the systematic examination and optimization of several, frequently incompatible criteria [Mondal 2024]. VIKOR and COPRAS have become well-known among MCDM approaches because of their strong frameworks for managing trade-offs between qualitative and quantitative criteria. When dealing with situations involving conflicting objectives, the VIKOR method—which is well-known for emphasizing the importance of ranking and choosing among a range of alternatives based on proximity to the optimal solution—works especially well. It helps reach a compromise solution that strikes a balance between several performance metrics and concentrates on reducing the

decision-maker's regret. The COPRAS (Complex Proportional Assessment) approach, on the other hand, is a useful tool for thorough analysis and prioritizing of many possibilities since it ranks alternatives by assessing the relative importance of each criterion and proportionally comparing them. Both approaches are notable for their ability to combine subjective preferences with performance criteria that can be tested objectively, providing important information about how to choose the best process parameters in AWJM. Perec et al. studied the optimization of steel machining with AWJM using combinative distance-based assessment (CODAS) adjusting cutting parameters like pump pressure, flow rate of abrasive, and feed rate to improve depth of cutting and surface quality in terms of roughness, initially determined by the entropy weight method (EWM) to simplify multiple responses into a single one [Parec 2023]. Kalita et al. examined how multi-criteria decision making (MCDM) techniques optimize unconventional machining (UCM) processes like electro discharge machining (EDM) and electrochemical machining (ECM) highlighting the need for precision in UCM, which requires capital-intensive optimization, and suggests future directions for enhancing MCDM tools for practical solutions [Kalita 2023]. Sahoo et al. studied the importance of multi-criteria decision making (MCDM) and recent advancements in techniques like multi-objective methods and fuzzy-based approaches exploring diverse applications across various domains and identifying emerging trends and challenges in MCDM research, providing valuable insights for decision-makers and researchers [Sahoo 2023]. By including the VIKOR and COPRAS techniques into the analysis of AWJM, producers can more efficiently assess and improve their machining tactics. By using these strategies, it is feasible to prioritize process factors and modify the machining procedure to meet particular production objectives, such as speed, accuracy, or cost-effectiveness. By contrasting the advantages and approaches of VIKOR and COPRAS, this paper investigates the use of MCDM strategies to maximize AWJM. This work aims to demonstrate how these MCDM tools can support well-informed decision-making, resulting in increased productivity and quality in advanced manufacturing techniques, using empirical data and in-depth analysis. For academics and practitioners wishing to incorporate state-of-the-art MCDM techniques into their machining processes, the comparative approach offers a thorough guide that helps them understand which methodology would be more appropriate in particular situations. The continued relevance of MCDM processes underscores their indispensable role in shaping the future direction of the machining industry [Das 2024, Taherdeost 2023, Büyükožkan 2024]. In our present study, two different MCDM techniques have been applied over experimental dataset to optimize the process parameters of AWJM method.

2. METHODOLOGY

The present research utilizes experimental data sourced from the past experimental work carried out by K. Gowthama et al. in which Aluminium metal matrix composites with matrix AA6026 incorporated with 20-30µm sized Silicon Carbide (SiC) particles as reinforcements through stir casting method were machined using AWJM technique

[Gowthama 2023]. The input parameters used for optimization are provided in the subsequent table for reference:

2.1. VIKOR Method:

Vlsekriterijumska Optimizacija I Kompromisno Resenje (VIKOR) technique was initially coined by Opricovic in 1998 for multi-criteria optimization of complex systems. [Opricovic 1998]. It is an optimization technique that firstly calculates a positive ideal solution (PIS) and a negative ideal solution. Selecting the best solution involves measuring how closely each option's evaluation score aligns with the Positive Ideal Solution (PIS), ensuring that the benefits are satisfactory and the decision-making process is consistent. According to Mardani and colleagues, the VIKOR method typically yields a solution that represents a middle ground, closely approximating the ideal solution [Mardani 2016]. This approach, facilitated by the VIKOR algorithm, achieves a balanced solution acceptable to decision-makers by optimizing collective advantages while reducing personal drawbacks creating an algorithm close to the ideal solution.

Step 1: decision matrix Formulation.

Step 2: Calculating best f_i^+ , f_i^- and worst values.

Step 3: Calculation of S_i and R_i data using below mwntioned equations formulae:

$$S_j = \sum_{i=1}^n w_i \frac{f_i^+ - f_{ij}}{f_i^+ - f_i^-} \quad (1)$$

$$R_i = \max_i [w_i \frac{f_i^+ - f_{ij}}{f_i^+ - f_i^-}] \quad (2)$$

Where, w_i indicates weight allotted for each criterion.

Step 4: Calculation of Q_i

$$Q_i = v \left[\frac{S_i - (S_i)_{\min}}{(S_i)_{\max} - (S_i)_{\min}} \right] - (1 - v) \left[\frac{R_i - (R_i)_{\min}}{(R_i)_{\max} - (R_i)_{\min}} \right] \quad (3)$$

Step 5: Ranking is done as per ascending order of Q_i .

2.2. COPRAS Method:

Complex Proportional Assessment (COPRAS) is a widely used MCDM method developed by Zavadskas and group [Zavadskas 2017]. It aids in ranking alternatives based on various criteria while considering associated criteria weights and the utility degree of alternatives. COPRAS determines the best alternative by comparing ideal and anti-ideal solution assuming a direct solution, and proportional relationship between criteria importance, utility degree, and alternative evaluation. COPRAS offers several advantages over other MCDM methods such as EVAMIX, TOPSIS, VIKOR, and AHP. It requires less computational time, boasts a transparent computation process, and seamlessly integrates cost and benefit type criteria within a single evaluation process. Moreover, COPRAS can be easily adapted to different decision problems [Kang 2023, Erdebilli 2023]. One notable advantage of COPRAS is its consideration of the utility degree, which quantifies the superiority or inferiority of alternatives compared to others.

This information aids decision-makers in making informed choices. Recent studies have shown that COPRAS outperforms TOPSIS and Simple Additive Weighting in terms of efficiency and bias reduction. However, conventional COPRAS has limitations. It relies on criteria weights and alternative ratings provided by a limited number of decision-makers, leading to vagueness and imprecision in real-life scenarios [Chakraborty 2024]. Additionally, it does not incorporate randomness features, and criteria weighting is not part of the procedure. Increasing the number of experts can improve the evaluation process's performance.

Step 1: Setup the criteria evolution matrix of alternatives

The evaluation is denoted as x_{kj} . x_{kj} forms criteria evaluation matrix X given in Eq 1

$$[X] = \begin{matrix} DM_2 \\ \vdots \\ DM_1 \end{matrix} \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{11} & x_{12} & \dots & x_{1n} \end{bmatrix} \quad (4)$$

Step 2: In COPRAS involves normalizing the decision matrix to convert performance values into dimensionless, comparable values. The formula utilized for normalization is as follows:

$$n_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}} \quad (5)$$

Step 3: Computes the weighted normalized decision matrix by multiplying each normalized decision matrix element by the weight that corresponds to it (w_j).

$$D = [d_{ij}]; d_{ij} = n_{ij} \times w_j \quad (6)$$

Step 4: Involves categorizing each alternative based on whether it minimizes the (S_-) index or maximizes the S_+ index, utilizing specific formulas.

$$S_+ = \sum_{j=1}^k d_{ij} \quad (7)$$

$$S_- = \sum_{j=k+1}^n d_{ij} \quad (8)$$

Step 5: Entails calculating the relative weight (Q_i) of the i_{th} alternative using the following method:

Step 6. The values of the alternatives are arranged in descending order of (Q_i) to determine their priority order. The option deemed most acceptable is the one with the largest relative weight.

$$Q_i = S_+ + \frac{\min(S_-) \sum_{i=1}^m S_-}{S_- \sum_{i=1}^m \frac{\min(S_-)}{S_-}} \quad (9)$$

2.3 Weight Allocation of Responses

The selection of process parameters in MCDM is significantly influenced by the weight allocation. To offer the ranking of options, MCDM techniques can be used with a variety of weight allocation strategies. Three distinct weight allocations—mean weight, standard deviation, and entropy—are taken into consideration in this instance in order to determine the ranking.

2.3.1 Mean weight (MW) method

All of the replies (MRR, Ra, and Ka) are given identical weight in this manner, so $W_{MRR} = 0.333$, $W_{Ra} = 0.333$, and $W_{Ka} = 0.333$. The majority of earlier studies used this simplest method for allocating criteria weights, mostly to minimize computational work.

2.3.2 Standard deviation (SDV) method

This approach minimizes personal bias in the decision-making process while impartially allocating weight to each criterion, greatly increasing the accuracy of the MCDM approaches' solutions. In this method, the criteria weights are calculated after the data in the initial decision matrix has been normalized..

$$n_{ij}'' = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})} \quad (10)$$

$$SDV_j = \sqrt{\frac{\sum_{i=1}^m (n_{ij}'' - n_j'')^2}{m}} \quad (j=1,2,\dots,n) \quad (11)$$

where n_j'' indicates average normalized values for j^{th} criterion.

$$w_j = \frac{SDV_j}{\sum_{j=1}^n SDV_j} \quad (12)$$

Based on above mentioned formulations and experimental dataset taken from Gowthama et al. [17], weights of the responses considered here are estimated as $W_{MRR} = 0.40332$, $W_{Ra} = 0.3179$ and $W_{Ka} = 0.2788$.

3. Results and Discussion

The response of the experimental data for AWJ machining is taken to be the decision matrix for the MCDM problem. MCDM techniques namely, COPRAS and VIKOR methods are used for both equal weightage and standard deviation method to calculate the rankings of the given problem set. The methodology of each of these techniques was strictly followed to ensure proper results. Firstly, a decision matrix table is created with three criteria, Surface Roughness (Ra) (μm), Material Removal Rate (MRR) (mm^3/min) and Kerf width (Ka) (degree), where Surface Roughness and Kerf width are to be minimized (cost criteria) and Material Removal Rate is to be maximized (beneficial criteria). After this the normalized decision matrix is made to ensure performance values are conformed to the same standard. For mean weight method, significance of each criterion is the same whereas for standard deviation method the weightage values for COPRAS

and VIKOR methods was calculated to be 0.3179 and 0.2788 respectively, with Material Removal Rate having the highest weightage and Kerf width having the least weightage. The second step in any MCDM method is to create a normalized matrix to give each criteria a similar significance. Next, their weighted normalized matrix is created by factoring in the weight of each criteria. Upon conducting the MCDM methods on the data, their COPRAS analysis. Among the process parameters it has been observed that transverse speed (S) had the most visibility on the rankings of the parameters with trial no. 8, 7 and 9 having the highest consecutive rankings. The better rankings were achieved for transverse speed as 150 mm/min. It was also observed that the weight percentage of the input parameters parameters like stand-off distance (D) and SiC particulates (F) had lesser visibility comparatively on the rankings.

Table 1. Calculation of Performance index from weighted normalized values for equal weightage

| Trial | Ra | MRR | Ka | Si+ | Si- | 1/Si- | Qi | Pi |
|-------|----------|----------|----------|----------|----------|----------|----------|----------|
| 1 | 0.012539 | 0.002886 | 0.012957 | 0.002886 | 0.025496 | 0.930986 | 0.026788 | 0.525886 |
| 2 | 0.011597 | 0.002886 | 0.012384 | 0.002886 | 0.023981 | 0.989783 | 0.028297 | 0.555521 |
| 3 | 0.012606 | 0.002886 | 0.012843 | 0.002886 | 0.025448 | 0.932721 | 0.026832 | 0.52676 |
| 4 | 0.012505 | 0.011545 | 0.012843 | 0.011545 | 0.025348 | 0.936432 | 0.035587 | 0.698618 |
| 5 | 0.01153 | 0.011545 | 0.012613 | 0.011545 | 0.024143 | 0.983138 | 0.036786 | 0.722158 |
| 6 | 0.01264 | 0.011545 | 0.012843 | 0.011545 | 0.025482 | 0.931491 | 0.03546 | 0.696128 |
| 7 | 0.011967 | 0.025976 | 0.012613 | 0.025976 | 0.02458 | 0.965659 | 0.050768 | 0.996649 |
| 8 | 0.011799 | 0.025976 | 0.012613 | 0.025976 | 0.024412 | 0.972308 | 0.050938 | 1 |
| 9 | 0.012135 | 0.025976 | 0.012613 | 0.025976 | 0.024749 | 0.959101 | 0.050599 | 0.993344 |
| 10 | 0.012438 | 0.010582 | 0.012613 | 0.010582 | 0.025051 | 0.947518 | 0.034909 | 0.68531 |
| 11 | 0.011564 | 0.010582 | 0.012269 | 0.010582 | 0.023833 | 0.995941 | 0.036152 | 0.709716 |
| 12 | 0.012505 | 0.010582 | 0.012613 | 0.010582 | 0.025118 | 0.944982 | 0.034844 | 0.684032 |
| 13 | 0.012471 | 0.02381 | 0.012384 | 0.02381 | 0.024855 | 0.954979 | 0.048327 | 0.94874 |
| 14 | 0.011967 | 0.02381 | 0.012269 | 0.02381 | 0.024236 | 0.979365 | 0.048953 | 0.961031 |
| 15 | 0.012539 | 0.02381 | 0.012384 | 0.02381 | 0.024923 | 0.952402 | 0.048261 | 0.947442 |
| 16 | 0.01227 | 0.002645 | 0.01204 | 0.002645 | 0.02431 | 0.976416 | 0.027713 | 0.544048 |
| 17 | 0.012203 | 0.002645 | 0.011811 | 0.002645 | 0.024013 | 0.988474 | 0.028023 | 0.550126 |
| 18 | 0.012707 | 0.002645 | 0.01204 | 0.002645 | 0.024747 | 0.959173 | 0.02727 | 0.535358 |
| 19 | 0.012808 | 0.021646 | 0.012613 | 0.021646 | 0.025421 | 0.933735 | 0.045619 | 0.895568 |
| 20 | 0.012438 | 0.021646 | 0.012384 | 0.021646 | 0.024822 | 0.956272 | 0.046197 | 0.906927 |
| 21 | 0.012606 | 0.021646 | 0.012613 | 0.021646 | 0.025219 | 0.941203 | 0.045811 | 0.899332 |
| 22 | 0.012808 | 0.002402 | 0.011811 | 0.002402 | 0.024618 | 0.964179 | 0.027156 | 0.533122 |
| 23 | 0.01227 | 0.002402 | 0.011467 | 0.002402 | 0.023736 | 1 | 0.028076 | 0.551176 |
| 24 | 0.012808 | 0.002402 | 0.011811 | 0.002402 | 0.024618 | 0.964179 | 0.027156 | 0.533122 |
| 25 | 0.012539 | 0.009619 | 0.01204 | 0.009619 | 0.024579 | 0.965732 | 0.034413 | 0.675576 |
| 26 | 0.012371 | 0.009619 | 0.011811 | 0.009619 | 0.024181 | 0.981604 | 0.03482 | 0.683576 |
| 27 | 0.012707 | 0.009619 | 0.01204 | 0.009619 | 0.024747 | 0.959173 | 0.034244 | 0.67227 |

Table 2. Calculation of performance index with standard deviation

| Trial | Qi | Pi |
|-------|----------|----------|
| 1 | 0.024908 | 0.462789 |
| 2 | 0.026285 | 0.488374 |
| 3 | 0.024937 | 0.463344 |
| 4 | 0.035505 | 0.659698 |
| 5 | 0.036626 | 0.680527 |
| 6 | 0.035384 | 0.657447 |
| 7 | 0.053657 | 0.996964 |
| 8 | 0.053821 | 1 |
| 9 | 0.053496 | 0.993971 |
| 10 | 0.034587 | 0.642629 |
| 11 | 0.035734 | 0.663944 |
| 12 | 0.034525 | 0.641475 |
| 13 | 0.050747 | 0.942899 |
| 14 | 0.051331 | 0.953747 |
| 15 | 0.050684 | 0.941728 |
| 16 | 0.025623 | 0.476077 |
| 17 | 0.025889 | 0.481032 |
| 18 | 0.025202 | 0.468251 |
| 19 | 0.047636 | 0.885095 |
| 20 | 0.048162 | 0.894858 |
| 21 | 0.047819 | 0.88849 |
| 22 | 0.025003 | 0.464571 |
| 23 | 0.025834 | 0.48001 |
| 24 | 0.025003 | 0.464571 |
| 25 | 0.0338 | 0.628013 |
| 26 | 0.03416 | 0.634702 |
| 27 | 0.03364 | 0.625038 |

The normalized matrix is calculated for COPRAS method using equation (5). Then the weighted normalized matrix was done using equation (6). The values of S+ and S- were determined by aggregating the elements in the weighted normalized matrix corresponding to the beneficial and the cost criteria as indicated in equation (7) and (8). The relative importance of each alternative was computed using equation, after which the alternatives were ordered based on the descending values of Qi. Now with weightage as 0.3179, 0.4033 and 0.2788 through standard deviation method, and using the same method as done previously, the performance index for standard deviation is calculated in Table (4). It has been observed that for equal weightage, Trial 8 shows the best ranking with values of Ra, MRR and Ka as 3.51, 83.58 and 1.1 respectively as well as for standard deviation.

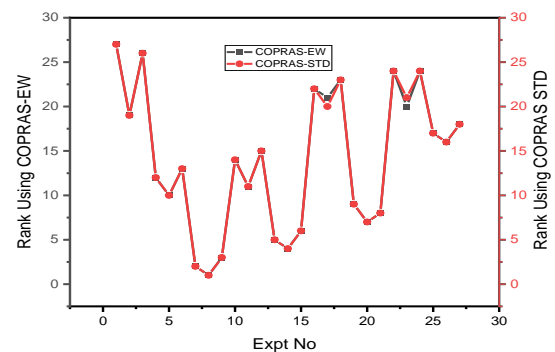


Fig. 1: Rank using COPRAS-EW and COPRAS-STD

3.1. VIKOR Analysis:

Table 3. Weighted normalized matrix using equal weightage.

| Trial | Ra | MRR | Ka | S _j | R _j | Q _j |
|-------|--------|--------|--------|----------------|----------------|----------------|
| 1 | 0.2605 | 0.3232 | 0.3300 | 0.9138 | 0.3300 | 1.0000 |
| 2 | 0.0174 | 0.3232 | 0.2031 | 0.5437 | 0.3232 | 0.6657 |
| 3 | 0.2779 | 0.3232 | 0.3046 | 0.9057 | 0.3232 | 0.9710 |
| 4 | 0.2518 | 0.2020 | 0.3046 | 0.7585 | 0.3046 | 0.7857 |
| 5 | 0.0000 | 0.2020 | 0.2538 | 0.4559 | 0.2538 | 0.3638 |
| 6 | 0.2866 | 0.2020 | 0.3046 | 0.7932 | 0.3046 | 0.8150 |
| 7 | 0.1129 | 0.0000 | 0.2538 | 0.3667 | 0.2538 | 0.2887 |
| 8 | 0.0695 | 0.0000 | 0.2538 | 0.3233 | 0.2538 | 0.2520 |
| 9 | 0.1563 | 0.0000 | 0.2538 | 0.4102 | 0.2538 | 0.3253 |
| 10 | 0.2345 | 0.2155 | 0.2538 | 0.7038 | 0.2538 | 0.5729 |
| 11 | 0.0087 | 0.2155 | 0.1777 | 0.4019 | 0.2155 | 0.1924 |
| 12 | 0.2518 | 0.2155 | 0.2538 | 0.7212 | 0.2538 | 0.5876 |
| 13 | 0.2432 | 0.0303 | 0.2031 | 0.4766 | 0.2432 | 0.3462 |
| 14 | 0.1129 | 0.0303 | 0.1777 | 0.3209 | 0.1777 | 0.0000 |
| 15 | 0.2605 | 0.0303 | 0.2031 | 0.4939 | 0.2605 | 0.4179 |
| 16 | 0.1911 | 0.3266 | 0.1269 | 0.6446 | 0.3266 | 0.7618 |
| 17 | 0.1737 | 0.3266 | 0.0762 | 0.5764 | 0.3266 | 0.7044 |
| 18 | 0.3039 | 0.3266 | 0.1269 | 0.7575 | 0.3266 | 0.8571 |
| 19 | 0.3300 | 0.0606 | 0.2538 | 0.6445 | 0.3300 | 0.7729 |
| 20 | 0.2345 | 0.0606 | 0.2031 | 0.4982 | 0.2345 | 0.3359 |
| 21 | 0.2779 | 0.0606 | 0.2538 | 0.5923 | 0.2779 | 0.5579 |
| 22 | 0.3300 | 0.3300 | 0.0762 | 0.7362 | 0.3300 | 0.8502 |
| 23 | 0.1911 | 0.3300 | 0.0000 | 0.5211 | 0.3300 | 0.6688 |
| 24 | 0.3300 | 0.3300 | 0.0762 | 0.7362 | 0.3300 | 0.8502 |
| 25 | 0.2605 | 0.2290 | 0.1269 | 0.6164 | 0.2605 | 0.5212 |
| 26 | 0.2171 | 0.2290 | 0.0762 | 0.5222 | 0.2290 | 0.3382 |
| 27 | 0.3039 | 0.2290 | 0.1269 | 0.6598 | 0.3039 | 0.7003 |

Table 4. Weighted normalized matrix for standard deviation.

| Trial | Ra | MRR | Ka |
|-------|--------|--------|--------|
| 1 | 0.2510 | 0.3950 | 0.2788 |
| 2 | 0.0167 | 0.3950 | 0.1716 |
| 3 | 0.2677 | 0.3950 | 0.2573 |
| 4 | 0.2426 | 0.2469 | 0.2573 |
| 5 | 0.0000 | 0.2469 | 0.2145 |
| 6 | 0.2761 | 0.2469 | 0.2573 |
| 7 | 0.1088 | 0.0000 | 0.2145 |

| | | | |
|----|--------|--------|--------|
| 8 | 0.0669 | 0.0000 | 0.2145 |
| 9 | 0.1506 | 0.0000 | 0.2145 |
| 10 | 0.2259 | 0.2634 | 0.2145 |
| 11 | 0.0084 | 0.2634 | 0.1501 |
| 12 | 0.2426 | 0.2634 | 0.2145 |
| 13 | 0.2342 | 0.0371 | 0.1716 |
| 14 | 0.1088 | 0.0371 | 0.1501 |
| 15 | 0.2510 | 0.0371 | 0.1716 |
| 16 | 0.1840 | 0.3992 | 0.1072 |
| 17 | 0.1673 | 0.3992 | 0.0643 |
| 18 | 0.2928 | 0.3992 | 0.1072 |
| 19 | 0.3179 | 0.0741 | 0.2145 |
| 20 | 0.2259 | 0.0741 | 0.1716 |
| 21 | 0.2677 | 0.0741 | 0.2145 |
| 22 | 0.3179 | 0.4033 | 0.0643 |
| 23 | 0.1840 | 0.4033 | 0.0000 |
| 24 | 0.3179 | 0.4033 | 0.0643 |
| 25 | 0.2510 | 0.2799 | 0.1072 |
| 26 | 0.2091 | 0.2799 | 0.0643 |
| 27 | 0.2928 | 0.2799 | 0.1072 |

In VIKOR method S_j and R_j values are calculated using formulae (1) and (2) after which Q_j is finally calculated using (3). Finally ranking is done as per ascending order of Q_j . Trial 14 had the highest ranking for both equal weightage and standard deviation methods.

3.2. Ranking of alternatives using COPRAS and VIKOR :

The ranking of all the 27 experiments with respect to the response parameters liketh R_a , MRR and K_a are observed as follows:

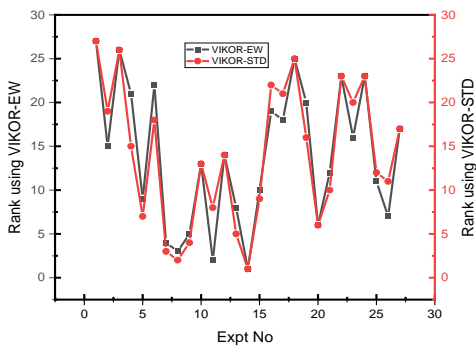


Fig. 2: Rank using VIKOR-EW and VIKOR-STD

3.3. Correlation analysis of MCDM Techniques:

The correlation of rankings of all MCDM techniques for both equal weightage and weighted standard deviation technique was calculated to be as follows:

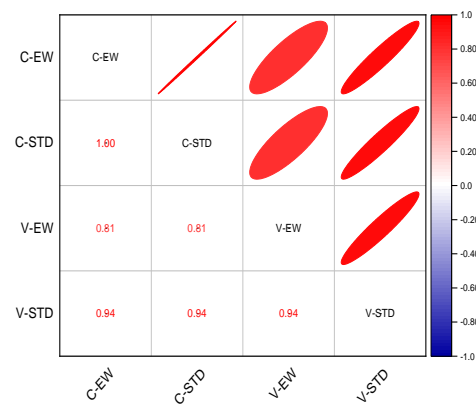


Fig. 3: Correlation analysis of COPRAS and VIKOR methods

4. Conclusion

Present work shows the well compared results between two MCDM and weight calculation techniques. The correlation between COPRAS-VIKOR for equal weight criteria was 0.8133 and for standard deviation method was 0.9420 respectively. The highest correlation achieved was between COPRAS (equal weightage) and COPRAS (standard deviation) with a value of 1. These results shows that there is no major variation of ranking with respect to weight calculation and MCDM techniques, which shows the robustness of the techniques. By using COPRAS MCDM technique expt no 8 shows the best alternatives, however by using VIKOR expt no 14 proved to be the best alternatives. In both 8th and 14th expt the input parameters are same except the SiC particulates. It is also noticed that machining with highest traverse speed and with out silicon carbide (SiC) is giving good response parameters. However, machining with low traverse speed is giving worst response parameters. In future these MCDM techniques can be used to optimize the other machining parameters.

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