# Multi-Criteria Decision Making in the Milling Process Using the PARIS Method

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*Received: 8 July 2022 | Revised: 25 July 2022 | Accepted: 25 July 2022*

**Abstract-The Multi-Criteria Decision-Making (MCDM) process of milling SNCM439 steel is presented in this study. In this experimental study, 3 cutting tool parameters, namely the number of pieces, cutting piece material, and tip radius were considered and 3 cutting mode parameters, i.e. cutting speed, feed rate, and depth of cut changed in each experiment. SR and MRR are selected as the output parameters of the milling process. The PARIS method was used for MCDM, in which, the weights of SR and MRR were determined by 3 methods, namely AW, EW, and MW. Twenty-seven sets of ranking results for 27 alternatives (experiments) are presented. The GINI index was used to evaluate the stability of ranking alternatives. The results have determined the value of 6 input parameters to ensure the minimum SR and the maximum MRR simultaneously.**

***Keywords-MCDM; PARIS; average weight; entropy weight; Merec weight; GINI index; milling***

## I. INTRODUCTION

Milling the plane with a face milling cutter is a machining method that gives the highest productivity of all cutting machining methods, because it has many teeth simultaneously involved in cutting and a tool with a large diameter can be chosen [1-3]. Therefore, this method is increasingly used in machine manufacturing. Thanks to the development of machine tools as well as cutting tool manufacturing technology, the accuracy of this method is increasingly improved. This method is even used instead of grinding when it is necessary to machine surfaces that require high precision. In addition, the residual stress on the surface layer of the part during milling is usually compressive residual stress, whereas the residual stress on the surface layer during grinding is usually tensile residual stress. This is also the advantage of milling over the grinding method. Among many criteria to evaluate the machining process, such as MRR, surface hardness, cutting force, cutting heat, etc., SR and MRR are the two most used parameters in published documents. This can be easily understood because MRR is an important parameter to evaluate cutting productivity, while SR is a parameter that has a great influence on the workability as well as the life of the product. On the other hand, determining the value of SR and MRR is also quite simple, specifically an SR measuring device is quite more popular than a force measuring device or a heat measuring device, and MRR can be calculated from simple math formulas. As with most machining processes, it is desirable to have minimum SR and maximum MRR when milling the plane with a face mill. However, these requirements cannot be achieved simultaneously with each specific machining condition. Some examples to support this statement follow. In [4], when performing 27 tests of milling SCM440 steel, the one with the smallest SR was also the one with the smallest MRR. When performing 9 tests for milling 060A4 steel, the one with the smallest SR is had a very small MRR [5]. Among 27 SKD11 steel milling experiments, the one with the smallest SR almost had the smallest MRR [6], etc. Thus, in cases like these it is necessary to define an experiment where SR is considered smallest and MRR is considered maximum, i.e. an MCDM [4-6] problem. There are various mathematical methods that support MCDM such as: SAW, WASPAS, TOPSIS, VIKOR, MOORA, COPRAS, PIV, PSI, EDAS, MARCOS, CODAS, WASPAS, WPAS, etc. These methods have been widely applied to MCDM in many different fields. The common feature of these methods is that each method gives only one set of ranking results for the alternatives.

The PARIS method was first proposed in 2020 by Ardil [7]. PARIS is also an MCDM method, but, unlike the above techniques, it performs threefold data normalization in 3 different ways. In addition, for each data normalization method, the ranking of the alternatives is performed in 3 stages. Thus, when applying this method, 9 different ratings will be conducted for the alternatives. In the next section of this paper, this method will be presented in detail. This method has been applied to make multi-criteria decisions in some specific cases such as: When deciding in choosing 1 of 6 aircraft types, each aircraft is evaluated through 7 criteria. The PARIS method was applied to accomplish this in [7]. In this study, two methods, i.e. AW and EW were used to determine the weights for 7 criteria. The TOPSIS method was also used and compared with the PARIS method. When using the PARIS method with two different weighting methods (AW and EW) it gave 18 ranking options. When using the TOPSIS method with two different weighting methods two ranking options were proposed. An interesting result was obtained that all 20 ranking options identified the best aircraft according to the 7 given criteria. Besides, Ardil also used the PARIS method [8] to decide which one of the 3 types of military aircraft to choose. In this case, each aircraft is evaluated on 7 criteria. AW and EW were again

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used to determine the weights of the criteria and TOPSIS was also used and compared with the PARIS method. The calculated results showed that all 20 ranking options (including 18 options of PARIS and 2 options of TOPSIS) identified the same best aircraft. In [9], the PARIS method was also used to select 1 out of 5 software candidates, considering 8 criteria. In total, there were 31 sub-criteria out of which 8 were applied. In addition, 3 different sets of weights that are random numbers (RN) have been assigned to the criteria. The calculated results showed 27 rating options. In particular, the different best alternatives depended on the random weights assigned to the criteria.

The above results show that the use of PARIS method is quite effective. However, the PARIS method has only been used in the mentioned studies. Up to now, and to the best of our knowledge, there have been no studies using this method in MCDM for the milling process and mechanical processing in general. AW, EW, and RN methods were used to determine the weights for the criteria in the above studies when applying the PARIS method. This is understandable because AW is the simplest method to determine the weights for criteria where the weights of the criteria are equal, and EW is a method with high accuracy that has been widely used. Its use is recommended in MCDM [10]. The RN method was used because out of the 31 criteria for software evaluation, there are both qualitative and quantitative criteria. However, for quantitative criteria it is not necessary to use this method. The MW weighting method was first proposed in 2021 [11]. It has been used in several studies to determine weights in MCDM [12, 13]. However, this method has not been used to determine weights for the criteria of any milling process. Therefore, the use of the MW method for determining the weights for the criteria of the milling process along with the two methods already used (AW and EW) ensures the novelty of the current study. The use of 3 methods of determining weights in a study is the basis for assessing the stability in determining the best solution.

SNCM439 steel (according to JIS standard - Japan) is a high-alloy steel and products like gears, wood cutters, dies, etc. are usually made from it. This steel is equivalent to some steels according to other standards such as, AISI - 4340, EN - 36CrNiMo4, BS - EN24, JIS - SNCM439, DIN - 150Cr14, GOST - 9CrSi (or 9XC or 9HS or 9KHS). There have been a few studies regarding the milling of this steel (or equivalent steels). In [14], the authors investigated the influence of the parameters of the MQL-type cooling lubrication on SR when hard milling of 9CrSi steel. In [15], the Response Surface Method (RSM) and an Artificial Neural Network (ANN) model were combined to predict the value of tool wear and cutting force for the dry milling of EN24 steel. In [16], the shear force and friction force were investigated when milling EN24 steel with different cooling lubrication conditions. In [17], the optimal values of cutting speed, feed rate, and depth of cut were determined to ensure minimum SR when milling En24 steel. The influence of cutting speed, feed rate, and depth of cut on SR on cutting temperature when hard milling AISI-4340 steel were investigated in [18]. In [19], it was determined that the value of cutting speed, feed rate, and depth of cut improve the surface hardness when milling AISI-4340 steel. Research on milling steel SNCM439 (or equivalent steels) has been conducted in a number of studies as described above. However, to date, there has not been any research done in MCDM when machining this steel. This is the reason that this steel was chosen as the research object in this paper.

Like the SR parameter, the MRR is a very common parameter used to evaluate the milling process. This parameter reflects the processing capacity. Considering both SR and MRR in a study makes both economic and technical implications. That is why this study has selected both SR and MRR as the criteria to evaluate the milling process. Besides, the three cutting parameters (cutting speed, feed rate, and depth of cut) that have been investigated in many studies, the parameters of the cutting tool (number of inserts, cutting tool material, and nose radius) are also parameters that have a great influence on the surface roughness during milling [20-22]. However, until now, no study has been found that considers all 6 of these parameters during the milling process. Therefore, the consideration of all these 6 parameters is also a novelty of this work.

This study will conduct SNCM439 steel milling experiments. In each experiment, 6 parameters will be changed including cutting speed, feed rate, depth of cut, number of inserts, insert material, and nose radius. SR and MRR were selected as the two output criteria. PARIS method is used for MCDM with 3 weighting methods including AW, EW, and MW.

## II. THE PARIS METHOD

The PARIS method is performed according to the following steps [7].

Step 1: Building of the decision matrix.

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{1j} & x_{1n} \\ x_{21} & x_{22} & x_{2j} & x_{2n} \\ x_{i1} & x_{i2} & x_{ij} & x_{in} \\ x_{m1} & x_{m2} & x_{mj} & x_{mn} \end{bmatrix} \quad (1)$$

In which: $m$ is the number of options, $i = 1, 2, \ldots, m$ and $n$ is the number of criteria, $j = 1, 2, \ldots, n$.

If $x_{ij}$ is negative then do the calculation $x'_{ij} = x_{ij} = \min(x_{ij})$, then $x'_{ij}$ is used to calculate the next steps.

Step 2: Normalizing the decision matrix.

Normalizing way 1 (Vector normalization):

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad \text{If } j \text{ is the criterion, the bigger the better} \quad (2)$$

$$r_{ij} = 1 - \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad \text{If } j \text{ is the criterion, the smaller the better} \quad (3)$$

Normalizing way 2 (Linear normalization):

$$r_{ij} = \frac{x_{ij}}{x_j^{max}} \quad \text{If } j \text{ is the criterion, the bigger the better} \quad (4)$$

$$r_{ij} = \frac{x_j^{min}}{x_{ij}} \quad \text{If } j \text{ is the criterion, the smaller the better} \quad (5)$$

Normalizing way 3 (Max - Min linear normalization):

$$r_{ij} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}} \quad \text{If } j \text{ is the criterion, the bigger the better} \quad (6)$$

$$r_{ij} = \frac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}} \quad \text{If } j \text{ is the criterion, the smaller the better} \quad (7)$$

Step 3: Calculating of the weighted normalized value:

$$z_{ij} = \omega_j \cdot r_{ij} \quad (8)$$

Step 4: Summarizing the weighted normalized values as:

$$\pi_i^{\omega} = \sum_{j=1}^{n} \omega_j \cdot r_{ij} \quad (9)$$

where $i = 1, 2, \ldots m; j = 1, 2, \ldots, n$.

Step 5: Rank the alternatives. The solution with the largest value of $\pi_i^{\omega}$ is the best solution.

Step 6: Identify the elements of the reference ideal solution:

$$z_j^* = \{z_1^*, \ldots, z_j^*\} = \{(max_i\, z_{ij} \mid j \in B), (min_i z_{ij} \mid j \in C)\} \quad (10)$$

where *B* represents a criterion as large as possible, *C* represents a criterion as small as possible.

Step 7: Calculate the distance from the reference ideal solution:

$$\pi_i^* = \sum_{j=1}^{n} (z_j^* - z_{ij}) \quad (11)$$

Step 8: Rank the alternatives according to the principle that the one with the smallest value of $\pi_i$ is the best one.

Step 9: Calculate the distance from the alternatives to the ideal solution:

$$R_i = \sqrt{(\pi_i^{\omega} - \pi_i^{\omega,max})^2 + (\pi_i^* - \pi_i^{*,min})^2} \quad (12)$$

Step 10: Rank the alternatives according to the principle that the one with the smallest $R_i$ value is the best one.

## III. METHODS OF DETERMINING WEIGHTS

### A. The Average Weight Method

AW is determined according to the following formula [23]:

$$w_j = \frac{1}{n} \quad (13)$$

where *n* is the number of criteria.

### B. The Entropy Weighted Method

EW is determined according to the following steps [10].

Step 1: Determine the normalized values for the indicators:

$$p_{ij} = \frac{x_{ij}}{m + \sum_{i=1}^{m} x_{ij}^2} \quad (14)$$

where $x_{ij}$ is the value of criterion *j* corresponding to option *i* and *m* is the number of alternatives.

Step 2: Calculate the value of the Entropy measure for each indicator with:

$$me_j = -\sum_{i=1}^{m} \left[ p_{ij} \cdot \ln(p_{ij}) \right] - \left(1 - \sum_{i=1}^{m} p_{ij}\right) \cdot \ln\left(1 - \sum_{i=1}^{m} p_{ij}\right) \quad (15)$$

Step 3: Calculate the weight for each indicator:

$$w_j = \frac{1 - me_j}{\sum_{j=1}^{m}(1 - me_j)} \quad (16)$$

### C. The MEREC Weight Method

MW is determined according to the following steps [11]:

Step 1: Is similar to step 1 of the PARIS method.

Step 2: Calculate the normalized values according to:

$$h_{ij} = \frac{min x_{ij}}{x_{ij}} \quad \text{If } j \text{ is the criterion, the bigger the better.} \quad (17)$$

$$h_{ij} = \frac{x_{ij}}{max x_{ij}} \quad \text{If } j \text{ is the criterion, the smaller the better} \quad (18)$$

Step 3: Calculate the overall efficiency of the alternatives according to:

$$S_i = Ln\left[1 + \left(\frac{1}{n}\sum_j^n \left|ln(h_{ij})\right|\right)\right] \quad (19)$$

Step 4: Calculate the performance of the alternatives according to:

$$S'_{ij} = Ln\left[1 + \left(\frac{1}{n}\sum_{k,k\neq j}^n \left|ln(h_{ij})\right|\right)\right] \quad (20)$$

Step 5: Calculate the absolute value of the deviations according to:

$$E_j = \sum_i^m \left|S'_{ij} - S_i\right| \quad (21)$$

Step 6: Calculate the weight for the criteria according to:

$$w_j = \frac{E_j}{\sum_k^m E_k} \quad (22)$$

## IV. MILLING EXPERIMENT

### A. Experimental Design

Experiments were carried out on a 3-axis machining center. The values of the 6 input parameters are presented in Table I [1, 24]. As the number of inserts varies in each experiment, 3 different types of inserts have been used. In addition, each type of tool head has several insert positions of 2, 3, and 4. All 3 types of cutters have a diameter of 40mm. The basic geometrical parameters of the selected insert types are the same. Specifically, the main cutting angle is $90^0$, the main cutting-edge length is 10mm, and the blade width is 6.8mm [24]. The Taguchi method was used for the experimental design due to its advantages [25, 26]. In this experiment, an experimental matrix of 27 experiments was designed (Table II).

TABLE I. INPUT PARAMETERS

| Parameter | Symbol | Unit | Value at level | | |
|---|---|---|---|---|---|
| | | | 1 | 2 | 3 |
| Number of insert | $N$ | - | 2 | 3 | 4 |
| Insert material | $M$ | - | TiN | TiCN | TiAlN |
| Nose radius | $r$ | mm | 0.3 | 0.5 | 0.8 |
| Cutting speed | $v_c$ | m/min | 120 | 150 | 180 |
| Feed rate | $v_f$ | mm/min | 300 | 400 | 500 |
| Depth of cut | $a_p$ | mm | 0.2 | 0.35 | 0.5 |

TABLE II. EXPERIMENTAL MATRIX AND RESULTS

| Trial | $N$ | $M$ | $r$ (mm) | $v_c$ (m/min) | $v_f$ (mm/min) | $a_p$ (mm) | $MRR$ (mm$^3$/min) | $SR$ (µm) |
|---|---|---|---|---|---|---|---|---|
| 1 | 2 | TiN | 0.3 | 120 | 300 | 0.2 | 2400 | 2.287 |
| 2 | 2 | TiN | 0.3 | 120 | 400 | 0.35 | 5600 | 3.152 |
| 3 | 2 | TiN | 0.3 | 120 | 500 | 0.5 | 10000 | 4.017 |
| 4 | 2 | TiCN | 0.5 | 150 | 300 | 0.2 | 2400 | 1.377 |
| 5 | 2 | TiCN | 0.5 | 150 | 400 | 0.35 | 5600 | 2.242 |
| 6 | 2 | TiCN | 0.5 | 150 | 500 | 0.5 | 10000 | 3.107 |
| 7 | 2 | TiAlN | 0.8 | 180 | 300 | 0.2 | 2400 | 0.490 |
| 8 | 2 | TiAlN | 0.8 | 180 | 400 | 0.35 | 5600 | 1.240 |
| 9 | 2 | TiAlN | 0.8 | 180 | 500 | 0.5 | 10000 | 2.105 |
| 10 | 3 | TiN | 0.5 | 180 | 300 | 0.35 | 4200 | 0.245 |
| 11 | 3 | TiN | 0.5 | 180 | 400 | 0.5 | 8000 | 0.793 |
| 12 | 3 | TiN | 0.5 | 180 | 500 | 0.2 | 4000 | 1.163 |
| 13 | 3 | TiCN | 0.8 | 120 | 300 | 0.35 | 4200 | 1.104 |
| 14 | 3 | TiCN | 0.8 | 120 | 400 | 0.5 | 8000 | 1.969 |
| 15 | 3 | TiCN | 0.8 | 120 | 500 | 0.2 | 4000 | 2.339 |
| 16 | 3 | TiAlN | 0.3 | 150 | 300 | 0.35 | 4200 | 0.838 |
| 17 | 3 | TiAlN | 0.3 | 150 | 400 | 0.5 | 8000 | 1.703 |
| 18 | 3 | TiAlN | 0.3 | 150 | 500 | 0.2 | 4000 | 2.073 |
| 19 | 4 | TiN | 0.8 | 150 | 300 | 0.5 | 6000 | 0.345 |
| 20 | 4 | TiN | 0.8 | 150 | 400 | 0.2 | 3200 | 0.456 |
| 21 | 4 | TiN | 0.8 | 150 | 500 | 0.35 | 7000 | 0.890 |
| 22 | 4 | TiCN | 0.3 | 180 | 300 | 0.5 | 6000 | 0.611 |
| 23 | 4 | TiCN | 0.3 | 180 | 400 | 0.2 | 3200 | 0.241 |
| 24 | 4 | TiCN | 0.3 | 180 | 500 | 0.35 | 7000 | 0.624 |
| 25 | 4 | TiAlN | 0.5 | 120 | 300 | 0.5 | 6000 | 0.657 |
| 26 | 4 | TiAlN | 0.5 | 120 | 400 | 0.2 | 3200 | 1.027 |
| 27 | 4 | TiAlN | 0.5 | 120 | 500 | 0.35 | 7000 | 1.892 |

### B. Results and Discussion

The SR for each experiment can be seen presented in Table II. These values are the mean values of at least 3 consecutive measurements. In addition, the MRR at each experiment is also been summarized in Table II. The values are calculated by (23), where $v_f$, $a_p$ and $b_w$ are the feed rate, the depth of cut, and the wide cut respectively.

$$MRR = v_f \cdot a_p \cdot b_w \quad (23)$$

The extent and influence of the parameters on SR are shown in Figure 1. From this graph, it is shown that:

- The number of inserts, cutting speed, and feed rate have a great influence on SR. The nose radius and depth of cut also affect the SR, but to a lesser extent than the 3 mentioned above parameters. The insert material has no significant effect on SR.
- When the number of insert increases, the SR decreases. This can be explained by the fact that as the number of inserts increases, each area of the machined surface is cut more than once. That means that after a insert cuts off a layer of the material, the metal layer on the surface of the part will be elastically deformed. This metal is then removed by other cuttings, which causes the SR to decrease.
- As the cutting speed increases, the cutting tool rotates at a faster speed. Then a point on the surface of the workpiece will be repeatedly cut by the cutting edges, even the undulations caused by plastic deformation will be eliminated, which leads to a reduced SR. The case is similar with the increasing of the number of inserts discussed above.
- As the feed rate increases, the time the cutting tool is in contact between an area of the part surface and the cutting edge decreases, causing plastic layers of metal on the surface to not be removed, leading to an increase in SR. Increasing the nose radius will cause the SR to decrease. It can be understood that the height of the surface undulation is inversely proportional to the nose radius, as discussed in [27]. Furthermore, the large SR at large feed rates and small nose radius are also consistent with the SR calculation formula used in some studies [27]:

$$R_a = 1000 \cdot 0.0321 \cdot v_f^2 / r$$

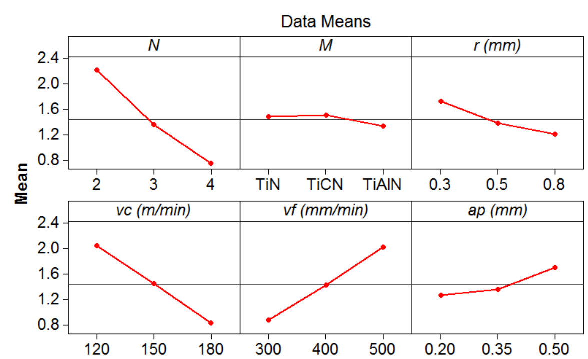


Fig. 1. Main effects plot for surface roughness.

From Figure 1, if the SR has a small value, choose a large cutting speed, a small feed rate, and a small depth of cut. However, according to (23), when the feed rate and cutting depth are small, the MRR will also be small, which is undesirable. Therefore, choosing the value of the cutting parameters to ensure that the SR is small and the MRR is large, it is necessary to make the right decisions. This right decision can be made with a MCDM method. In this problem, the PARIS method will be used.

## V. MULTI-CRITERIA DECISION MAKING

### A. Determining the Weights of the Criteria

Equation (1) is used to build the decision matrix. The last two columns in Table II are the decision matrix. Equation (13) was applied to determine the weights of the criteria according to the AW method. In addition, (14)-(16) are used to determine the weights for the criteria according to the EW method. Equations (17)-(22) determine the weights of the criteria of the MW method. The results are shown in Table III.

TABLE III. CRITERIA WEIGHTS

| Method | *Ra* | MRR |
|---|---|---|
| AW | 0.5 | 0.5 |
| EW | 0.6859 | 0.3141 |
| MW | 0.3663 | 0.6337 |

## *B. Applying the PARIS Method*

Equations (2) and (3) are used to normalize the matrix in way 1. Equations (4) and (5) are applied to normalize the matrix in way 2. Equations (6) and (7) are used to normalize the matrix in way 3. The results are presented in Table V.

TABLE IV. VALUE OF $Z^{*}_{J}$

| Normalization | SR | MRR |
|---|---|---|
| Way 1 | 0.255 | 0.200 |
| Way 2 | 0.030 | 0.500 |
| Way 3 | 0.000 | 0.500 |

To rank the alternatives for weight calculation according to the AW method we apply (8) to calculate the weighted normalized value ($z_{ij}$) and (9) to calculate the weighted normalized sum ($\pi^{\omega}_{i}$). The results are presented in Table VI. The results of ranking the alternatives according to the value of $\pi^{\omega}_{i}$ are also presented in this Table. Equation (10) was applied to determine the factors of the ideal solution ($z^{*}_{j}$) and the results are presented in Table IV. Equation (11) is used to determine the distance from the reference ideal solution ($\pi_i$). The results are presented in Table VII. The results of ranking the alternatives according to the value of $\pi^{*}_{i}$ are also presented in this Table. The distance from the alternatives to the ideal solution ($R_i$) is calculated by (12). The results are presented in Table VIII. The results of ranking options according to the value of $R_i$ are also shown in this Table.

TABLE V. NORMALIZED MATRICES

| Trial. | Way 1 | | Way 2 | | Way 3 | |
|---|---|---|---|---|---|---|
| | SR | MRR | SR | MRR | SR | MRR |
| 1 | 0.721 | 0.096 | 0.105 | 0.240 | 0.458 | 0.000 |
| 2 | 0.616 | 0.224 | 0.076 | 0.560 | 0.229 | 0.421 |
| 3 | 0.511 | 0.400 | 0.060 | 1.000 | 0.000 | 1.000 |
| 4 | 0.832 | 0.096 | 0.175 | 0.240 | 0.699 | 0.000 |
| 5 | 0.727 | 0.224 | 0.107 | 0.560 | 0.470 | 0.421 |
| 6 | 0.622 | 0.400 | 0.078 | 1.000 | 0.241 | 1.000 |
| 7 | 0.940 | 0.096 | 0.492 | 0.240 | 0.934 | 0.000 |
| 8 | 0.849 | 0.224 | 0.194 | 0.560 | 0.735 | 0.421 |
| 9 | 0.744 | 0.400 | 0.114 | 1.000 | 0.506 | 1.000 |
| 10 | 0.970 | 0.168 | 0.984 | 0.420 | 0.999 | 0.237 |
| 11 | 0.903 | 0.320 | 0.304 | 0.800 | 0.854 | 0.737 |
| 12 | 0.858 | 0.160 | 0.207 | 0.400 | 0.756 | 0.211 |
| 13 | 0.866 | 0.168 | 0.218 | 0.420 | 0.771 | 0.237 |
| 14 | 0.760 | 0.320 | 0.122 | 0.800 | 0.542 | 0.737 |
| 15 | 0.715 | 0.160 | 0.103 | 0.400 | 0.444 | 0.211 |
| 16 | 0.898 | 0.168 | 0.288 | 0.420 | 0.842 | 0.237 |
| 17 | 0.793 | 0.320 | 0.142 | 0.800 | 0.613 | 0.737 |
| 18 | 0.747 | 0.160 | 0.116 | 0.400 | 0.515 | 0.211 |
| 19 | 0.958 | 0.240 | 0.699 | 0.600 | 0.972 | 0.474 |
| 20 | 0.944 | 0.128 | 0.529 | 0.320 | 0.943 | 0.105 |
| 21 | 0.892 | 0.280 | 0.271 | 0.700 | 0.828 | 0.605 |
| 22 | 0.926 | 0.240 | 0.394 | 0.600 | 0.902 | 0.474 |
| 23 | 0.971 | 0.128 | 1.000 | 0.320 | 1.000 | 0.105 |
| 24 | 0.924 | 0.280 | 0.386 | 0.700 | 0.899 | 0.605 |
| 25 | 0.920 | 0.240 | 0.367 | 0.600 | 0.890 | 0.474 |
| 26 | 0.875 | 0.128 | 0.235 | 0.320 | 0.792 | 0.105 |
| 27 | 0.770 | 0.280 | 0.127 | 0.700 | 0.563 | 0.605 |

TABLE VI. SOME PARAMETERS IN PARIS RANKED BY THE VALUE OF $\pi^{\omega}_{i}$

| Trial | Way 1 | | | | Way 2 | | | | Way 3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $z_{ij}$ | | $\pi^{\omega}_{i}$ | Rank | $z_{ij}$ | | $\pi^{\omega}_{i}$ | Rank | $z_{ij}$ | | $\pi^{\omega}_{i}$ | Rank |
| | SR | MRR | | | SR | MRR | | | SR | MRR | | |
| 1 | 0.361 | 0.048 | 0.409 | 27 | 0.053 | 0.120 | 0.173 | 27 | 0.229 | 0.000 | 0.229 | 27 |
| 2 | 0.308 | 0.112 | 0.420 | 26 | 0.038 | 0.280 | 0.318 | 21 | 0.115 | 0.211 | 0.325 | 26 |
| 3 | 0.255 | 0.200 | 0.455 | 23 | 0.030 | 0.500 | 0.530 | 8 | 0.000 | 0.500 | 0.500 | 18 |
| 4 | 0.416 | 0.048 | 0.464 | 22 | 0.088 | 0.120 | 0.208 | 26 | 0.350 | 0.000 | 0.350 | 24 |
| 5 | 0.363 | 0.112 | 0.476 | 21 | 0.054 | 0.280 | 0.334 | 19 | 0.235 | 0.211 | 0.446 | 22 |
| 6 | 0.311 | 0.200 | 0.511 | 18 | 0.039 | 0.500 | 0.539 | 7 | 0.120 | 0.500 | 0.620 | 10 |
| 7 | 0.470 | 0.048 | 0.518 | 16 | 0.246 | 0.120 | 0.366 | 17 | 0.467 | 0.000 | 0.467 | 20 |
| 8 | 0.424 | 0.112 | 0.537 | 12 | 0.097 | 0.280 | 0.377 | 16 | 0.368 | 0.211 | 0.578 | 13 |
| 9 | 0.372 | 0.200 | 0.572 | 7 | 0.057 | 0.500 | 0.557 | 4 | 0.253 | 0.500 | 0.753 | 2 |
| 10 | 0.485 | 0.084 | 0.569 | 8 | 0.492 | 0.210 | 0.702 | 1 | 0.499 | 0.118 | 0.618 | 11 |
| 11 | 0.452 | 0.160 | 0.612 | 1 | 0.152 | 0.400 | 0.552 | 5 | 0.427 | 0.368 | 0.795 | 1 |
| 12 | 0.429 | 0.080 | 0.509 | 19 | 0.104 | 0.200 | 0.304 | 22 | 0.378 | 0.105 | 0.483 | 19 |
| 13 | 0.433 | 0.084 | 0.517 | 17 | 0.109 | 0.210 | 0.319 | 20 | 0.386 | 0.118 | 0.504 | 17 |
| 14 | 0.380 | 0.160 | 0.540 | 11 | 0.061 | 0.400 | 0.461 | 13 | 0.271 | 0.368 | 0.640 | 9 |
| 15 | 0.358 | 0.080 | 0.438 | 25 | 0.052 | 0.200 | 0.252 | 25 | 0.222 | 0.105 | 0.327 | 25 |
| 16 | 0.449 | 0.084 | 0.533 | 14 | 0.144 | 0.210 | 0.354 | 18 | 0.421 | 0.118 | 0.539 | 15 |
| 17 | 0.396 | 0.160 | 0.556 | 9 | 0.071 | 0.400 | 0.471 | 12 | 0.306 | 0.368 | 0.675 | 8 |
| 18 | 0.374 | 0.080 | 0.454 | 24 | 0.058 | 0.200 | 0.258 | 24 | 0.257 | 0.105 | 0.363 | 23 |
| 19 | 0.479 | 0.120 | 0.599 | 3 | 0.349 | 0.300 | 0.649 | 3 | 0.486 | 0.237 | 0.723 | 4 |
| 20 | 0.472 | 0.064 | 0.536 | 13 | 0.264 | 0.160 | 0.424 | 14 | 0.472 | 0.053 | 0.524 | 16 |
| 21 | 0.446 | 0.140 | 0.586 | 4 | 0.135 | 0.350 | 0.485 | 10 | 0.414 | 0.303 | 0.717 | 5 |
| 22 | 0.463 | 0.120 | 0.583 | 5 | 0.197 | 0.300 | 0.497 | 9 | 0.451 | 0.237 | 0.688 | 6 |
| 23 | 0.485 | 0.064 | 0.549 | 10 | 0.500 | 0.160 | 0.660 | 2 | 0.500 | 0.053 | 0.553 | 14 |
| 24 | 0.462 | 0.140 | 0.602 | 2 | 0.193 | 0.350 | 0.543 | 6 | 0.449 | 0.303 | 0.752 | 3 |
| 25 | 0.460 | 0.120 | 0.580 | 6 | 0.183 | 0.300 | 0.483 | 11 | 0.445 | 0.237 | 0.682 | 7 |
| 26 | 0.437 | 0.064 | 0.501 | 20 | 0.117 | 0.160 | 0.277 | 23 | 0.396 | 0.053 | 0.449 | 21 |
| 27 | 0.385 | 0.140 | 0.525 | 15 | 0.064 | 0.350 | 0.414 | 15 | 0.281 | 0.303 | 0.584 | 12 |

TABLE VII. $\pi^*_i$ VALUES AND RATINGS

| Trial | Way 1 | | Way 2 | | Way 3 | |
|---|---|---|---|---|---|---|
| | $\pi^*_i$ | Rank | $\pi^*_i$ | Rank | $\pi^*_i$ | Rank |
| 1 | 0.047 | 27 | 0.357 | 27 | 0.271 | 27 |
| 2 | 0.035 | 26 | 0.212 | 21 | 0.175 | 26 |
| 3 | 0.000 | 23 | 0.000 | 8 | 0.000 | 18 |
| 4 | -0.009 | 22 | 0.322 | 26 | 0.150 | 24 |
| 5 | -0.020 | 21 | 0.196 | 19 | 0.054 | 22 |
| 6 | -0.055 | 18 | -0.009 | 7 | -0.120 | 11 |
| 7 | -0.063 | 16 | 0.164 | 17 | 0.033 | 20 |
| 8 | -0.081 | 12 | 0.153 | 16 | -0.078 | 13 |
| 9 | -0.116 | 7 | -0.027 | 4 | -0.253 | 2 |
| 10 | -0.114 | 8 | -0.172 | 1 | -0.118 | 6 |
| 11 | -0.156 | 1 | -0.022 | 5 | -0.295 | 1 |
| 12 | -0.054 | 19 | 0.226 | 22 | 0.017 | 19 |
| 13 | -0.061 | 17 | 0.211 | 20 | -0.004 | 17 |
| 14 | -0.085 | 11 | 0.069 | 13 | -0.140 | 10 |
| 15 | 0.018 | 25 | 0.278 | 25 | 0.173 | 25 |
| 16 | -0.078 | 14 | 0.176 | 18 | -0.039 | 15 |
| 17 | -0.101 | 9 | 0.059 | 12 | -0.175 | 9 |
| 18 | 0.002 | 24 | 0.272 | 24 | 0.137 | 23 |
| 19 | -0.144 | 3 | -0.119 | 3 | -0.223 | 4 |
| 20 | -0.081 | 13 | 0.106 | 14 | -0.024 | 16 |
| 21 | -0.130 | 4 | 0.045 | 10 | -0.217 | 5 |
| 22 | -0.127 | 5 | 0.033 | 9 | -0.188 | 7 |
| 23 | -0.094 | 10 | -0.130 | 2 | -0.053 | 14 |
| 24 | -0.147 | 2 | -0.013 | 6 | -0.252 | 3 |
| 25 | -0.125 | 6 | 0.047 | 11 | -0.182 | 8 |
| 26 | -0.046 | 20 | 0.253 | 23 | 0.051 | 21 |
| 27 | -0.069 | 15 | 0.116 | 15 | -0.084 | 12 |

TABLE VIII. $R_i$ VALUES AND RATINGS

| Trial | Way 1 | | Way 2 | | Way 3 | |
|---|---|---|---|---|---|---|
| | $R_i$ | Rank | $R_i$ | Rank | $R_i$ | Rank |
| 1 | 0.287 | 27 | 0.748 | 27 | 0.976 | 27 |
| 2 | 0.271 | 26 | 0.543 | 21 | 0.750 | 18 |
| 3 | 0.221 | 23 | 0.243 | 8 | 0.418 | 3 |
| 4 | 0.209 | 22 | 0.699 | 26 | 0.912 | 26 |
| 5 | 0.193 | 21 | 0.521 | 19 | 0.681 | 14 |
| 6 | 0.143 | 18 | 0.231 | 7 | 0.343 | 2 |
| 7 | 0.132 | 16 | 0.475 | 17 | 0.860 | 25 |
| 8 | 0.106 | 12 | 0.459 | 16 | 0.624 | 13 |
| 9 | 0.056 | 7 | 0.204 | 4 | 0.298 | 1 |
| 10 | 0.060 | 8 | 0.000 | 1 | 0.700 | 15 |
| 11 | 0.000 | 1 | 0.212 | 5 | 0.427 | 4 |
| 12 | 0.145 | 19 | 0.563 | 22 | 0.757 | 19 |
| 13 | 0.134 | 17 | 0.541 | 20 | 0.737 | 17 |
| 14 | 0.101 | 11 | 0.340 | 13 | 0.454 | 6 |
| 15 | 0.246 | 25 | 0.637 | 25 | 0.834 | 24 |
| 16 | 0.111 | 14 | 0.492 | 18 | 0.724 | 16 |
| 17 | 0.078 | 9 | 0.327 | 12 | 0.444 | 5 |
| 18 | 0.223 | 24 | 0.627 | 24 | 0.814 | 22 |
| 19 | 0.018 | 3 | 0.074 | 3 | 0.563 | 10 |
| 20 | 0.107 | 13 | 0.393 | 14 | 0.791 | 21 |
| 21 | 0.037 | 4 | 0.306 | 10 | 0.499 | 8 |
| 22 | 0.041 | 5 | 0.289 | 9 | 0.569 | 11 |
| 23 | 0.088 | 10 | 0.059 | 2 | 0.781 | 20 |
| 24 | 0.014 | 2 | 0.224 | 6 | 0.495 | 7 |
| 25 | 0.045 | 6 | 0.309 | 11 | 0.570 | 12 |
| 26 | 0.156 | 20 | 0.600 | 23 | 0.820 | 23 |
| 27 | 0.123 | 15 | 0.408 | 15 | 0.536 | 9 |

TABLE IX. RANKING WHEN THE WEIGHTS ARE DETERMINED WITH THE EW METHOD

| Trial | Ranking by value of $\pi^{\omega}_i$ | | | Ranking by value of $\pi^*_i$ | | | Ranking by value of $R_i$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | Way 1 | Way 2 | Way 3 | Way 1 | Way 2 | Way 3 | Way 1 | Way 2 | Way 3 |
| 1 | 25 | 27 | 26 | 25 | 27 | 25 | 25 | 27 | 27 |
| 2 | 26 | 23 | 27 | 26 | 23 | 27 | 26 | 23 | 24 |
| 3 | 27 | 13 | 25 | 27 | 13 | 26 | 27 | 13 | 13 |
| 4 | 20 | 26 | 20 | 20 | 2 | 20 | 20 | 26 | 26 |
| 5 | 21 | 22 | 22 | 21 | 22 | 22 | 21 | 22 | 17 |
| 6 | 23 | 12 | 21 | 23 | 12 | 21 | 23 | 12 | 3 |
| 7 | 10 | 9 | 13 | 10 | 9 | 13 | 10 | 9 | 22 |
| 8 | 12 | 17 | 14 | 12 | 17 | 14 | 12 | 17 | 12 |
| 9 | 17 | 11 | 10 | 17 | 11 | 10 | 17 | 11 | 1 |
| 10 | 4 | 1 | 5 | 2 | 1 | 5 | 2 | 1 | 14 |
| 11 | 3 | 6 | 1 | 4 | 6 | 1 | 4 | 6 | 2 |
| 12 | 16 | 20 | 17 | 15 | 20 | 17 | 15 | 20 | 18 |
| 13 | 13 | 19 | 15 | 13 | 19 | 15 | 13 | 19 | 16 |
| 14 | 18 | 15 | 16 | 18 | 15 | 16 | 18 | 15 | 5 |
| 15 | 24 | 25 | 24 | 24 | 25 | 24 | 24 | 25 | 25 |
| 16 | 11 | 16 | 11 | 11 | 16 | 11 | 11 | 16 | 15 |
| 17 | 14 | 14 | 12 | 16 | 14 | 12 | 16 | 14 | 4 |
| 18 | 22 | 24 | 23 | 22 | 24 | 23 | 22 | 24 | 23 |
| 19 | 1 | 3 | 2 | 1 | 3 | 2 | 1 | 3 | 8 |
| 20 | 9 | 5 | 9 | 9 | 5 | 9 | 9 | 5 | 20 |
| 21 | 8 | 10 | 7 | 8 | 10 | 7 | 8 | 10 | 7 |
| 22 | 5 | 7 | 4 | 6 | 7 | 4 | 6 | 7 | 9 |
| 23 | 7 | 2 | 8 | 5 | 2 | 8 | 5 | 2 | 19 |
| 24 | 2 | 4 | 3 | 3 | 4 | 3 | 3 | 4 | 6 |
| 25 | 6 | 8 | 6 | 7 | 8 | 6 | 7 | 8 | 10 |
| 26 | 15 | 21 | 18 | 14 | 21 | 19 | 14 | 21 | 21 |
| 27 | 19 | 18 | 19 | 19 | 18 | 18 | 19 | 18 | 11 |

TABLE X. RANKING WHEN THE WEIGHTS ARE DETERMINED WITH THE MW METHOD

| Trial | Ranking by value of $\pi^{\omega}_i$ | | | Ranking by value of $\pi^{*}_i$ | | | Ranking by value of $R_i$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | Way 1 | Way 2 | Way 3 | Way 1 | Way 2 | Way 3 | Way 1 | Way 2 | Way 3 |
| 1 | 27 | 27 | 27 | 27 | 27 | 27 | 27 | 27 | 27 |
| 2 | 24 | 18 | 22 | 24 | 18 | 22 | 24 | 18 | 15 |
| 3 | 14 | 3 | 9 | 14 | 3 | 10 | 14 | 3 | 3 |
| 4 | 25 | 26 | 26 | 25 | 26 | 26 | 25 | 26 | 26 |
| 5 | 20 | 17 | 16 | 20 | 17 | 17 | 20 | 17 | 14 |
| 6 | 10 | 2 | 3 | 9 | 2 | 3 | 10 | 2 | 2 |
| 7 | 21 | 21 | 23 | 21 | 21 | 23 | 21 | 21 | 25 |
| 8 | 13 | 15 | 13 | 13 | 15 | 14 | 13 | 15 | 13 |
| 9 | 2 | 1 | 1 | 2 | 1 | 1 | 2 | 1 | 1 |
| 10 | 11 | 5 | 14 | 11 | 5 | 15 | 11 | 5 | 16 |
| 11 | 1 | 6 | 2 | 1 | 6 | 2 | 1 | 6 | 4 |
| 12 | 19 | 22 | 20 | 19 | 22 | 8 | 19 | 22 | 19 |
| 13 | 18 | 20 | 18 | 18 | 20 | 19 | 18 | 20 | 18 |
| 14 | 9 | 10 | 7 | 10 | 10 | 7 | 9 | 10 | 6 |
| 15 | 26 | 24 | 25 | 26 | 25 | 25 | 26 | 24 | 23 |
| 16 | 16 | 19 | 15 | 16 | 19 | 16 | 16 | 19 | 17 |
| 17 | 6 | 9 | 5 | 6 | 9 | 5 | 6 | 9 | 5 |
| 18 | 23 | 23 | 24 | 23 | 23 | 24 | 23 | 23 | 21 |
| 19 | 5 | 4 | 8 | 5 | 4 | 9 | 5 | 4 | 10 |
| 20 | 17 | 16 | 19 | 17 | 16 | 20 | 17 | 16 | 22 |
| 21 | 4 | 11 | 6 | 4 | 11 | 6 | 4 | 11 | 8 |
| 22 | 7 | 12 | 10 | 7 | 12 | 11 | 7 | 12 | 11 |
| 23 | 15 | 8 | 17 | 15 | 8 | 18 | 15 | 8 | 20 |
| 24 | 3 | 7 | 4 | 3 | 7 | 4 | 3 | 7 | 7 |
| 25 | 8 | 13 | 11 | 8 | 13 | 12 | 8 | 13 | 12 |
| 26 | 22 | 25 | 21 | 22 | 24 | 21 | 22 | 25 | 24 |
| 27 | 12 | 14 | 12 | 12 | 14 | 13 | 12 | 14 | 9 |

The ranking results in Tables V-X show 27 different ranking options. From these results it is shown that:

- 22/27 times experiment #1 was determined to be the worst. In this experiment, MRR = 2400mm$^3$/min was one of the 3 smallest values in Table II (equal to the MRR in experiments #4 and #7). In addition, $Ra$ = 2.287µm is very large compared to the surface texture in other experiments (only smaller than the surface texture in 4 experiments: #2, #3, #5, and #15). That allows the claim that the experiment #1 is the worst to be entirely reasonable.
- 8/27 times determined experiment #9, 6/27 times determined experiment #10, 10/27 times determined experiment #11, and 3/27 times determined experiment #19 as the best. Thus, determining which experiment is the best would not be achieved if the work stopped here. To determine the best experiment, in addition to the ranking results, it is also necessary to add the stability of the ratings. In this study, the GINI index value will be used to determine the stability in ranking the alternatives [29]. The *GINI* index value is determined by [29, 30]:

$$D(R) = \frac{4}{(m-1)\left(z^2-\left|\sin(z\cdot\frac{\pi}{2})\right|\right)}\sum_{h=1}^{z-1}\sum_{l=h+1}^{z}|R_h - R_l| \quad (24)$$

where $m$ is the number of options, $z$ is the number of MCDM methods used, $R_h$ and $R_l$ are the ranking values of the alternatives of the decision method $h$ and $l$, and $D(R) \in [0,1]$. When $D(R) = 0$, the rank of an alternative is the same when ranking by different methods. In contrast, when $D(R) = 1$, the ranking of the alternatives is most different when using different ranking methods. When comparing two alternatives, the one with the smaller GINI index value is the better one. Equation (24) has been applied to calculate the GINI index value for the data in Tables V-X. The results are presented in Table XI.

TABLE XI. GINI INDEX VALUE OF THE ALTERNATIVES

| Experiment | GINI index | Experiment | GINI index |
|---|---|---|---|
| 1 | 0.002536 | 15 | 0.003381 |
| 2 | 0.018808 | 16 | 0.015427 |
| 3 | 0.048605 | 17 | 0.017751 |
| 4 | 0.018174 | 18 | 0.004861 |
| 5 | 0.012468 | 19 | 0.013314 |
| 6 | 0.040152 | 20 | 0.019231 |
| 7 | 0.01754 | 21 | 0.019019 |
| 8 | 0.014159 | 22 | 0.015216 |
| 9 | 0.019442 | 23 | 0.040997 |
| 10 | 0.032967 | 24 | 0.012046 |
| 11 | 0.016272 | 25 | 0.015216 |
| 12 | 0.018597 | 26 | 0.016061 |
| 13 | 0.014582 | 27 | 0.011834 |
| 14 | 0.017117 | | |

The results in Table XI show that:

- In experiment #1, the minimum GINI index value is 0.002536. This proves that experiment #1 has the highest stability when ranking in different times. Up to 22/27 options confirmed this experiment as the worst (ranked 27th), 4/27 options indicate that this experiment is the second worst (ranked 26), and 1/27 indicates that this experiment is the third worst (ranked 25). On the other hand, 27th or 26th or 25th ranking is very close. That proves that experiment #1 has the highest stability when ranking according to different options.

- In experiment #3, the largest GINI index value was 0.048605, proving that this experiment has the lowest rank stability when ranking according to the alternatives. According to the data in Tables VI, VIII-XI, experiment #3 came 5 times at the 3rd place, 3 times at the 8th, 1 time at the 9th, 1 time 10th, 4 times came at the 13th, 3 times at the 14th place, 2 at the 18th, 3 at the 23rd place, and 1 at the $25^{th}$, 26th time, and 27th place. So, the stability in the ranking of experiment #3 is very weak. This experiment ranked in a variety of categories, with both good (3) and bad (27) ranks.
- Among the 4 experiments #9, #10, #10 and #19, experiment #19 has the smallest GINI index value. That proves that experiment #19 has a higher stability rating than the other 3 experiments. Thus experiment #19 is the best of these 4 experiments and it is also the best of the 27 experiments performed. The best values of the input parameters to ensure minimum SR and maximum MRR at the same time are: 4 as the number of inserts, TiN as the insert material, 0.8mm nose radius, 150m/min cutting speed, 30mm/min feed rate, and 0.5 mm depth of cut.
- The use of different weighting methods leads to different ranking orders. Responding to different data normalization ways will result in different ranking orders for the alternatives. However, the simultaneous use of multiple weighting and multiple data normalization methods to give different ranking results, and then the use of the GINI index to choose the best solution will form the basis for determining which option is the best.

## VI. CONCLUSIONS

In this study, 27 SNCM439 steel milling experiments were performed. At each experiment, 6 parameters were considered: number of inserts, cutting material, nose radius, cutting speed, feed rate, and depth of cut. SR and MRR were determined in each experiment. The PARIS method was used to rank the alternatives, and the stability in ranking was evaluated by the GINI index. Some drawn conclusions are:

- The number of inserts, cutting speed, and feed rate have a great influence on surface roughness. Increasing the number of inserts or cutting speed reduces the surface roughness, while increasing the feed rate increases it. The nose radius and depth of cut also affect the surface roughness. Surface roughness is reduced if the tip radius is increased, or the depth of cut is decreased. On the other hand, the insert material does not significantly affect surface roughness.
- The use of 3 data normalization methods is what distinguishes the PARIS method from other methods. For each data normalization method, the PARIS method also gives 3 ranking results for the alternatives. This is also its difference from the other MCDM methods.
- The combination of the PARIS method and 3 different weighting methods (AW, EW, and MW) resulted in 27 different ranking options. The combination of the PARIS method and the GINI index to determine the best solution has higher reliability instead of using just one method that only gives a ranking solution for the alternatives.
- To ensure minimum SR and maximum MRR simultaneously, it is recommended to use the TiN insert with parameter values of the number of inserts, tool radius, cutting speed, feed rate, and depth of cut respectively as 4 pieces, 0.8mm, 150m/min, 30mm/min, and 0.5mm.

## NOMENCLATURE

| | |
|---|---|
| PARIS | Preference Analysis for Reference Ideal Solution |
| SAW | Simple Additive Weighting |
| WASPAS | Weighted Aggregates Sum Product ASsessment |
| TOPSIS | Technique for Order of Preference by Similarity to Ideal Solution |
| VIKOR | VIsekriterijumska optimizacija i kompromisno resenje in Serbian |
| MOORA | Multiobjective Optimization On the basis of Ratio Analysis |
| COPRAS | COmplex Proportional ASsessment |
| PIV | Proximity Indexed Value |
| PSI | Preference Selection Index |
| EDAS | Evaluation based on Distance from Average Solution |
| MARCOS | Measurement Alternatives and Ranking according to COmpromise Solution |
| CODAS | COmbinative Distance based Assessment |
| WASPAS | Weighted Aggregated Sum Product Assessment |
| WPAS | Weighted Product Assessment |
| MCDM | Multi-Criteria Decision-Making |
| MEREC | Method based on the Removal Effects of Criteria |
| AW | Average Weight |
| EW | Entropy Weight |
| MW | Merec Weight |

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