Application of Multi Criteria Decision Making Methods for the Determination of the Best Dressing Factors for Surface Grinding Hardox 500

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ABSTRACT

This study applies Multi-Criteria Decision-Making (MCDM) methods to identify the optimal dressing parameters for the surface grinding of Hardox 500 steel. The investigation focuses on three key objectives: Surface Roughness (*SR*), Material Removal Rate (MRR), and Wheel lifespan (L_w). Five dressing variables were considered: non-feeding dressing (n_n), fine dressing depth (d_f), fine dressing times (n_f), rough dressing depth (d_r), and rough dressing times (n_r). Three MCDM methods—Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS), Simple Additive Weighting (SAW), and Evaluation based on Distance from Average Solution (EDAS)—were employed to solve the MCDM problem. Additionally, the Entropy technique was used to determine the criterion weights. A total of 16 experimental runs were conducted based on the L16 (4^4 x 2^1) design configuration. The analysis identified Option 7 as the optimal dressing mode, characterized by the input parameters: d_r = 0.02 mm, n_r = 3 times, d_f = 0.05 mm, n_f = 3 times, and n_n = 0. To validate the consistency of rankings obtained from the three MCDM methods, the Spearman's rank correlation coefficient (*R*) was employed. The results demonstrated a strong correlation among the rankings, confirming the reliability of the proposed approach. These findings provide a robust framework for optimizing surface grinding parameters to enhance performance and productivity.

Keywords-surface grinding; Hardox 500; MARCOS; SAW; EDAS; entropy method; surface roughness; material removal rate; wheel life

I. INTRODUCTION

Surface grinding is a machining process that employs a grinding wheel to remove material from a flat surface, and is widely utilized to achieve smooth finishes, shape components, and enhance precision. Identifying the optimal grinding conditions is essential to maximize the efficiency of surface grinding operations. Numerous studies have investigated various aspects of the grinding process, including temperature control, dressing parameters, and *SR* optimization.

Authors in [1] conducted a study to evaluate the grinding temperatures in the High-Efficiency Deep Grinding (HEDG) and Ultrasonic Vibration-assisted High-Efficiency Deep Grinding (UVHEDG) of γ-TiAl materials. Both an analytical thermal model and a finite element simulation model were developed to predict the grinding temperatures. Comparative trials between HEDG and UVHEDG were performed to verify the precision of the simulation. The findings indicate that incorporating ultrasonic vibrations into HEDG reduced the peak grinding temperature by 39.1%, significantly mitigating grinding burns. In [2], authors determined the ideal dressing conditions for the grinding SKD11 tool steel utilizing a HaiDuong grinding wheel. This study examined the impact of six input parameters: feed rate, depth of rough dressing cut, rough dressing duration, depth of finish dressing cut, finish dressing duration, and non-feeding dressing (n_n). Based on their results, the following optimum dressing parameters were proposed: fine dressing times (n_f) of 3, non-feeding dressing times (n_o) of 3, fine dressing depth (a_f) of 0.01 mm, rough dressing times (n_r) of 3, rough dressing depth (a_r) of 0.03 mm, and dressing feed rate (S_d) of 1.0 m/min. Authors in [4] introduced a novel approach to dressing diamond grinding wheels using the Abrasive Waterjet (AWJ) technology. This method was designed to address issues, like workpiece damage and wheel clogging associated with grinding challenging materials using traditional diamond grinding wheels. Key process parameters were determined according to a theoretical model for treating diamond grinding wheels with AWJ. Regression models linking process factors with microgroove features were developed using the Response Surface Methodology (RSM) and Backpropagation Artificial Neural Networks (BP-ANN). A comparison of the two methodologies revealed that both RSM and BP-ANN are highly effective for predicting microgroove characteristics. Additionally, authors in [5] examined the influence of process parameters on *SR* during the surface grinding of the 90CrSi tool steel. Parameters, such as coolant concentration, coolant flow, cross-feed, table speed, and depth of cut, were analyzed. The study assessed their impact on *SR* and proposed a predictive method for estimating roughness based on these variables. Authors in [6] performed a Multi-Criteria Decision-Making (MCDM) analysis for the CBN grinding of cylindrical components on CNC milling machines. Three MCDM methods -Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Multi-Attributive Ideal-Real Comparative Analysis (MAIRCA), and Evaluation by an Area-based Method of Ranking (EAMR)- were applied. Additionally, the Method based on the Removal Effects of criterion (MEREC) and Entropy approaches were employed to calculate the weights of the criteria. Furthermore, four input variables were examined: the depth of the dressing cut, spindle speed, feed rate, and wheel diameter. The study analyzed four input parameters: depth of the dressing cut, spindle speed, feed rate, and wheel diameter. Two output criteria, *SR* and MRR, were evaluated to identify the optimal dressing configuration that balances minimal *SR* with maximum MRR. In [7], authors investigated the optimal exchanged grinding wheel diameter to minimize costs in the surface grinding of stainless steel. Their analysis included developing mathematical models to describe the relationship between grinding costs and the optimal exchanged grinding wheel diameter. Parameters, such as the initial grinding wheel diameter, total dressing depth, radial grinding wheel wear per dressing, wheel life, machine tool hours, and grinding wheel cost were considered. The findings identified the ideal exchanged grinding wheel diameter to achieve cost-effective operations.

Other studies have focused on optimizing the dressing parameters to achieve superior surface finish and MRR. For instance, authors in [8] utilized kinematic simulations to predict the *SR* resulting from grinding. Their research examined three configurations of abrasive grains (spherical, truncated conical, and conical) using a single-point diamond dressing model. The proposed *SR* model was validated experimentally, demonstrating a deviation of 7-11%, which indicated good predictive accuracy. Authors in [9] conducted a multi-criteria optimization of the dressing parameters in the surface grinding of 90CrSi tool steel. The primary objectives were to minimize the *SR* and normal shear force while enhancing the grinding wheel longevity. The study employed the Taguchi method and Grey Relational Analysis (GRA) to identify the optimal parameters. The experimental validation confirmed the accuracy of the proposed model and the recommended dressing parameters. The study in [10], focused on optimizing the dressing parameters for the internal cylindrical grinding process of 9CrSi tool steel. Utilizing the Taguchi method and GRA, the study aimed to reduce the *SR* and enhance the MRR. The results indicated that the optimal dressing parameters included a coarse dressing depth of 0.02 mm, one coarse dressing instance, a fine dressing depth (a_f) of 0.005 mm, three fine dressing instances, five non-feeding dressing (n_n) instances, and a dressing feed rate (S_d) of 1.4 m/min. Extensive studies have been conducted to identify efficient dressing techniques. In [11], an optimization analysis was carried out to determine the ideal exchanged grinding wheel diameter for external grinding. This analysis considered seven input parameters: initial grinding wheel diameter, grinding wheel width, wheel life, radial grinding wheel wear per dressing, total depth of dressing cut, machine tool hourly rate, and grinding wheel cost. The study evaluated the influence of these parameters and their interactions on the optimal exchanged grinding wheel diameter. A regression equation for calculating the optimal diameter was presented, providing a valuable tool for cost-effective grinding operations. Authors in [12] explored the effects of surface grinding factors, including dressing parameters, grinding wheel velocity, workpiece velocity, and depth of cut, on *SR*. Their study highlighted the conceptual impact of the dressing settings on *SR*. An experiment was designed and executed to analyze these effects, with the measured *SR* values aligning closely with the calculated predictions. In [13], a multi-objective optimization study was conducted to minimize the *SR* during the internal cylindrical grinding of the SKD11 steel. Six dressing parameters were examined: coarse dressing depth, number of coarse dressings, fine dressing depth (a_f), number of fine dressings, non-feeding dressing (n_n), and dressing feed speed. The study identified an optimal *SR* value of 0.111 µm, achieved with dressing parameters set as follows: fine dressing depth (a_f) at level 2, number of fine dressings at level 3, number of non-feeding dressings (n_n) at level 4, number of coarse dressings at level 3, coarse dressing depth at level 2, and dressing feed rate at level 1. The research presented in [14] proposed an optimization strategy for the external grinding of the 9XC steel to minimize the *SR*. Three dressing modes were analyzed: coarse dressing, fine dressing, and non-feeding dressing (n_n). The optimal dressing parameters suggested include a coarse dressing depth of 0.07 mm, a fine dressing depth (a_f) of 0.02 mm, and three non-feeding dressing (n_n) cycles. In [15], a study on optimizing the dressing parameters for the internal grinding of the SKD11 steel was conducted using the Taguchi method. The input parameters included the coarse dressing depth, quantity of coarse dressings, fine dressing depth (a_f), quantity of fine dressings, non-feeding dressing (n_n), and dressing feed velocity. The quantity of the coarse dressing exerted the most significant influence on *Ra* (88.28%). The difference between the experimental and predicted roughness averages was minimal, demonstrating the accuracy of the optimization process.

The MCDM technique has proven effective across various domains for determining the optimal solutions. For instance, the MCDM has been used for selecting input parameters to identify the best airport [16], ranking universities [17], determining primary design factors for a two-stage gearbox [18], and enhancing the efficiency of the Ranking Alternatives by Perimeter Similarity (RAPS) method in MCDM contexts [19]. This study reports on a MCDM assessment to identify the most effective dressing technique for surface grinding Hardox 500. The analysis utilized three methods: MARCOS, SAW, and EDAS, combined with the Entropy methodology. By evaluating the MCDM problem with three criteria *SR, MRR*, and L_w, the optimal dressing factors were proposed.

II. METHODOLOGY

A. MARCOS Method

To apply the MARCOS technique, it is essential to follow the following steps [20]:

- Step 1: Formation of the initial decision-making matrix:

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

where *m*, *n* are the number of options and criteria, respectively.

- Step 2: Formation of an extended initial matrix, including an ideal solution (*AI*) and a anti-ideal solution (*AAI*):

$$X = \begin{array}{c} AAI \\ A_1 \\ A_2 \\ \vdots \\ A_m \\ AI \end{array} \begin{bmatrix} x_{aa1} & \cdots & x_{aan} \\ x_{11} & \cdots & x_{1n} \\ x_{21} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots \\ x_{m1} & \cdots & x_{mn} \\ x_{ai1} & \cdots & x_{ain} \end{bmatrix} \quad (2)$$

where i = *1, 2,..., m*, and j = 1, 2,..., n. $AAI = min(x_{ij})$ and $AI = max(x_{ij})$id for the *MRR* and L_w targets, while $AAI = max(x_{ij})$ and $AI = min(x_{ij})$ is for the *SR* target.

- Step 3: Normalization of the extended initial matrix (*X*). The elements of the normalized matrix $N = [n_{ij}]_{m\times n}$ are obtained by:

$$n_{ij} = \frac{x_{ai}}{x_{ij}} \quad (3)$$

$$n_{ij} = \frac{x_{ij}}{x_{ai}} \quad (4)$$

where (3) is applied for the *SR* target, and (4) is used for the *MRR* and L_w.

- Step 4: Determination of the weighted matrix $C = [c_{ij}]_{m\times n}$ by:

$$c_{ij} = n_{ij} \times w_j \quad (5)$$

where w_j is the weight coefficient of the criterion j.

- Step 5: Calculation of the utility degree of alternatives K_i^- and Ki^+ by:

$$K_i^- = \frac{S_i}{S_{aai}} \quad (6)$$

$$K_i^+ = \frac{S_i}{S_{ai}} \quad (7)$$

where S_i represents the sum of the elements of the weighted matrix C:

$$S_i = \sum_{i=1}^{m} c_{ij} \quad (8)$$

- Step 6: : Determination of the utility function of the alternatives $f(K_i)$ by:

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1-f(K_i^+)}{f(K_i^+)} + \frac{1-f(K_i^-)}{f(K_i^-)}} \quad (9)$$

where $f(K_i^-)$ represents the utility function in relation to the anti-ideal solution, while $f(K_i^+)$ represents the utility function connected with the ideal solution.

Utility functions in relation to the ideal and anti-ideal solution are determined by:

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^l} \quad (10)$$

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \quad (11)$$

- Step 7: Ranking the alternatives by maximizing $f(K_i)$.

B. SAW Method

The implementation of the SAW approach is carried out through the following steps [21]:

- Step 1: Formation of the initial decision-making matrix as in Step 1 of the MARCOS method.
- Computation of the normalized matrix by:

$$n_{ij} = \frac{r_{ij}}{\max r_{ij}} \tag{12}$$

$$n_{ij} = \frac{\min r_{ij}}{r_{ij}} \tag{13}$$

Noted that (12) is used for the *MRR* and L_w objectives, and (13) for the *SR* target.

- Finding the preference values obtained from the multiplication of weights *W* with normalized matrix *R*:

$$V_i = \sum_{j=1}^{n} w_j \times n_{ij} \tag{14}$$

- Ranking the option's order by maximizing *Vi*.

C. EDAS Method

To implement the EDAS approach, the following actions must be undertaken [22]:

- Step 1: Formation of the first decision-making matrix as in Step 1 of the MARCOS method.
- Step 2: Compute the average of each criterion's solutions:

$$AV_j = \frac{\sum_{i=1}^{m} r_{ij}}{m} \tag{15}$$

- Step 3: Calculation of the positive and negative distances from the average solution by:

For the criterion *SR*:

$$PDA_{ij} = \frac{max\left(0,(r_{ij}-AV_j)\right)}{AV_j} \tag{16}$$

$$NDA_{ij} = \frac{max\left(0,(AV_j-r_{ij})\right)}{AV_j} \tag{17}$$

For the *MRR* and *Lw* criteria:

$$PDA_{ij} = \frac{max\left(0,(AV_j-r_{ij})\right)}{AV_j} \tag{18}$$

$$NDA_{ij} = \frac{max\left(0,(r_{ij}-AV_j)\right)}{AV_j} \tag{19}$$

- Step 4: Determination of the weighted *PDA* and *NDA* of each alternative:

$$SP_i = \sum_{j=1}^{n} PDA_{ij} \times w_j \tag{20}$$

$$SN_i = \sum_{j=1}^{n} NDA_{ij} \times w_j \tag{21}$$

- Step 5: Normalization of weighted *PDA* and *NDA* by:

$$NSP_i = \frac{SP_i}{\max_i(SP_i)} \tag{22}$$

$$NSN_i = \frac{SN_i}{\max_i(SN_i)} \tag{23}$$

- Step 6: Calculation of the appraisal score for each option by:

$$AS_i = \frac{1}{2}(NSP_i + NSN_i) \tag{24}$$

- Step 7: Ranking the option by maximizing AS_i.

D. Entropy Method

In this work, the criterion weights were calculated utilizing the Entropy method. This method is executed through the subsequent steps [23].

- Step 1: Calculation of the indicator normalized values:

$$p_{ij} = \frac{x_{ij}}{m+\sum_{i=1}^{m} x_{ij}^2} \tag{25}$$

- Step 2: Determination of the Entropy for each indicator:

$$me_j = -\sum_{i=1}^{m}\left[p_{ij} \times ln(p_{ij})\right] - \left(1 - \sum_{i=1}^{m} p_{ij}\right) \times ln\left(1 - \sum_{i=1}^{m} p_{ij}\right) \tag{26}$$

- Step 3: Calculation of the weight of each indicator:

$$w_j = \frac{1-me_j}{\sum_{j=1}^{m}(1-me_j)} \tag{27}$$

III. EMPERIMENTAL WORK

An experiment was conducted to determine the optimal dressing parameters for the surface grinding Hardox 500. Table I presents the levels of the input factors utilized during the experiment. The experiment employed an $L16\,(4^4 \times 2^1)$ orthogonal array and was executed using the Minitab R19 software. Figure 1 illustrates the experimental setup.

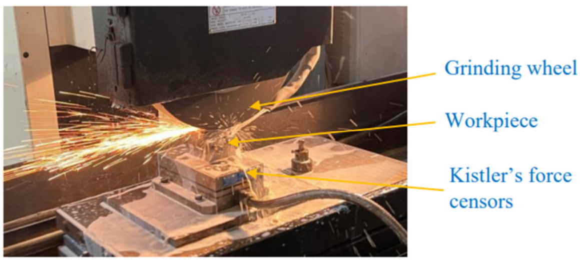

Fig. 1. Expermental setup.

TABLE I. INPUT DRESSING PARAMETERS

No.	Factors	Symbol	Level			
			1	2	3	4
1	Rough dressing depth (mm)	d_r	0.015	0.02	0.025	0.03
2	Rough dressing times	n_r	1	2	3	4
3	Fine dressing depth (mm)	d_f	0.005	0.01	-	-
4	Fine dressing times	n_f	0	1	2	3
5	Non-feeding dressing	n_n	0	1	2	3

The apparatus included:

- A surface grinding machine (PSG-CL3060AH, Taiwan), a grinding wheel (Cn60MV1G V1, 350x40x127 mm, 35 m/s), a dressing tool (3908-0088C type 2, Russia), a piezoelectric dynamometer (Kistler 9257BA, Germany).

The experimental procedure was as follows:

- Each experiment was conducted in triplicate to ensure the reliability of results.
- *SR* was evaluated using an *SR* meter (model SJ201).
- The lifespan of the grinding wheel was assessed based on the time required to initiate effective grinding after dressing and the use of a standard PySpike.
- The total material volume removed was measured, and the *MRR* was calculated based on these data.

The experimental plan and the resulting findings are presented in Table II.

TABLE II. EXPERIMENTAL PLAN AND OUTPUT RESULTS

No	d_r	n_r	n_f	n_n	d_f	*SR* (µm)	*MRR* (mm^3/s)	L_w (min)
1	0.015	1	0	0	0.005	0.67	5.73	23.07
2	0.015	2	1	1	0.005	0.59	5.71	33.20
3	0.015	3	2	2	0.010	0.59	5.51	5.05
4	0.015	4	3	3	0.010	0.65	6.43	1.90
5	0.020	1	1	2	0.010	0.44	8.49	19.90
6	0.020	2	0	3	0.010	0.48	5.22	41.20
7	0.020	3	3	0	0.005	0.62	3.36	44.00
8	0.020	4	2	1	0.005	0.79	11.77	23.73
9	0.025	1	2	3	0.005	0.45	5.64	5.23
10	0.025	2	3	2	0.005	0.81	6.53	36.67
11	0.025	3	0	1	0.010	1.22	3.97	28.03
12	0.025	4	1	0	0.010	0.87	6.01	37.27
13	0.030	1	3	1	0.010	0.94	7.40	26.47
14	0.030	2	2	0	0.010	0.69	6.65	35.17
15	0.030	3	1	3	0.005	1.38	5.60	41.77
16	0.030	4	0	2	0.005	0.77	11.10	16.97

IV. FINDING THE BEST DRESSING PARAMETERS

To address the MCDM problem for identifying the optimal dressing parameters, the weights were determined using the Entropy technique. The calculated weights for the criteria were as follows: *SR* = 0.4606, *MRR* = 0.3056, and L_w = 0.2338. Table III outlines the ranking and parameter calculations using the MARCOS approach. Option 7 emerged as the optimal choice, with the maximum $f(K_i)$ value of 0.0287. Additionally, Table VI displays the rankings and parameter calculations using the SAW method. Option 7 was identified as the most advantageous, with the highest V_i value of 1.6311. Table V presents the rankings and parameter calculations using the EDAS technique. Option 7 was confirmed as the optimal choice, with the highest AS_i value of 1.0000. Figure 2 visually represents the rankings derived from the three MCDM methods (MARCOS, SAW, and EDAS), confirming that Option 7 is consistently identified as the optimal solution. Based on Table II, the optimal dressing parameters were: rough dressing depth: d_r = 0.02 mm, rough dressing times: n_r = 3 times, Fine dressing depth: d_f = 0.005 mm, Fine dressing times: n_f = 3 times, Non-feeding dressing: n_n = 0.

TABLE III. CALCULATED RESULTS AND RANKING OF ALTERNATIVES USING MARCOS METHOD

Trial	K_i^+	K_i^-	$f(K_i^+)$	$f(K_i^-)$	$f(K_i)$	Rank
1	0.0186	0.1579	0.8943	0.1057	0.0184	6
2	0.0204	0.1727	0.8943	0.1057	0.0202	4
3	0.0181	0.1534	0.8943	0.1057	0.0179	8
4	0.0157	0.1325	0.8943	0.1057	0.0155	13
5	0.0176	0.1491	0.8943	0.1057	0.0174	12
6	0.0236	0.1997	0.8943	0.1057	0.0233	2
7	0.0290	0.2456	0.8943	0.1057	0.0287	1
8	0.0122	0.1035	0.8943	0.1057	0.0121	15
9	0.0197	0.1671	0.8943	0.1057	0.0195	5
10	0.0177	0.1496	0.8943	0.1057	0.0174	11
11	0.0217	0.1837	0.8943	0.1057	0.0214	3
12	0.0183	0.1546	0.8943	0.1057	0.0180	7
13	0.0149	0.1264	0.8943	0.1057	0.0148	14
14	0.0181	0.1532	0.8943	0.1057	0.0179	9
15	0.0180	0.1520	0.8943	0.1057	0.0177	10
16	0.0120	0.1015	0.8943	0.1057	0.0118	16

TABLE IV. CALCULATED RESULTS AND RANKING OF ALTERNATIVES USING SAW METHOD

Trial	n_{ij}			V_j	Rank
	SR	*MRR*	L_w		
1	0.6469	2.0541	0.5243	1.0482	6
2	0.7386	2.0623	0.7545	1.1468	4
3	0.7340	2.1388	0.1148	1.0185	8
4	0.6739	1.8309	0.0432	0.8799	13
5	1.0000	1.3861	0.4523	0.9899	12
6	0.9083	2.2549	0.9364	1.3263	2
7	0.7063	3.5081	1.0000	1.6311	1
8	0.5554	1.0000	0.5393	0.6875	15
9	0.9646	2.0859	0.1189	1.1095	5
10	0.5367	1.8033	0.8334	0.9931	11
11	0.3586	2.9636	0.6370	1.2197	3
12	0.4985	1.9601	0.8470	1.0266	7
13	0.4624	1.5902	0.6016	0.8395	14
14	0.6288	1.7706	0.7993	1.0176	9
15	0.3150	2.1014	0.9493	1.0092	10
16	0.5636	1.0604	0.3857	0.6738	16

TABLE V. CALCULATED RESULTS AND RANKING OF ALTERNATIVES USING SAW METHOD

Trial	SP_i	SN_i	NSP_i	NSN_i	AS_i	Rank
1	0.0848	0.0281	0.2181	0.9281	0.5731	5
2	0.1995	0.0000	0.5134	1.0000	0.7567	3
3	0.1446	0.1888	0.3720	0.5175	0.4448	10
4	0.0689	0.2169	0.1772	0.4458	0.3115	11
5	0.1922	0.1458	0.4947	0.6273	0.5610	8
6	0.3614	0.0000	0.9301	1.0000	0.9650	2
7	0.3886	0.0000	1.0000	1.0000	1.0000	1
8	0.0000	0.2868	0.0000	0.2671	0.1335	15
9	0.2255	0.1872	0.5803	0.5216	0.5510	9
10	0.0950	0.0394	0.2446	0.8993	0.5719	6
11	0.1369	0.2879	0.3523	0.2643	0.3083	12
12	0.1247	0.0778	0.3209	0.8012	0.5611	7
13	0.0022	0.1586	0.0056	0.5947	0.3001	13
14	0.1136	0.0037	0.2923	0.9906	0.6414	4
15	0.1836	0.3913	0.4725	0.0000	0.2362	14
16	0.0000	0.3089	0.0000	0.2106	0.1053	16

To evaluate the association between the rankings obtained from the three MCDM techniques, the *R* coefficient was applied. The coefficient is calculated using the following formula [24]:

$$R = 1 - \frac{6 \cdot \sum_{i=1}^{n} D_i^2}{n \cdot (n^2 - 1)} \quad (28)$$

where: n = 16 is the number of alternatives and D is the difference between the rankings assigned to each alternative by the respective MCDM methods.

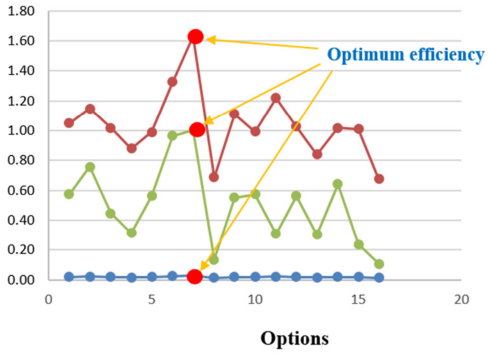

Fig. 2. Ranking of alternatives using the MCDM techniques.

Table VI presents the R coefficient for the rankings derived from the various methodologies. The data reveal that all coefficients exceed 0.99, which is significantly higher than the minimum threshold of 0.9 [24]. The highest correlation coefficient, 0.9969 is observed between the MARCOS and SAW methods, while the lowest, 0.9910, is identified between the MARCOS and EDAS methods.

TABLE VI. COEFFICIENT OF SPEARMAN'S RANK COLLERATION/ R COEFFICIENT

MARCOS and SAW	MARCOS and EDAS	SAW and EDAS
0.9969	0.9910	0.9949

V. CONCLUSIONS

This study reports the findings of a Multi-Criteria Decision-Making (MCDM) analysis aimed at identifying the optimal dressing modes for the surface grinding Hardox 500 steel. The investigation focused on three primary objectives: minimizing the Surface Roughness (SR), maximizing the Material Removal Rate (MRR) and wheel lifespan (L_w). To address the MCDM problem, three methods— Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS), Simple Additive Weighting (SAW), and Evaluation based on Distance from Average Solution (EDAS)—were employed, with the Entropy technique having been utilized to determine the criterion weights. Five input parameters were examined: rough dressing depth (d_r), rough dressing times (n_r), fine dressing depth (d_f), fine dressing times (n_f), and non-feeding dressing (n_n). The experimental design followed the Taguchi method using an L16 (4^4 x 2^1) configuration, and the analysis was conducted with the Minitab R19 software. The study successfully addressed the MCDM problem and proposed optimal input parameters. The results reveal that the ideal dressing parameters to simultaneously achieve minimal SR, maximal MRR, and maximal L_w are: d_r = 0.02 mm, n_r = 3 times, d_f = 0.005 mm, n_f = 3 times, and n_n = 0. These findings represent the first published results on optimal dressing methods for the surface grinding Hardox 500 steel to achieve the three objectives simultaneously. The outcomes provide valuable insights for optimizing the grinding process and enhancing its efficiency and effectiveness.

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