Determination of Best Input Parameters for Internal Grinding SKD11 Tool Steel using MCDM

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Received: 5 November 2024 | Revised: 11 December 2024 | Accepted: 29 December 2024

 DOI: https://doi.org/10.48084/etasr.9505

ABSTRACT

This article presents the results of an optimization study on the determination of the best input parameters for the internal grinding process when processing cylindrical-shaped parts of SKD11 tool steel. For this purpose, three Multi-Criteria Decision Making (MCDM) methods including the Evaluation based on Distance from Average Solution (EDAS), Multi-Attributive Border Approximation Area Comparison (MABAC), and Multi Attribute Utility Theory (MAUT) were used to solve the MCDM problem, while the entropy method was applied to find the criteria weights. Three objectives, namely the Surface Roughness (SR), Material Removal Rate (MRR), and wheel life (Tw), were also investigated. Six input factors, involving the coarse dressing depth (a_r), coarse dressing times (n_r), fine dressing depth (a_f), fine dressing times (n_f), non-feeding dressing (n_0), and dressing feed rate (S_d), were examined. Additionally, the Taguchi method with the L16 (4^4+2^2) design and the Minitab R19 program were deployed to design this study's experiment and investigate its outcomes. The MCDM work was successfully solved and the best process factors are proposed.

Keywords-internal grinding; MCDM; EDAS; MABAC; MAUT; surface roughness; material removal rate; wheel life

I. INTRODUCTION

Various studies have been conducted on the grinding process. Authors in [1] analyzed the grinding temperature in High-Efficiency Deep Grinding (HEDG) and Ultrasonic Vibration-assisted High-Efficiency Deep Grinding (UVHEDG) of the γ-TiAl materials. Both an analytical thermal model and a finite element simulation model were developed in their work. Subsequent comparative trials between HEDG and UVHEDG were performed to verify the precision of the simulation. The results indicated that the incorporation of ultrasonic vibrations into the HEDG reduced the maximum grinding temperature by 39.1%, thereby significantly mitigating the grinding burns. Authors in [2] examined the effects of surface grinding factors, including dressing parameters, grinding wheel velocity, workpiece velocity, and depth of cut, on surface roughness.

The study conceptually highlighted the impact of the dressing settings on surface roughness. Furthermore, an experiment was devised and conducted to assess the effects of the dressing parameters on surface roughness. The measured surface roughness from the experiment was in agreement with the calculated values. Authors in [3] tried to optimize the dressing parameters in order to achieve the minimum surface roughness for the internal grinding of SKD11 steel using the Taguchi method. The input parameters used were the coarse dressing depth, quantity of coarse dressings, fine dressing depth, quantity of fine dressings, non-feeding dressing, and dressing feed velocity. The amount of coarse dressing had the most significant influence on Ra, accounting for 88.28%. Moreover, the variance between the experimental roughness average and the predicted value was negligible. Authors in [4] constructed a mathematical model for the Grinding Force (GF) and Grinding Temperature (GT) of a single particle. A numerical simulation was performed to evaluate the interaction among the grinding parameters, grinding force-thermal coupling, and the residual stress of a single particle. At the same time, an experimental study of crystal fragmentation, elemental composition, and residual stress of both serviceable and non-serviceable aviation precision high-speed bearing rings was conducted, focusing on multi-grain grinding. The simulation showed that the residual stress in the Y direction exceeds that in the X direction, which exceeds that in the Z direction, all under identical grinding force and temperature conditions.

Authors in [5] proposed a novel approach to setting up diamond grinding wheels using the Abrasive Waterjet (AWJ) technology to mitigate the workpiece damage and wheel clogging associated with grinding challenging materials using conventional diamond grinding wheels. The primary process parameters were determined according to the theoretical model of diamond grinding wheels treatment using AWJ. The Response Surface Methodology (RSM) and Backpropagation Artificial Neural Networks (BP-ANN) were utilized to develop regression models that correlated process factors with microgroove features. A comparative analysis was conducted to assess the predictive efficacy of both RSM and BP-ANN. The findings demonstrated that both BP-ANN and RSM are effective methodologies for forecasting microgroove attributes. Authors in [6] presented a study on the computation of the optimal exchanged grinding wheel diameter in the external grinding of the 90CrSi tool steel. The impact of grinding process factors, such as the starting grinding wheel diameter, total dressing depth, radial grinding wheel wear per dress, and wheel life on the exchanged grinding wheel diameter, was investigated. Additionally, the influence of cost factors, such as the machine tool hourly rate and grinding wheel expense, was examined. A model was presented to determine the optimal swapped grinding wheel diameter based on the obtained data. Authors in [7] carried out a study on the optimization of the dressing parameters in internal cylindrical grinding to achieve the maximum material removal rate. The effects of the dressing parameters, including the dressing feed rate, coarse dressing depth, coarse dressing frequency, fine dressing depth, fine dressing frequency, and dressing count without depth of cut, on the material removal rate were investigated. Authors in [8] attempted to improve alternative approaches by examining the grinding of hardened AISI 4340 steel with four lubricooling fluids: base fluid, Volatile Corrosion Inhibitor (VCI), VCI Low Cost (VCI LC), and VCI Extreme Pressure (VCI EP). The parameters obtained in the study entail the surface roughness, roundness error, wheel wear, grinding power, pollution, and cost. Corrosion inhibitors can enhance workpiece quality, but yield varying results across different parameters.

Authors in [9] carried out a study on the impact of the grinding wheel wear on the cutting forces, analyzing the grinding wheel topography to create a measure that non-destructively quantifies the grinding wheel wear. It was reported that after a short conditioning phase, the cutting forces increase in an essentially linear manner with the machined length. During this second phase, the force ratio converges to a constant value, and the predominant wear mechanism is the formation of flat surfaces on the diamond grains. Under these circumstances, the 3D surface roughness metrics Sa, Sq, Spk, and Sku have demonstrated their effectiveness in monitoring the wheel wear. Authors in [10] attempted to improve the dressing parameters of the grinding wheels for the 9CrSi tool steel with the aim of reducing the average roughness and flatness tolerance using the Taguchi technique and Grey Relational Analysis (GRA). The results indicate that the optimum dressing parameters for achieving minimum average roughness and flatness tolerance are a coarse dressing depth of 0.025 mm, three coarse dressing cycles, a fine dressing depth of 0.005 mm, two fine dressing cycles, three non-feeding dressings, and a dressing feed rate of 1.6 m/min. Experiments were conducted with the optimized dressing parameters to validate the predictive model. Authors in [11] analyzed the impact of coolant parameters on surface roughness during the internal cylindrical grinding of annealed 9CrSi steel. Thirteen experiments were carried out using a central composite design and response surface methodology to investigate the coolant concentration and flow rate. The influence of each parameter and their interaction on surface roughness were examined through their regression model. Optimal parameters were derived from this model to achieve the lowest surface roughness.

Authors in [12] investigated the impact of speed on the creation of machined surfaces during ultra-high-speed grinding of the IN718 superalloy at velocities reaching 240 m/s. In this study, the grinding forces and surface integrity are carefully analyzed over several speed ranges. Various methods are utilized to characterize and examine the subsurface microstructure. The findings indicate that the brittle-mode removal of IN718 superalloy occurs at a grinding speed greater than 190 m/s, substantially reducing work hardening and thermal generation caused by increased plastic deformation. Moreover, the grinding speed affects the formation mechanism of the recrystallization layer, which gradually shifts from the dominance of discontinuous Dynamic Recrystallization (dDRX) to the dominance of continuous Dynamic Recrystallization (cDRX) as the grinding speed increases. Authors in [13] performed a study to identify the optimal dressing parameters for achieving the minimal flatness tolerance when grinding SKD11 steel with a HaiDuong grinding wheel. In this study, the impact of six input parameters: feed rate (S), a_r, n_r, a_f, n_f, and non-feeding dressing (nnon) on flatness tolerance was investigated. Authors in [14] performed a study on the optimal computation of the exchanged diameter of grinding wheels in the internal grinding of stainless steel. The influence of the grinding process parameters, including the initial diameter, total depth of dressing cut, wheel life, radial grinding wheel wear per dress, and the ratio of length to diameter of workpieces, on the exchanged grinding wheel diameter was investigated. The impact of cost considerations, involving the hourly rate of machine tools and wheel cost, was also examined. Based on the results of the study, a proposed model for determining the optimal swapped grinding wheel diameter was presented. Authors in [15] attempted to determine the ideal dressing method for the external grinding of SKD11 tool steel. For this purpose, they used the MABAC method. The aim of their research was to determine the ideal dressing technique that simultaneously minimizes RS, maximizes Tw, and enhances Roundness (R). To accomplish this task, an experiment was performed using six input parameters: depth of fine dressing, number of fine dressing passes, depth of coarse dressing, number of coarse dressing passes, non-feeding dressing, and dressing feed rate. Based on the results obtained, an ideal dressing method for cylindrical external grinding was proposed.

The MCDM method has demonstrated its effectiveness in identifying optimal answers in a variety of domains. For instance, selecting the optimal airport [16], assessing the impact of criterion weights on the ranking of the top ten universities in Vietnam [17], identifying the ideal design parameters for a two-stage helical gearbox [18], or determining the most appropriate input parameters for the milling process [19]. In the context of internal grinding, four MCDM methods, TOPSIS, MARCOS, EAMR, and MAIRCA, were used in [20] to identify the optimal dressing factors aimed at achieving both a minimum SR and MRR, concurrently. Authors in [21] employed the Evaluation based on the EDAS technique to determine the optimal dressing parameters to achieve both a minimum SR and maximum wheel life, concurrently. The influence of the dressing parameters on surface roughness and wheel life in internal grinding was examined in [22] deploying the Taguchi and GRA techniques to achieve the same objectives as in [21].

There have been numerous studies on the use of MCDM methods to determine the optimal choice in a variety of sectors; however, no study has yet used multiple MCDM techniques to determine the optimal dressing mode for the internal grinding process with three distinct objective functions. This study reports the results of a multi-criteria decision-making analysis conducted on the internal grinding of SKD11 steel components. Three objectives were examined: minimum SR, maximum MRR, and maximum Tw. Also, three MCDM techniques, namely EDAS, MABAC, and MAUT, were employed to address the MCDM problem, and the entropy method was utilized to calculate the criteria weights. The study's results indicate the optimal input parameters for concurrently minimizing SR, maximizing MRR, and maximizing Tw.

II. METHODOLOGY

A. The Method to Solve Multi-Criteria Decision Making

1) The EDAS Method

To use the EDAS method, the following steps must be taken [23]:

Step 1: Create the first decision-making matrix:

$$X = \begin{bmatrix} r_{11} & \cdots & r_{1j} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r_{1} & \cdots & r_{ij} & \cdots & r_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mj} & \cdots & r_{mn} \end{bmatrix}_{m\times n} \quad (1)$$

where m is the number of options and n is the number of criteria.

Step 2: Find the average of each criterion's solutions:

$$AV_{\mathrm{j}} = \frac{\sum_{i=1}^{m} r_{ij}}{m} \quad (2)$$

Step 3: Compute the positive and negative distances from the average solution.

For the SR target:

$$PDA_{ij} = \frac{max\left(0,(r_{ij}-AV_j)\right)}{AV_j} \quad (3)$$

$$NDA_{ij} = \frac{max\left(0,(AV_j-r_{ij})\right)}{AV_j} \quad (4)$$

For MRR and Tw targets:

$$PDA_{ij} = \frac{max\left(0,(AV_j-r_{ij})\right)}{AV_j} \quad (5)$$

$$NDA_{ij} = \frac{max\left(0,(r_{ij}-AV_j)\right)}{AV_j} \quad (6)$$

Step 4: Determine the weighted PDA and NDA:

$$SP_i = \sum_{j=1}^{n} PDA_{ij} \cdot w_j \quad (7)$$

$$SN_i = \sum_{j=1}^{n} NDA_{ij} \cdot w_j \quad (8)$$

Step 5: Calculate the weighted normalized PDA and NDA:

$$NSP_i = \frac{SP_i}{\max_i(SP_i)} \quad (9)$$

$$NSN_i = \frac{SN_i}{\max_i(SN_i)} \quad (10)$$

Step 6: Determine the appraisal score for each alternative by:

$$AS_i = (NSP_i + NSN_i)/2 \quad (11)$$

Step 7: Sort the options by maximizing AS_i.

2) The MABAC Method

The following are the steps to use the MABAC technique to solve the MCDM problem [23]:

Step 1: Construct the initial decision-making matrix:

$$X = \begin{bmatrix} r_{11} & \cdots & r_{1j} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r_1 & \cdots & r_{ij} & \cdots & r_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mj} & \cdots & r_{mn} \end{bmatrix}_{m \times n} \quad (12)$$

where *m* is the number of options and *n* is the number of the criteria.

Step 2: Find the normalized values r_{ij}^* by:

$$r_{ij}^* = \frac{r_{ij}-r_i^-}{r_i^+-r_i^-} \quad (13)$$

$$r_{ij}^* = \frac{r_{ij}-r_i^+}{r_i^--r_i^+} \quad (14)$$

with $i = 1,2,\ldots,m$ and $j = 1,2,\ldots,n$. Equation (13) is used for the MRR and Tw criteria, and (14) is used to generate the SR. Also, $r_i^+ = max(r_1, r_2, \ldots, r_m)$ and $r_i^- = min(r_1, r_2, \ldots, r_m)$.

Step 3: Calculate the weighted matrix elements by:

$$v_{ij} = w_j + w_j \times r_{ij}^* \quad (15)$$

Step 4: Compute the border approximation area matrix:

$$g_j = \left(\prod_{i=1}^{m} v_{ij}\right)^{1/m} \quad (16)$$

with $j = 1,2,\ldots,n$.

Step 5: Determine the space between the options and the border approximation area by:

$$q_{ij} = v_{ij} - g_i \quad (17)$$

with $i = 1,2,\ldots,m$ and $j = 1,2,\ldots,n$.

Step 6: Calculate the total distances of each option from the approximate border area:

$$S_i = \sum_{j=1}^{n} q_{ij} \quad i = 1, 2, \ldots, m \quad (18)$$

Step 7: Rank the options by maximizing S_i.

3) The MAUT Method

The implementation steps for the MAUT approach are outlined as follows [23]:

Step 1: Build the initial decision-making matrix:

$$X = \begin{bmatrix} r_{11} & \cdots & r_{1j} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r_1 & \cdots & r_{ij} & \cdots & r_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mj} & \cdots & r_{mn} \end{bmatrix}_{m \times n} \quad (19)$$

where *m* is the number of options and *n* is the number of criteria.

Step 2: Create normalized decision matrices.

For the MRR and Tw targets:

$$r_{ij}^* = \frac{r_{ij}-min(r_{ij})}{max(r_{ij})-min(r_{ij})} \quad (20)$$

For the SR target:

$$r_{ij}^* = 1 + \frac{min(r_{ij})-r_{ij}}{max(r_{ij})-min(r_{ij})} \quad (21)$$

with $i = 1,2,\ldots,m$ and $j = 1,2,\ldots,n$.

Step 3: Find the marginal utility score by:

$$u_{ij} = \frac{e^{(r_{ij})^2}-1}{1.71} \quad (22)$$

Step 3: Calculate the final utility score by:

$$U_i = \sum_{j=1}^{n} u_{ij} \cdot w_j \quad (23)$$

with $i = 1,2,\ldots,m$.

Step 4: Rank the options by maximizing U_i.

B. Method for Determining Creation Weights

The entropy approach was employed to determine the weights of the criteria in this research. The following procedures can be utilized to implement this method [24].

Step 1: Calculate the indicator's normalized values by:

$$p_{ij} = \frac{x_{ij}}{m+\sum_{i=1}^{m} x_{ij}^2} \quad (24)$$

Step 2: Estimate the entropy of each indicator by:

$$me_j = -\sum_{i=1}^{m}\left[p_{ij} \times ln(p_{ij})\right] - \left(1 - \sum_{i=1}^{m} p_{ij}\right) \times ln\left(1 - \sum_{i=1}^{m} p_{ij}\right) \quad (25)$$

Step 3: Determine the weight for each indicator:

$$w_j = \frac{1-me_j}{\sum_{j=1}^{m}(1-me_j)} \quad (26)$$

III. EXPERIMENTAL WORK

In this study, the input data for the MCDM problem were constructed by conducting an experiment. The experiment was designed based on the Taguchi method with the L16 (4^4+2^2) configuration. This investigation examines six input dressing factors: a_r, n_r, a_f, n_f, n_0, and S_d, based on [21, 22]. Table I shows the input parameters and their levels. Figure 1 displays the experimental setup with the use of the following equipment: a MACHT-701 (Japan) grinding machine, SKD11 tool steel workpieces with dimensions of $\varphi 25 \times \varphi 36 \times 22$ mm and hardness of 58-60 HRC, grinding wheels of 19A 120L 8 ASI T S 1A (Japan) with dimensions of $23 \times 25 \times 8$ mm, Mitutoyo SV-3100 surface roughness tester, diamond dresser DKB3E002110, and Caltex Aquatex 3180 oil with concentration of 2%–5%.

The experiment was conducted as follows: The SR of each sample was measured utilizing surface roughness equipment. To find the Tw and MRR, each sample was ground until the SR exceeded 0.4 μm. The processing time for each sample was recorded during the experiment to determine the Tw. The diameter of each sample was measured before and after each run to calculate the MRR:

$$MRR_i = \frac{\pi \cdot \left(d_{pbi}^2 - d_{pai}^2\right) \cdot l_{pi}}{4 \cdot T_{wi}} \quad (27)$$

where d_{pbi} and d_{pai} are the diameters of workpiece i before and after machining (mm), l_{pi} is the length of workpiece i (mm), and T_{wi} is the wheel life (min).

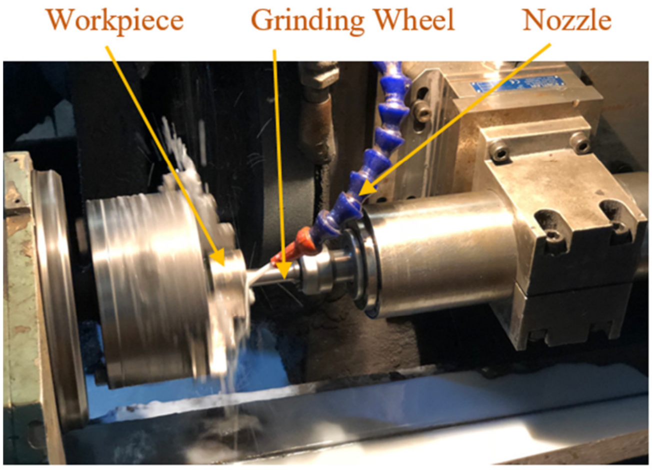

Fig. 1. Experimental setup.

TABLE I. INPUT PARAMETERS

No	Input parameters	Code	Unit	Levels 1	2	3	4
1	Coarse dressing depth	a_r	mm	0.03	0.04	-	-
2	Coarse dressing times	n_r	times	1	2	3	4
3	Fine dressing depth	a_f	mm	0.005	0.01	0.015	0.02
4	Fine dressing times	n_f	times	0	1	2	3
5	Non-feeding dressing	n_0	times	0	1	2	3
6	Dressing feed rate	S_d	m/min	1	1.5	-	-

Table II presents the experimental plan and the SR (*Ra*), MRR, and Tw outcomes of the experiment.

TABLE II. EXPERIMENTAL MATRIX AND OUTPUT RESULTS

No.	a_f	n_f	n_0	n_r	a_r	S_d	*Ra* (µm)	MRR (mm^3/s)	Tw (min.)
1	0.005	0	0	1	0.03	1	0.365	0.919	11.267
2	0.005	1	1	2	0.03	1.5	0.214	1.041	12.733
3	0.005	2	2	3	0.04	1	0.195	1.122	12.697
4	0.005	3	3	4	0.04	1.5	0.242	1.111	11.423
5	0.01	0	1	3	0.04	1.5	0.185	1.246	11.803
6	0.01	1	0	4	0.04	1	0.248	1.267	12.430
7	0.01	2	3	1	0.03	1.5	0.252	1.178	11.147
8	0.01	3	2	2	0.03	1	0.217	1.225	12.077
9	0.015	0	2	4	0.03	1.5	0.306	1.488	12.547
10	0.015	1	3	3	0.03	1	0.324	1.372	12.077
11	0.015	2	0	2	0.04	1.5	0.341	1.271	12.027
12	0.015	3	1	1	0.04	1	0.354	1.199	12.503
13	0.02	0	3	2	0.04	1	0.318	1.227	12.177
14	0.02	1	2	1	0.04	1.5	0.313	1.265	10.620
15	0.02	2	1	4	0.03	1	0.326	1.125	13.153
16	0.02	3	0	3	0.03	1.5	0.363	1.190	12.230

IV. DETERMINING THE BEST INPUT PARAMETERS

At the end of the experiment, the values of SR, MRR, and Tw are used as input variables to solve the MCDM problem. The weights for the criteria in the MCDM problem were determined deploying the entropy technique, as described in Section B. The values of p_{ij} were standardized according to (24). The entropy value for each indicator me_j was determined using (25). The weight of the criteria w_j was calculated using (26). The calculated weights for *Ra*, MRR, and Tw were 0.3324, 0.4241, and 0.2435, respectively.

Section A provides guidance on the effective application of the EDAS, MABAC, and MAUT methods in addressing the MCDM problem. The calculations are provided below.

Section A.1 presents the specific requirements for implementing the EDAS technique in solving the MCDM problem: Equation (2) is used to determine the average solution for each criterion. Then, (3) and (4) are used to determine the surface roughness and (5) and (6) to assess the wheel life by calculating both the positive and negative deviations from the mean solution. Then, (7) and (8) are used to calculate the weighted PDA and NDA. The weighted normalized PDA and NDA are calculated using (9) and (10). The evaluation score AS_i for each trial is determined by (11). The ranking of the options facilitated the identification of the optimal choice, since it has the highest AS_i value. Table III lists the computed results along with the alternative rankings.

TABLE III. CALCULATED RESULTS AND RANKING OF OPTIONS BY EDAS METHOD

Trial	*Spi*	*Sni*	*NSPi*	*NSNi*	*ASi*	Rank
1	0.1002	0.1094	0.6513	0.1274	0.3893	9
2	**0.1539**	**0.0000**	**1.0000**	**1.0000**	**1.0000**	**1**
3	0.1469	0.0000	0.9547	1.0000	0.9773	2
4	0.0829	0.0128	0.5391	0.8979	0.7185	5
5	0.1167	0.0203	0.7586	0.8379	0.7983	3
6	0.0511	0.0225	0.3324	0.8202	0.5763	7
7	0.0473	0.0184	0.3072	0.8533	0.5803	6
8	0.0802	0.0079	0.5210	0.9373	0.7291	4
9	0.0099	0.1253	0.0643	0.0000	0.0321	16
10	0.0004	0.1050	0.0026	0.1618	0.0822	15
11	0.0000	0.0893	0.0000	0.2871	0.1436	14
12	0.0104	0.0805	0.0678	0.3580	0.2129	11
13	0.0024	0.0469	0.0157	0.6259	0.3208	10
14	0.0000	0.0829	0.0000	0.3384	0.1692	12
15	0.0497	0.0476	0.3229	0.6204	0.4716	8
16	0.0081	0.0913	0.0525	0.2714	0.1620	13

The process of employing the MABAC method is outlined in Section A.2. The initial matrix is constructed according to (12). Then, (13) for the MRR and Tw objectives and (14) for the SR objective are used to compute the normalized values of r_{ij}^{*}. The normalized weighted values of v_{ij} are then calculated utilizing (15). Equation (16) is used to compute the border approximation area matrix. The distance between the alternatives and the border approximation area q_{ij} is computed using (17). Finally, the total distances between each option and the approximate border area S_i are computed utilizing (18). To determine the ranking of the options, S_i is optimized. Table IV shows the calculated parameters and the ranking of the options derived from the MABAC method. According to the data presented in Table IV, option 2 is identified as the most favorable choice. This is due to its highest value for S_i ($S_i = 0.3425$).

Section A.3 describes the application of the MAUT technique. After calculating the decision-making matrices using (19), the normalized decision matrix is generated utilizing (20) and (21). The marginal utility score is then determined by (22). The final utility score is then determined by (23). The ranking of the options is determined by optimizing U_i. Table V presents various calculated parameters along with the ranking of the options derived from this method. According to Table V, option 2 is optimal, exhibiting the highest U_i value ($U_i = 0.5537$).

TABLE IV. CALCULATED RESULTS AND RANKING OF OPTIONS BY MABAC METHOD

Trial	g_{ij}			q_{ij}			S_i	Rank
	SR	MRR	Tw	SR	MRR	Tw		
1	0.4675	0.6292	0.3761	-0.1350	0.2189	-0.0704	0.0135	9
2	**0.4675**	**0.6292**	**0.3761**	**0.1445**	**0.1275**	**0.0705**	**0.3425**	**1**
3	0.4675	0.6292	0.3761	0.1793	0.0678	0.0670	0.3141	2
4	0.4675	0.6292	0.3761	0.0928	0.0755	-0.0554	0.1129	6
5	0.4675	0.6292	0.3761	0.1974	-0.0249	-0.0188	0.1536	3
6	0.4675	0.6292	0.3761	0.0817	-0.0404	0.0414	0.0827	7
7	0.4675	0.6292	0.3761	0.0738	0.0255	-0.0820	0.0174	8
8	0.4675	0.6292	0.3761	0.1389	-0.0094	0.0074	0.1369	4
9	0.4675	0.6292	0.3761	-0.0266	-0.2051	0.0526	-0.1791	15
10	0.4675	0.6292	0.3761	-0.0588	-0.1192	0.0074	-0.1706	14
11	0.4675	0.6292	0.3761	-0.0897	-0.0435	0.0026	-0.1306	13
12	0.4675	0.6292	0.3761	-0.1146	0.0102	0.0484	-0.0560	11
13	0.4675	0.6292	0.3761	-0.0478	-0.0111	0.0170	-0.0418	10
14	0.4675	0.6292	0.3761	-0.0380	-0.0389	-0.1326	-0.2095	16
15	0.4675	0.6292	0.3761	-0.0625	0.0654	0.1109	0.1137	5
16	0.4675	0.6292	0.3761	-0.1317	0.0169	0.0222	-0.0927	12

TABLE V. CALCULATED RESULTS AND RANKING OF OPTIONS BY MAUT METHOD

Trial	r_{ij}*			u_{ij}			U_i	Rank
	Ra	MRR	Tw	Ra	MRR	Tw		
1	0.0000	1.0000	0.2553	0.0000	1.0047	0.0394	0.4356	3
2	**0.8407**	**0.7844**	**0.8342**	**0.6008**	**0.4972**	**0.5879**	**0.5537**	**1**
3	0.9456	0.6435	0.8198	0.8451	0.3000	0.5603	0.5446	2
4	0.6853	0.6618	0.3171	0.3506	0.3214	0.0619	0.2679	7
5	1.0000	0.4250	0.4671	1.0047	0.1157	0.1426	0.4178	4
6	0.6521	0.3884	0.7145	0.3098	0.0952	0.3895	0.2382	8
7	0.6282	0.5439	0.2079	0.2829	0.2013	0.0258	0.1857	9
8	0.8241	0.4615	0.5750	0.5684	0.1388	0.2291	0.3036	6
9	0.3263	0.0000	0.7605	0.0657	0.0000	0.4580	0.1334	13
10	0.2292	0.2027	0.5750	0.0315	0.0245	0.2291	0.0767	15
11	0.1365	0.3811	0.5553	0.0110	0.0914	0.2112	0.0938	14
12	0.0616	0.5077	0.7434	0.0022	0.1719	0.4315	0.1787	10
13	0.2625	0.4577	0.6145	0.0417	0.1362	0.2683	0.1370	12
14	0.2919	0.3920	0.0000	0.0520	0.0971	0.0000	0.0585	16
15	0.2181	0.6379	1.0000	0.0285	0.2936	1.0047	0.3786	5
16	0.0100	0.5235	0.6355	0.0001	0.1844	0.2910	0.1491	11

Figure 2 presents the efficiency of the alternatives derived from the results of solving the MCDM problem using the three MCDM methods mentioned above, as obtained from the data in Tables III-V. The graph indicates that the efficiency values calculated by all three methods exhibit consistent trends, whether high or low, across the options presented. In addition, the findings from all three methods demonstrate that option 2 is the best option. Based on the analysis and Table II, the best input parameters for achieving the minimum SR, maximum MRR, and maximum Tw simultaneously are: a_r=0.03 mm, n_r=2 times, a_f=0.005 mm, n_f=1 times, n_0=1, and S_d=1 m/min.

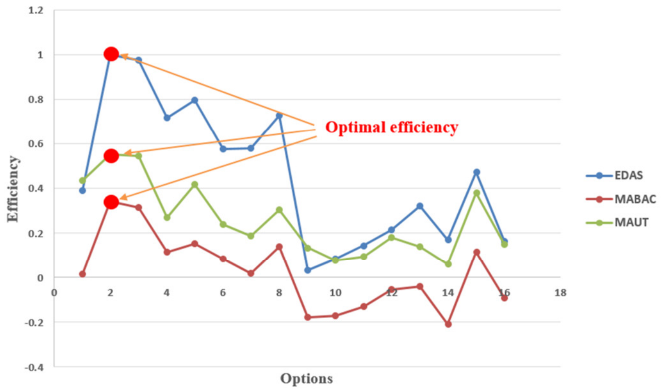

Fig. 2. Ranking of options by three MCDM techniques.

In this study, the Spearman's rank correlation coefficient (R) was used to evaluate the association between the ranks obtained from the MCDM techniques. The value of these coefficients (R_i) must fall within the range of 0.9 to 1. The coefficient is identified as [23]:

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

where $n = 16$ is the number of options and D is the difference between the ranks.

Table VI presents the Spearman's rank correlation coefficient for the rankings derived from the different methods. It is demonstrated that the maximum correlation coefficient is 0.9969 between EDAS and MABAC, whereas the minimum is 0.9610 between EDAS and MAUT.

TABLE VI. SPEARMAN'S RANK CORRELATION COEFFICIENT

EDAS and MABAC	EDAS and MAUT	MABAC and MAUT
0.9969	0.9610	0.9949

V. CONCLUSIONS

This paper presents the results of a Multi-Criteria Decision Making (MCDM) analysis aimed at identifying the best input factors in internal grinding of cylindrical shaped part made of SKD11 tool steel. In this work, three objectives, including minimizing Surface Roughness (SR), maximizing Material Removal Rate (MRR), and maximizing wheel life (Tw), have been examined. In addition, six input parameters were investigated: coarse dressing depth (a_r), coarse dressing times (n_r), fine dressing depth (a_f), fine dressing times (n_f), non-feeding dressing (n_0), and dressing feed rate (S_d). The experiment was designed using the Taguchi method with the L16 (4^4+2^2) design, and the results were analyzed employing the Minitab R19 program. The MCDM problem was successfully solved, and the best input parameters were recommended. The study's results indicate that the most effective input parameters to obtain the minimum SR, maximum MRR, and maximum Tw simultaneously are: a_r=0.03 mm, n_r=2 times, a_f=0.005 mm, n_f=1 times, n_0=1, and S_d=1 m/min. Moreover, it can be noted that the Evaluation based on the Distance from Average Solution (EDAS), Multi-Attributive Border Approximation Area Comparison (MABAC), and Multi Attribute Utility Theory (MAUT) techniques can deal with the MCDM problems in the internal grinding process.

ACKNOWLEDGMENT

The present work was supported by Thai Nguyen University of Technology.

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