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Integration Of Entropy and Ram Methods for Multi-Objective Optimization of The Skd11 Steel Grinding Process

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Abstract
Grinding is a common method in mechanical engineering for machining products that require high precision. This study focuses on the multi-objective optimization of the SKD11 steel grinding process on a surface grinding machine. An experimental plan consisting of a total of 9 experiments was designed using the Taguchi method. In each experiment, three cutting parameters were varied: workpiece speed, feed rate, and depth of cut. In each of these experiments, four performance criteria were measured: surface roughness (Ra), cutting force component in the x-direction (Fx), cutting force component in the y-direction (Fy), and cutting force component in the z-direction (Fz). The ENTROPY method was used to calculate the weights for these criteria, while the RAM method was employed to solve the multi-objective optimization problem. The results showed that the optimal values for workpiece speed, feed rate, and depth of cut were 10 (m/min), 4 (mm/stroke), and 0.01 (mm), respectively. With these optimal cutting parameter values, the corresponding values for the performance criteria Ra, Fx, Fy, and Fz were 0.49 (μm), 18.4 (N), 15.2 (N), and 28.4 (N), respectively.
Keywords: *surface grinding, SKD11 steel, multi-objective optimization, ENTROPY method, RAM method*

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I. Introduction

Grinding is a highly prevalent machining method in mechanical manufacturing [1]. This process is frequently employed for producing parts that demand a high degree of precision [2]. To fully capitalize on the advantages of grinding, it is essential to conduct research aimed at optimizing the process [3]. Numerous studies have been carried out on multi-objective optimization of the grinding process to ensure that multiple parameters simultaneously achieve desired values. Published research shows that scientists have applied various algorithms to solve multi-objective optimization problems and have used different methods to assign weights to the objectives. This article will not summarize all published studies but will focus on a selection of recent research on this topic.

The Nelder–Mead algorithm, integrated into the DESIGN EXPERT V7.1.3 software, has been used for the multi-objective optimization of EN-8 steel grinding. The goal was to simultaneously minimize surface roughness and maximize the material removal rate, with both criteria being assigned an equal weight of 0.5 [4]. In [5], the DEAR algorithm was also used for the multi-objective optimization of SAE420 steel grinding. The objective was to minimize surface roughness and the vibration of the grinding machine spindle in three directions (x, y, and z). In this study, the weights of the objectives were calculated using the DEAR algorithm itself. The MOORA and COPRAS algorithms were utilized for the multi-objective optimization of SKD11 steel grinding, with the aim of achieving the lowest possible surface roughness and the highest material removal rate. Here, the weights of these two criteria were calculated using the Entropy method [6]. The GA algorithm was applied to optimize the grinding of Pinus sylvestris wood, specifically to minimize surface roughness [7]. The GA algorithm was also used for the multi-objective optimization of SKD11 steel grinding, where the weights for three objectives—surface roughness, grinding time, and the deviation between the actual and desired grinding depths—were chosen to be equal, at 1/3 each [8]. The DEAR algorithm was applied for the multi-objective optimization of AISI 4140 steel grinding to ensure low surface roughness and a high material removal rate, with the objective weights being determined by the DEAR algorithm itself [9]. The TOPSIS algorithm was employed for the multi-objective optimization of DIN 1.2379 steel grinding, aiming to simultaneously minimize surface roughness and the x, y, z-direction spindle vibrations while maximizing the material removal rate. In this case, the weights of the objectives were all set to an equal value of 0.2 [10]. In [11], the Nelder-Mead algorithm was also used for the multi-objective optimization of Hardox 500 steel grinding to ensure the minimum possible surface roughness and the maximum material removal rate, with equal weights assigned to these two criteria. The PSO algorithm was used to perform multi-objective optimization on D2 tool steel grinding to ensure the maximum material removal rate and minimum dimensional error, though the weights of these two parameters were not clearly defined [12], etc.

This brief summary of several studies indicates that various algorithms and weighting methods have been applied to multi-objective grinding optimization. However, it appears that no existing literature has integrated the ENTROPY method for weighting criteria with the RAM algorithm for multi-objective optimization of the grinding process. This research gap motivated the current study.

II. Materials and Methods

2.1. Experimental Setup

The test specimens were made of SKD11 steel, with dimensions of 40 mm (length), 25 mm (width), and 8 mm (height). The chemical composition of some of the key elements of this steel is presented in Table 1. All experiments were performed on an APSG-820/8A surface grinding machine manufactured in Taiwan. Surface roughness (Ra) was measured using a Mitutoyo SJ-201 roughness tester from Japan. The cutting force components were measured with a Kistler dynamometer from Germany. To minimize the influence of random errors, each parameter (surface roughness and force components) was measured at least three times per experiment. The final value for each output parameter was the average of these repeated measurements.

Table 1. Chemical composition of SKD11 steel

C (%)	Si (%)	Mn (%)	P (%)	S (%)	Cr (%)	Ni (%)	Mo (%)
1.03	0.23	0.31	0.022	0.022	11.71	0.18	0.92

2.2. Experimental Matrix

In each experiment, three input parameters were varied: workpiece speed, feed rate, and depth of cut. These three parameters were selected due to their ease of adjustment by a machine operator [13]. For each parameter, three distinct levels were tested, corresponding to encoded levels 1, 2, and 3, as shown in Table 2. These values were chosen based on a review of relevant literature and the technical capabilities of the grinding machine used [13].

The experimental matrix was designed as a Taguchi L9 array, comprising 9 experiments (Table 3). This design is widely used for optimization experiments in mechanical engineering and has been frequently applied in recent years [13].

Table 2. Input parameters

Parameter	Unit	Symbol	Value at level		
			1	2	3
Workpiece velocity	m/min	v	5	10	15
Feed-rate	mm/stroke	f	4	6	8
Depth of cut	mm	t	0.005	0.01	0.015

Table 3. Experimental matrix

Exp.	Code value			Real value		
	v	f	t	v(m/min)	f(mm/stroke)	t(mm)
#1	1	1	1	5	4	0.005
#2	1	2	2	5	6	0.01
#3	1	3	3	5	8	0.015
#4	2	1	2	10	4	0.01
#5	2	2	3	10	6	0.015
#6	2	3	1	10	8	0.005

#7	3	1	3	15	4	0.015
#8	3	2	1	15	6	0.005
#9	3	3	2	15	8	0.01

2.3. Experimental Results

The experiments were conducted in the order listed in Table 3. The output parameters—Ra, Fx, Fy, and Fz—were measured for each run. The results are summarized in Table 4.

Table 4. Experimental results

Exp.	Input parameters			Responses			
	v(m/min)	f(mm/stroke)	t(mm)	Ra (µm)	Fx (N)	Fy (N)	Fz (N)
#1	5	4	0.005	0.82	21.7	11.3	27.1
#2	5	6	0.01	0.62	34.5	20.5	24.3
#3	5	8	0.015	0.75	39.4	16.4	26.2
#4	10	4	0.01	0.49	18.4	15.2	28.4
#5	10	6	0.015	0.51	22.5	20.6	30.4
#6	10	8	0.005	0.41	29.6	19.8	31.2
#7	15	4	0.015	0.94	31.7	22.7	22.8
#8	15	6	0.005	0.82	32.7	28.6	30.6
#9	15	8	0.01	0.73	28.1	18.4	31.5

From the data in Table 4, it is clear that the minimum Ra value of 0.41 µm occurred in Experiment #6, the minimum Fx value of 18.4 N was in Experiment #4, the minimum Fy value of 11.3 N was in Experiment #1, and the minimum Fz value of 22.8 N was in Experiment #7. This indicates that no single experimental run yielded the optimal (minimum) values for all four objectives simultaneously. Instead, it is necessary to identify a single best solution that balances these competing objectives. This cannot be achieved by simple observation of the data in Table 4; a ranking method is required to select the best alternative. For this reason, the RAM algorithm will be used to rank the experimental runs in this study, but first, the weights for each criterion must be calculated using the ENTROPY method.

2.4. Entropy Method

Let's assume there are *m* experiments, with *n* output parameters measured for each experiment. Let xij be the value of the *j-th* output parameter in the *i-th* experiment, where j=1...n and i=1...m. The weighting of each parameter *j* using the Entropy method follows these steps [14]:

Step 1: Normalize the values for each criterion using Formula (1).

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

Step 2: Calculate the entropy measure for each parameter *j* using Formula (2).

$$e_j = \sum_{i=1}^{m} [n_{ij} \times ln(n_{ij})] - \left(1 - \sum_{i=1}^{m} n_{ij}\right) \times ln\left(1 - \sum_{i=1}^{m} n_{ij}\right) \tag{2}$$

Step 3: Calculate the weight for each parameter using Formula (3).

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{n}(1 - e_j)} \tag{3}$$

2.5. RAM Algorithm

The steps for using the RAM method to rank the alternatives are as follows [15]:

Step 1: Similar to Step 1 of the ENTROPY method.

Step 2: Normalize the data according to Formula (4).

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{4}$$

Step 3: Calculate the weighted normalized values for each criterion using Formula (5).Here, wj is the weight of the *j-th* criterion

$$y_{ij} = w_j \cdot r_{ij} \tag{5}$$

Step 4: Calculate the total weighted normalized scores for each criterion using Formulas (6) and (7). The letters **B** and **C** denote "beneficial" and "cost" criteria, respectively.

$$S_{+i} = \sum_{j=1}^{n} y_{+ij} \quad if \quad j \in B \tag{6}$$

$$S_{-i} = \sum_{j=1}^{n} y_{-ij} \quad if \quad j \in C \tag{7}$$

Step 5: Calculate the final score for each alternative using Formula (8).

$$RI_i = \sqrt[2+S_{-i}]{2 + S_{+i}} \tag{8}$$

Step 6: Rank the alternatives in descending order based on their scores.

III. Results and Discussion

By applying formulas (1) to (3), the weights for the parameters Ra, Fx, Fy, and Fz were calculated to be 0.364, 0.208, 0.218, and 0.210, respectively.

Using formulas (4) to (8), the RI score for each experiment was calculated and is summarized in Table 5. The final column in this table also shows the ranking of the experiments based on their scores.

Table 5. Scores and rankings of the experiments

Exp.	Ra (μm)	Fx (N)	Fy (N)	Fz (N)	RIi	Rank
#1	0.82	21.7	11.3	27.1	1.390	4
#2	0.62	34.5	20.5	24.3	1.389	5
#3	0.75	39.4	16.4	26.2	1.387	7
#4	0.49	18.4	15.2	28.4	1.394	1
#5	0.51	22.5	20.6	30.4	1.391	3
#6	0.41	29.6	19.8	31.2	1.391	2
#7	0.94	31.7	22.7	22.8	1.385	8
#8	0.82	32.7	28.6	30.6	1.383	9
#9	0.73	28.1	18.4	31.5	1.388	6

The computational results identified Experiment #4 as the best among all performed tests. Accordingly, the optimal values for workpiece speed, feed rate, and depth of cut are 10 (m/min), 4 (mm/stroke), and 0.01 (mm), respectively. When grinding with these optimal cutting parameters, the resulting values for the criteria Ra, Fx, Fy, and Fz are 0.49 (μm), 18.4 (N), 15.2 (N), and 28.4 (N), respectively.

IV. Conclusion

This study successfully performed a multi-objective optimization of the SKD11 steel grinding process. For the first time, the RAM algorithm was integrated with the Entropy weighting method to solve the multi-objective optimization problem in surface grinding. Using the Entropy method, the weights for the criteria Ra, Fx, Fy, and Fz were determined to be 0.364, 0.208, 0.218, and 0.210, respectively. The RAM algorithm identified the optimal workpiece speed as 10 (m/min), the optimal feed rate as 4 (mm/stroke), and the optimal depth of cut as 0.01 (mm). With these optimal cutting parameters, the corresponding values for surface roughness (Ra) and the force components Fx, Fy, and Fz were 0.49 (μm), 18.4 (N), 15.2 (N), and 28.4 (N), respectively.

References

[1]. X. Li, Z. Tang, C. Chen, L. Wang, Y. Zhang, D. Wang,*An optimization method of grinding wheel profile for complex large shaft curve grinding*, Journal of Advanced Manufacturing Science and Technology,vol. 5, no. 2, Art. no. 2025008, 2025.

[2]. A. Heininen, S. Santa-aho, J. Röttger, P. Julkunen,K. T. Koskinen,*Grinding optimization using nondestructive testing (NDT) and empirical models*, Machining Science and Technology, vol. 28, no. 1, pp. 98-118, 2024.

[3]. M. M. Salem, S. S. Mohamed, A. A. Ibrahim, *Optimization of surface grinding parameters used in improved surface Integrity*, Research Square, pp. 1-14, 2022.

[4]. B. Dasthagiri, D. E. V.G. Goud, *Optimization Studies on Surface Grinding Process Parameters*, International Journal of Innovative Research in Science, Engineering and Technology, vol. 4, no. 7, pp. 6148-6156, 2015.

[5]. D. D. Trung, N. -T. Nguyen, D. H. Tien, H. L. Dang, *A research on multi-objective optimization of the grinding process using segmented grinding wheel by TAGUCHI-DEAR method*, Eureka: Physics and Engineering, vol. 2021, no. 1, pp. 67-77, 2021.

[6]. N.–T. Nguyen, D. D. Trung, *Combination of TAGUCHI method, MOORA and COPRAS techniques in multi-objective optimization of surface grinding process*, Journal of Applied Engineering Science, vol. 19, no. 2, pp. 390 – 398, 2021.

[7]. A. Gürgen, A. Çakmak, S. Yıldız, A. Malkoçoğlu, *Optimization of cnc operating parameters to minimize surface roughness of pinus sylvestris using integrated artificial neural network and genetic algorithm*, Maderas. Ciencia y tecnología,vol. 24, no. 1, pp. 1-12, 2022.

[8]. V. Nguyen, D. Nguyen, D. Do, T. Tra, *Multi-Objective Optimization of the Surface Grinding Process for Heat-Treated Steel*, International journal of automotive and mechanical engineering, vol. 21, no. 4, pp. 11831 – 11843, 2024.

[9]. D. D. Trung, H. X. Thinh, L. D. Ha, *Improving the efficiency of grinding process using the rubber-pasted grinding wheel*, Strojnícky časopis - Journal of Mechanical Engineering, vol. 72, no. 1, pp. 23-34, 2022.

[10]. D.D. Trung, N.V. Thien, N.-T. Nguyen, *Application of TOPSIS Method in Multi-Objective Optimization of the Grinding Process Using Segmented Grinding Wheel*, Tribology in Industry, vol. 43, no. 1, pp. 12-22, 2021.

[11]. T. H. Danh, L. H. Ky, *Optimization of Wheel Dressing Technological Parameters when Grinding Hardox 500 Steel*, Engineering, Technology & Applied Science Research, vol. 14, no. 4, pp. 15854-15859, 2024.

[12]. Z. Chen, X. Li, Z. Zhu, Z. Zhao, L. Wang, S. Jiang, Y. Rong, *The optimization of accuracy and efficiency for multistage precision grinding process with an improved particle swarm optimization algorithm*, Intelligent Manufacturing and Robotics-Research Article, pp. 1-13, 2020.

[13]. N. –T. Nguyen, D. D. Trung,*A study on the surface grinding process of the SUJ2 steel using CBN slotted grinding wheel*, AIMS Materials Science, vol. 7, no. 6, pp. 871–886, 2020.

[14]. D. D. Trung, *A combination method for multi-criteria decision making problem in turning process*, Manufacturing review, vol. 8, Art. no. 26, 2021.

[15]. A. Sotoudeh-Anvari, *Root Assessment Method (RAM): A novel multi-criteria decision making method and its applications in sustainability challenges*, Journal of Cleaner Production, vol. 423, Art. No. 138695, 2023.