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Integrating the Entropy Method and Root Assessment Method for Multi-Objective Optimization of the Surface Grinding Process of Scm400 Steel

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Abstract: Grinding is a widely employed machining technique for producing components requiring high dimensional and surface accuracy in mechanical manufacturing. This study performs a multi-objective optimization of the surface grinding process for SCM400 steel using a surface grinding machine. A total of nine experiments were designed based on the Taguchi approach. In each experiment, three cutting parameters—workpiece velocity, feed rate, and depth of cut—were varied. Four response variables, namely surface roughness (Ra), and the cutting force components in the x- (Fx), y- (Fy), and z-directions (Fz), were measured.

The ENTROPY method was adopted to determine the weighting coefficients of the performance criteria, while the Root Assessment Method (RAM) was employed to solve the multi-objective optimization problem. The results indicate that the optimal workpiece velocity, feed rate, and depth of cut are 10 m/min, 4 mm/stroke, and 0.01 mm, respectively. Under these optimal conditions, the corresponding values of Ra, Fx, Fy, and Fz are 0.49 μm, 18.4 N, 15.2 N, and 28.4 N.

Keywords: surface grinding, SCM400 steel, multi-objective optimization, Entropy method, RAM method.

1. Introduction

Grinding is one of the most common finishing operations in mechanical manufacturing [1]. It is typically used for producing components that require tight tolerances and superior surface quality [2]. To maximize the technological advantages of the grinding process, it is essential to conduct studies focusing on process optimization [3]. A significant number of investigations have been conducted to achieve multi-objective optimization of grinding operations, targeting the simultaneous improvement of various machining performance indicators.

Prior studies have demonstrated that many researchers employed diverse optimization algorithms as well as different weighting approaches for performance criteria. Due to space limitations, this paper only reviews selected recent works related to multi-objective optimization in grinding.

The Nead-Mean algorithm integrated in DESIGN EXPERT V7.1.3 was used to optimize the surface grinding of EN-8 steel, simultaneously minimizing surface roughness and maximizing material removal rate (MRR), where the weights of these two criteria were set equally at 0.5 [4]. In [5], the DEAR algorithm was applied to optimize the surface grinding of SAE420 steel, targeting minimum surface roughness and minimum spindle vibration in the x-, y-, and z-directions; the weights were estimated using DEAR. In [6], MOORA and COPRAS were both used to optimize the grinding of SCM400 steel to achieve minimum roughness and maximum MRR, with weights determined via the Entropy method.

A genetic algorithm (GA) was used in [7] to minimize the surface roughness when grinding Pinus sylvestris wood. Another study also used GA to perform multi-objective optimization of the grinding of SCM400 steel, where equal weights (1/3) were assigned to surface roughness, grinding time, and deviation between actual and desired depth of cut [8]. The DEAR algorithm was further used to optimize the grinding of AISI 4140 steel, aiming at both minimum roughness and maximum MRR, with weights obtained using DEAR [9]. In [10], the TOPSIS method was applied to optimize the grinding of DIN 1.2379 steel by minimizing roughness, minimizing spindle vibration in three directions, and maximizing MRR, with equal weights of 0.2.

Similarly, Nead-Mean was used in [11] to optimize the grinding of Hardox 500 steel, considering minimum surface roughness and maximum MRR. The PSO algorithm was applied in [12] to maximize MRR while minimizing dimensional deviation when grinding D2 tool steel, although the criterion weights were not explicitly defined.

This brief review highlights that a wide range of algorithms and weighting techniques has been used for multi-objective optimization in grinding. However, no published work has integrated the Entropy weighting method with the RAM algorithm for optimizing grinding operations. This research gap serves as the motivation for the present study.

2. Materials and Methods

2.1. Experimental System

The test specimens were fabricated from SCM400 steel with dimensions of 40 mm in length, 25 mm in width, and 8 mm in thickness. The chemical composition of the primary alloying elements in this steel is summarized in Table 1. A surface grinding machine, model APSG-820/8A manufactured in Taiwan, was employed to conduct the experiments. Surface roughness was measured using a profilometer model SJ-201 from Japan. Cutting force components were recorded using a dynamometer manufactured by KISTLER (Germany). To minimize the influence of random measurement errors, the response parameters (surface roughness and cutting force components) were measured at least three times in each experiment, and the reported value corresponds to the average of consecutive measurements.

Table 1: Chemical Composition of SCM400 Steel

C (%)	Si (%)	Mn (%)	P (%)	S (%)	Cr (%)	Ni (%)	Mo (%)
1.02	0.13	0.33	0.024	0.024	12.42	0.12	0.88

2.2. Experimental Matrix

During the experimental process, three parameters—workpiece velocity, feed rate, and depth of cut—were varied for each trial. These parameters can be easily adjusted by machine operators [13].

Each machining parameter was set at three levels, corresponding to coded values of 1, 2, and 3, as shown in Table 2. The selected levels were determined based on relevant literature and the technological capability of the grinding machine used in this study [13].

The experimental design followed a Taguchi orthogonal array consisting of nine trials, as presented in Table 3. This design is widely applied in optimization experiments and has been extensively used in mechanical engineering in recent years [13].

Table 2: Input Parameters

Parameter	Unit	Symbol	Level 1	Level 2	Level 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 (v–f–t)	Real value	v (m/min)	f (mm/stroke)	t (mm)
#1	1–1–1	7–6–0.005	5	4	0.005
#2	1–2–2	7–8–0.01	5	6	0.01
#3	1–3–3	7–10–0.015	5	8	0.015
#4	2–1–2	12–6–0.01	10	4	0.01
#5	2–2–3	12–8–0.015	10	6	0.015
#6	2–3–1	12–10–0.005	10	8	0.005
#7	3–1–3	18–6–0.015	15	4	0.015
#8	3–2–1	18–8–0.005	15	6	0.005
#9	3–3–2	18–10–0.01	15	8	0.01

2.3. Experimental Results

The experiments were carried out in the order given in Table 3. The measured responses included surface roughness (Ra) and the force components Fx, Fy, and Fz. 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 Table 4, the minimum Ra value of 0.41 μm occurs in experiment #6; the minimum Fx value of 18.4 N occurs in experiment #4; the minimum Fy value of 11.3 N corresponds to experiment #1; and the minimum Fz value of 22.8 N is obtained in experiment #7. Clearly, no single experiment simultaneously yields the minimum values for all response criteria (Ra, Fx, Fy, and Fz). Instead, the objective is to identify an experiment in which all four criteria are collectively "as small as possible." Such an assessment cannot be achieved by inspection alone; therefore, a ranking approach is required. For this reason, the RAM algorithm is employed in this study, but first, the weight of each criterion must be determined using the Entropy method.

2.4. Entropy Method

Assume that *m* experiments have been conducted and *n* response variables are measured in each experiment. Let xijx_{ij}xij denote the value of the *j*-th response in the *i*-th experiment, where j=1,…,nj = 1, …, nj=1,…,n and i=1,…,mi = 1, …, mi=1,…,m. The Entropy-based procedure for determining the weight of each response criterion is summarized as follows [14].

Step 1: Normalize the criteria using Eq. (1):

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

Step 2: Compute the Entropy measure for each criterion using Eq. (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 of each criterion using Eq. (3):

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

2.5. RAM Algorithm

The steps for applying the RAM (Ranking Alternatives Method) to rank the experimental alternatives are as follows [15]:

Step 1: Perform normalization as in Step 1 of the Entropy method.

Step 2: Normalize the data using Eq. (4):

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

Step 3: Compute the weighted normalized values using Eq. (5):

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

Where wjw_jwj is the weight of criterion *j*.

Step 4: Calculate the aggregated weighted scores for benefit-type (B) and cost-type (C) criteria using Eqs. (6) and (7):

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

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

Step 5: Compute the RAM index for each alternative using Eq. (8):

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

Step 6: Rank the alternatives in descending order of their RAM index values.

3. Results and Discussion

By applying Equations (1) to (3), the weights of the response parameters Ra, Fx, Fy, and Fz were determined to be 0.364, 0.208, 0.218, and 0.210, respectively.

Using Equations (4) through (8), the RAM index RIiRI_iRIi was computed for each experiment, and the results are summarized in Table 5. The last column of the table also presents the ranking of all experimental trials based on their RI values.

Table 5: RAM scores and ranking of experiments

Exp.	**Ra (μm)**	**Fx (N)**	**Fy (N)**	**Fz (N)**	**RIiRI_iRIi**	**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

Based on the calculated results, experiment #4 was identified as the best-performing trial among all conducted experiments. Under this condition, the optimal values of workpiece velocity, feed rate, and depth of cut were 10 m/min, 4 mm/stroke, and 0.01 mm, respectively. Grinding under these optimal cutting conditions yielded corresponding values of surface roughness and force components as follows: Ra = 0.49 μm, Fx = 18.4 N, Fy = 15.2 N, and Fz = 28.4 N.

4. Conclusion

This study performed a multi-objective optimization of the surface grinding process for SCM400 steel. The RAM algorithm and the Entropy weighting method were integrated for the first time to address the optimization of the surface grinding parameters in this research.

Using the Entropy method, the weights of the criteria Ra, Fx, Fy, and Fz were found to be 0.364, 0.208, 0.218, and 0.210, respectively. Application of the RAM algorithm identified the optimal process parameters as follows: workpiece velocity of 10 m/min, feed rate of 4 mm/stroke, and depth of cut of 0.01 mm. Under these optimized conditions, the resulting surface roughness and force components were Ra = 0.49 μm, Fx = 18.4 N, Fy = 15.2 N, and Fz = 28.4 N.

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