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Multi-Objective Optimization of Cutting Parameters in Turning AISI 304 Austenitic Stainless Steel

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Abstract: Energy conservation and emission reduction is an essential consideration in sustainable manufacturing. However, the traditional optimization of cutting parameters mostly focuses on machining cost, surface quality, and cutting force, ignoring the influence of cutting parameters on energy consumption in cutting process. This paper presents a multi-objective optimization method of cutting parameters based on grey relational analysis and response surface methodology (RSM), which is applied to turn AISI 304 austenitic stainless steel in order to improve cutting quality and production rate while reducing energy consumption. Firstly, Taguchi method was used to design the turning experiments. Secondly, the multi-objective optimization problem was converted into a simple objective optimization problem through grey relational analysis. Finally, the regression model based on RSM for grey relational grade was developed and the optimal combination of turning parameters (a_p = 2.2 mm, f = 0.15 mm/rev, and v = 90 m/s) was determined. Compared with the initial turning parameters, surface roughness (Ra) decreases 66.90%, material removal rate (MRR) increases 8.82%, and specific energy consumption (SEC) simultaneously decreases 81.46%. As such, the proposed optimization method realizes the trade-offs between cutting quality, production rate and energy consumption, and may provide useful guides on turning parameters formulation.

Keywords: AISI 304 austenitic stainless steel; multi-objective optimization; cutting parameters; specific energy consumption; grey relational analysis; response surface methodology (RSM)

1. Introduction

Cutting process is the main means of mechanical manufacturing, which plays an important role in the manufacturing industry. It was found that the formulation of cutting parameters has significant influence on cutting quality, production rate, and energy consumption [1–3]. In general, most of the cutting parameters are determined according to engineering experience and specialized handbooks, which cannot obtain the optimal machining effect. Consequently, the optimization of cutting parameters for different objectives has always been a hot issue in manufacturing enterprises and academia.

The surface integrity, machining efficiency, and cutting force are usually taken as objectives in most of the traditional optimization of cutting parameters. For example, Kumar [4] adopted surface roughness and material removal rate (MRR) as objectives to optimize the cutting parameters in turning C360 copper alloy. Zhou et al. [5] obtained the Pareto optimal solution with the maximum MRR and the minimum surface roughness in turning AISI 304 based on the genetic algorithm gradient boosting regression tree (GA-GBRT) model they established. Their experimental results demonstrated that MRR can be improved by increasing cutting depth and cutting speed in a small range of surface roughness variations. In addition, the grey relational analysis is often used as a powerful tool when dealing with multi-objective optimization of cutting parameters. Using grey relational analysis, Li and Wang [6] optimized the grinding parameters, which effectively reduces the workpiece surface roughness and flatness. Kuram and Ozcelik [7] measured MRR, cutting force, and surface roughness in micro-milling Al 7075 and used grey relational analysis to determine the optimal combination of milling parameters with these three machining characteristics as objectives. Significant work has been carried out based on machining science and cost consideration. However, the influence of cutting parameters on energy consumption in cutting process is not considered in the aforementioned research.

The rapid development of the manufacturing industry has brought great convenience to human society, while exacerbating the problem of resource shortage and environmental pollution as well [2]. As the basic unit in machining systems, machine tool has large quantity with high energy consumption [8]. Vijayaraghavan et al. [9] suggested that reducing the energy consumption of machine tool can dramatically improve the environmental performance of the manufacturing industry. Thus, many scholars have studied energy consumption characteristics of machine tool in order to improve the energy efficiency of machine tool. Based on the investigation of the relationship between energy consumption of machine tool and MRR, Kara and Li [10] proposed an energy consumption prediction model suitable for turning and milling processes. On this basis, Li et al. [11] improved the energy consumption prediction model of milling processes with taking the spindle speed into consideration. Moreover, Zhang et al. [12] developed the specific energy consumption (SEC) model based on cutting parameters and analyzed the influence of cutting parameters on SEC. These research projects show that the energy consumption of machine tool can be reduced by selecting reasonable cutting parameters, laying the foundation for energy efficiency optimization of machine tool.

Recently, the optimization of cutting parameters aiming at energy saving and emission reduction has become a research hotspot in sustainable manufacturing. For reducing the energy consumption of machine tool, Camposeco-Negrete [13] optimized the cutting parameters in turning of AISI 6061 T6 aluminum by using Taguchi method and ANOVA. His research also pointed out that higher feed speed provides minimum energy consumption but will lead to higher surface roughness. It is worth noticing that the optimal cutting parameters for one machining characteristic may worsen other machining characteristics. Hence, the multi-objective optimization of cutting parameters based on both technique requirements and energy-saving consideration is more reasonable in actual machining. Zhao et al. [14] optimized the milling parameters through grey relational analysis, which can reduce energy consumption and improve surface quality simultaneously. In order to minimize the cutting time and energy consumption per unit of removed material, Zhou et al. [15] proposed a multi-objective optimization model and obtained the optimal cutting parameters by genetic algorithm (GA). Similarly, Li et al. [16] established the RSM models of energy efficiency and cutting time, and optimized milling parameters through particle swarm optimization algorithm (PSOA). Yan and Li [17] presented an approach for optimization of milling parameters with multiple responses such as cutting energy consumption, surface roughness, and MRR, which integrated the weighted grey relational analysis and RSM. Furthermore, Li et al. [18] explored the influence of cutting parameters on tool wear and surface topography in turning AISI 304, and optimized the cutting parameters with the goal of the maximum MRR and the minimum specific cutting energy.

Based on the above literature, it is noted that the optimization of cutting parameters has changed from single objective optimization to multi-objective optimization considering both technique requirements and environmental performance. Although recent work has made valuable contributions towards energy conservation and emission reduction, the optimization of cutting parameters for sustainable manufacturing requires more comprehensive study, especially for some difficult-to-machine materials. Therefore, the objectives of this paper are to: (1) Investigate the multi-objective optimization framework of turning parameters for sustainable manufacturing; (2) propose the multi-objective optimization method based on grey relational analysis and RSM; (3) verify the optimization method with wet turning experiments of AISI 304 austenitic stainless steel.

2. Multi-Objective Optimization Framework of Turning Parameters

Lathes account for about 20–35% of the total number of cutting machine tool. They are mainly used for machining various rotating surfaces, such as internal cylindrical surfaces, external cylindrical surfaces, and conical surfaces. The traditional turning process improves production rate as much as possible on the premise of guaranteeing the cutting quality. However, the energy consumption of machine tool and the adverse effects on the environment are ignored.

In a specific machining system, the selection of cutting parameters becomes the basis of process optimization. For the turning process oriented to sustainable manufacturing, the optimization objectives should be expanded to cutting quality, production rate, and energy consumption. Surface roughness, MRR, and SEC are featured as evaluation criteria of machining characteristics. Therefore, the multi-objective optimization framework of turning parameters can be outlined in Figure 1 and the optimization problem can be described as Equation (1).

$$\begin{cases} \min Ra(a_p, f, v) \\ \max MRR(a_p, f, v) \\ \min SEC(a_p, f, v) \end{cases} \quad \begin{cases} a_{p\min} \leq a_p \leq a_{p\max} \\ f_{\min} \leq f \leq f_{\max} \\ v_{\min} \leq v \leq v_{\max} \end{cases} \tag{1}$$

where Ra is surface roughness, MRR is material removal rate, SEC is specific energy consumption of machine tool, a_p is cutting depth, f is feed speed, and v is cutting speed.

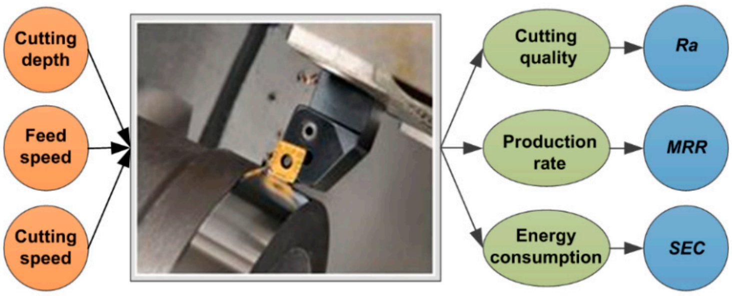

Figure 1. Multi-objective optimization framework of turning parameters.

2.1. Cutting Quality

The surface quality usually has a great influence on mechanical performance of parts [19]. It has been proved that the scrapping of many mechanical products is caused by the surface defects of parts. Surface roughness is therefore considered as a vital technical requirement in cutting process. Moreover, it was found that surface roughness is closely related to cutting conditions, especially cutting parameters [20].

2.2. Production Rate

MRR, as one of the criteria for evaluating production rate, is widely used for cutting process optimization. While the traditional selection of cutting parameters is conservative, which is not conducive to the realization of efficient machining. The value of MRR when turning external cylindrical surface can be calculated using Equation (2).

$$MRR = \frac{\pi[(\frac{d}{2})^2 - (\frac{d}{2} - a_p)^2]nf}{60} \tag{2}$$

where d is workpiece diameter in mm, n is spindle speed in rev/min, f is feed speed in mm/rev, and a_p is cutting depth in mm.

2.3. Energy Consumption

In general, the cutting stage is the most energy-consuming work process of machine tool. In this stage, the energy consuming components include machine control unit (MCU), spindle motor, feed-axis motors, cooling pump motor, and lighting device. The energy consumption can be obtained by monitoring the power consumption of machine tool [21].

SEC expresses the required energy consumption when cutting unit volume material and can be computed by Equation (3). Moreover, the advantage of SEC is that as long as the specific energy consumption is achieved, the machine tool energy consumption in machining can be predicted accurately.

$$SEC = \frac{E}{Q} = \frac{P \cdot t}{MRR \cdot t} = \frac{P}{MRR} \tag{3}$$

where E is machine tool energy consumption in J, Q is material removal volume in mm^3, P is total power of machine tool in cutting stage in W, MRR is material removal rate in mm^3/s, and t is cutting time in s.

3. Optimization Example

3.1. Experimental Details

3.1.1. Workpiece Material and Cutting Tool

AISI 304 austenitic stainless steel is used widely in machinery, aerospace, and medical device industry because of its good overall performance. However, it also belongs to one of the difficult-to-machine materials due to its high toughness, serious work hardening, and bad thermal conductivity. AISI 304 was chosen as workpiece material, and its chemical composition and physical properties are shown in Tables 1 and 2. In addition, the workpiece diameter is 55 mm and cutting length is 120 mm. The experiments were carried out with hard alloy external turning inserts CNMG 120408–PG SC2035.

Table 1. Chemical composition of AISI 304 austenitic stainless steel.

Composition	C	Mn	Si	P	S	Ni	Cr	Mo	Cu	Fe
wt%	0.065	1.78	0.3	0.027	0.02	8.1	18.2	0.13	0.14	71.2

Table 2. Physical properties of AISI 304 austenitic stainless steel.

Specific Heat Capacity	Elastic Modulus	Coefficient of Thermal Expansion	Thermal Conductivity	Density
(J·kg^{-1}·K^{-1})	(GPa)	(10^{-6}·K^{-1})	(W·m^{-1}·K^{-1})	(g/cm^3)
500	194	17.3	16.3	7.93

3.1.2. Experimental Equipment

Wet turning AISI 304 round bars and power measurement were performed and are shown in Figure 2. The computer numerical control (CNC) lathe is Yishui CKJ6163 (Yishui Inc., Shandong, China), with a maximum spindle speed of 1000 rev/min, a maximum spindle power of 11 kW, and a cooling pump power of 0.125 kW. The power analyzer WT500 (Yokogawa, Tokyo, Japan) and sensors were adopted to measure power consumption from the lathe input lines. Three-phase power signals were connected to WT500 and recorded with WTViewerEfree software. In addition, the surface roughness tester RTP120 (Shjingmi Inc., Shanghai, China) was employed to measure the workpiece machined surface roughness.

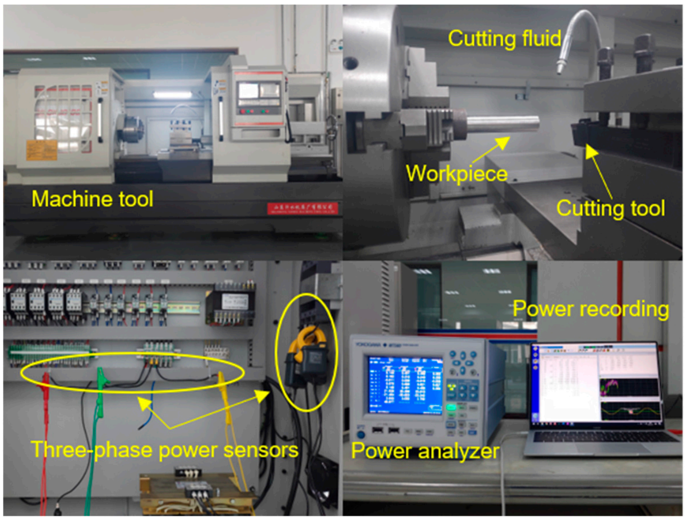

Figure 2. Experimental processing and measuring equipment.

3.1.3. Design of Experiments

The variances of cutting depth a_p, feed speed f, and cutting speed v were customized according to the capacity of the lathe and the cutting inserts. Table 3 shows the cutting parameters and their levels. Taguchi method was used to design the L_{25} (5^3) orthogonal experiments with three factors and five levels, as shown in Table 4. The initial cutting parameter used the recommended value, cutting depth of 1.2 mm, feed speed of 0.25 mm/rev, and cutting speed of 90 m/min.

Table 3. Cutting parameters and their levels.

Parameters	Range	Level 1	Level 2	Level 3	Level 4	Level 5
a_p (mm)	0.2–2.2	0.2	0.7	1.2	1.7	2.2
f (mm/rev)	0.15–0.35	0.15	0.20	0.25	0.30	0.35
v (m/min)	50–90	50	60	70	80	90

Table 4. Experiment design using L_{25} (5^3) orthogonal array and their measurement results.

No.	a_p (mm)	f (mm/rev)	v (m/min)	d (mm)	n (r/min)	Ra (μm)	MRR (mm^3/s)	SEC (J/mm^3)
1	0.2	0.15	50	47.40	336	1.0325	24.9116	73.8180
2	0.2	0.20	60	46.97	407	1.5835	39.8676	56.2968
3	0.2	0.25	70	46.55	479	2.3270	58.1238	46.4650
4	0.2	0.30	80	46.13	621	3.0725	89.6062	39.1952
5	0.2	0.35	90	45.71	627	3.9995	104.5854	34.9219
6	0.7	0.15	60	45.29	422	0.9995	103.4517	25.0040
7	0.7	0.20	70	43.87	508	1.6190	160.7579	19.7991
8	0.7	0.25	80	42.44	600	2.3195	229.4776	16.4892
9	0.7	0.30	90	41.03	699	3.0820	309.9726	14.3977
10	0.7	0.35	50	39.60	402	3.8170	200.6044	13.6178
11	1.2	0.15	70	38.17	584	0.8830	203.4855	18.3305
12	1.2	0.20	80	35.74	713	1.6265	309.4723	14.9285
13	1.2	0.25	90	33.32	860	2.4110	433.9042	13.2391
14	1.2	0.30	50	30.93	515	3.1150	288.6046	12.3712
15	1.2	0.35	60	46.98	407	3.8100	409.7492	1.4578
16	1.7	0.15	80	44.56	572	0.7810	327.3309	1.9894
17	1.7	0.20	90	41.14	697	1.4180	489.3811	1.5024
18	1.7	0.25	50	37.67	423	2.1520	338.5855	2.3185
19	1.7	0.30	60	34.28	557	3.0020	484.5907	1.4280
20	1.7	0.35	70	30.90	721	3.8335	655.8941	1.1752
21	2.2	0.15	90	46.85	612	0.7980	472.1559	2.4545
22	2.2	0.20	50	42.40	376	1.4105	348.2292	3.1293
23	2.2	0.25	60	37.03	516	1.7555	517.5645	2.1792
24	2.2	0.30	70	32.58	684	2.8110	718.1025	1.4547
25	2.2	0.35	80	43.53	585	3.6870	974.7890	1.1535

Before each set of experiments, the spindle speed was calculated according to Equation (4) for CNC programming.

$$n = \frac{1000v}{\pi d} \tag{4}$$

where v is cutting speed in m/min, d is workpiece diameter in mm, and n is spindle speed in rev/min.

After each set of experiments, the workpiece surface roughness was measured from three different locations, and the average value was taken as the surface roughness Ra in each experiment. The MRR and SEC under each set of cutting parameters were obtained according to Equation (2) and (3), respectively. Twenty-five sets of experimental results are summarized in Table 4.

Because the size of workpiece was small and turning experiments were performed using cutting fluid, the tool wear was not serious. In addition, all experiments used new cutting inserts and the tool flank wear was less than 0.10 mm. Therefore, the influence of tool wear was not considered in the paper.

3.2. Grey Relational Analysis

The advantage of grey relational analysis is that it can transform the complex multi-objective optimization problem into a single objective optimization problem through the calculation of grey relational grade (GRG). The calculation of GRG includes the following three steps [22].

Firstly, preprocess the experimental results of Ra, MRR, and SEC to avoid the effect of adopting different units. If the original data sequence is 'the-smaller-the-better', then this original data sequence is preprocessed using Equation (5); if the original data sequence is 'the-larger-the-better', then this original data sequence is preprocessed using Equation (6).

$$x_i^*(k) = \frac{\max x_i^{\circ}(k) - x_i^{\circ}(k)}{\max x_i^{\circ}(k) - \min x_i^{\circ}(k)} \tag{5}$$

$$x_i^*(k) = \frac{x_i^{\circ}(k) - \min x_i^{\circ}(k)}{\max x_i^{\circ}(k) - \min x_i^{\circ}(k)} \tag{6}$$

$$i = 1, 2, \ldots, m;\ k = 1, 2, \ldots, z \tag{7}$$

where m is the number of experiments, z is the number of data sequences, $x_i^{\circ}(k)$ is the original data sequence, $\max x_i^{\circ}(k)$ is the maximum value in the original data sequence, $\min x_i^{\circ}(k)$ is the minimum value in the original data sequence, and $x_i^*(k)$ is the contrast sequence. In this optimization example, the smaller Ra, the larger MRR, and the smaller SEC are desired. Therefore, the data sequences Ra, MRR, and SEC were preprocessed by Equation (5), Equation (6), and Equation (5), respectively. The results of data preprocessing are shown in Table 5.

Secondly, calculate the grey relational coefficient (GRC) based on the results of data preprocessing.

$$\xi_i(k) = \frac{\Delta\min + \varphi\Delta\max}{\Delta_{oi}(k) + \varphi\Delta\max} \tag{8}$$

$$\Delta_{oi}(k) = \left|X^o(k) - x_i^*(k)\right| \tag{9}$$

$$\Delta\min = \min_{\forall j \in i} \min_{\forall k} \left|X^o(k) - x_j^*(k)\right| \tag{10}$$

$$\Delta\max = \max_{\forall j \in i} \max_{\forall k} \left|X^o(k) - x_j^*(k)\right| \tag{11}$$

where $\xi_i(k)$ is GRC, $X^o(k)$ is the reference sequence and $X^o(k) = 1$, $\Delta_{oi}(k)$ is the deviation value between $X^o(k)$ and $x_i^*(k)$, and φ is the distinguishing coefficient and $\varphi = 0.5$ normally.

Table 5. The results of data preprocessing.

Contrast Sequence	*Ra*	MRR	SEC
1	0.9219	0.0000	0.0000
2	0.7507	0.0157	0.2411
3	0.5197	0.0350	0.3764
4	0.2880	0.0681	0.4765
5	0.0000	0.0839	0.5353
6	0.9321	0.0827	0.6718
7	0.7396	0.1430	0.7434
8	0.5220	0.2154	0.7890
9	0.2851	0.3001	0.8177
10	0.0567	0.1850	0.8285
11	0.9683	0.1880	0.7636
12	0.7373	0.2996	0.8104
13	0.4936	0.4306	0.8337
14	0.2748	0.2776	0.8456
15	0.0589	0.4051	0.9958
16	1.0000	0.3184	0.9885
17	0.8021	0.4890	0.9952
18	0.5740	0.3302	0.9840
19	0.3099	0.4839	0.9962
20	0.0516	0.6643	0.9997
21	0.9947	0.4708	0.9821
22	0.8044	0.3404	0.9728
23	0.6972	0.5186	0.9859
24	0.3693	0.7298	0.9959
25	0.0971	1.0000	1.0000

Finally, calculate the grey relation grade (GRG) according to the values of GRC and weights.

$$\gamma_i = \sum_{k=1}^{z} w_k \xi_i(k) \tag{12}$$

$$\sum_{k=1}^{z} w_k = 1 \tag{13}$$

where γ_i is GRG and w_k is weight. The weight of the output can be determined by the expert system according to actual production demand. In this optimization example, the weights of the three optimization objectives are the same, namely w_1:w_2:w_3 = 1:1:1.

The gray correlation coefficients (GRC_{MRR}, GRC_{Ra}, and GRC_{SEC}) and GRG of each set of experiments can be obtained by Equations (8)–(13). The results of grey relational analysis and sorting of GRG are shown in Table 6.

3.3. Process Modelling and ANOVA

The original relationship between cutting parameters and three optimization objectives has been transformed into a new relationship between cutting parameters and GRG through grey relational analysis. In order to find the optimal cutting parameters, the regression model of GRG based on cutting parameters needs to be established first. The RSM was applied to fit the regression model, and Equation (14) represents the general form of the second-order RSM model.

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i<j}\sum \beta_{ij} x_i x_j + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \varepsilon \tag{14}$$

where x are independent variables, namely cutting parameters, k is the number of independent variables, β is a coefficient of each term, and ε is a residual error.

Table 6. Results of grey relational analysis.

Contrast Sequence	GRC_{MRR}	GRC_{Ra}	GRC_{SEC}	GRG	Sort
1	0.3333	0.8648	0.3333	0.5105	20
2	0.3369	0.6673	0.3972	0.4671	22
3	0.3413	0.5100	0.4450	0.4321	23
4	0.3492	0.4125	0.4885	0.4167	24
5	0.3531	0.3333	0.5183	0.4016	25
6	0.3528	0.8805	0.6037	0.6123	12
7	0.3685	0.6576	0.6609	0.5623	16
8	0.3892	0.5112	0.7032	0.5345	17
9	0.4167	0.4115	0.7329	0.5204	19
10	0.3802	0.3464	0.7446	0.4904	21
11	0.3811	0.9404	0.6790	0.6668	8
12	0.4165	0.6556	0.7251	0.5991	13
13	0.4675	0.4968	0.7504	0.5716	15
14	0.4090	0.4081	0.7641	0.5271	18
15	0.4567	0.3470	0.9917	0.5984	14
16	0.4231	1.0000	0.9775	0.8002	2
17	0.4945	0.7164	0.9905	0.7338	4
18	0.4274	0.5400	0.9689	0.6454	10
19	0.4921	0.4201	0.9925	0.6349	11
20	0.5983	0.3452	0.9994	0.6476	9
21	0.4858	0.9895	0.9654	0.8136	1
22	0.4312	0.7188	0.9484	0.6995	6
23	0.5095	0.6228	0.9725	0.7016	5
24	0.6492	0.4422	0.9918	0.6944	7
25	1.0000	0.3564	1.0000	0.7855	3

The cutting depth, feed speed, and cutting speed were coded using Equations (15)–(17), respectively. The values of cutting parameters were normalized to the range of −1 to 1, which could cause the controlled factors to affect the responses more evenly [23]. The software Minitab17 was applied to fit the experimental data, with coded variables A, B, and C as continuous factors and GRG as output. The regression model for GRG was developed as Equation (18).

$$A = \frac{a_p - 1.2}{1} \tag{15}$$

$$B = \frac{f - 0.25}{0.1} \tag{16}$$

$$C = \frac{v - 70}{20} \tag{17}$$

$$\mathrm{GRG} = 0.5912 + 0.14701A - 0.04508B + 0.02142C - 0.0150A^2 + 0.0507B^2 - 0.0126C^2 + 0.0124AB + 0.0162AC \tag{18}$$

The predicted values for GRG of 25 sets of experiments can be computed according to Equation (18). The comparison of measured–predicted values from the regression model is depicted in Figure 3, and the average deviation of predicted values is 0.0937%.

The ANOVA results of the regression model are shown in Table 7. Based on the statistical analysis results, the coefficient of determination R-sq for this regression model is 97.21%, and the adjusted coefficient of determination R-sq (adj) is 95.82%, which indicates that the regression model can be used to predict GRG according to cutting parameters.

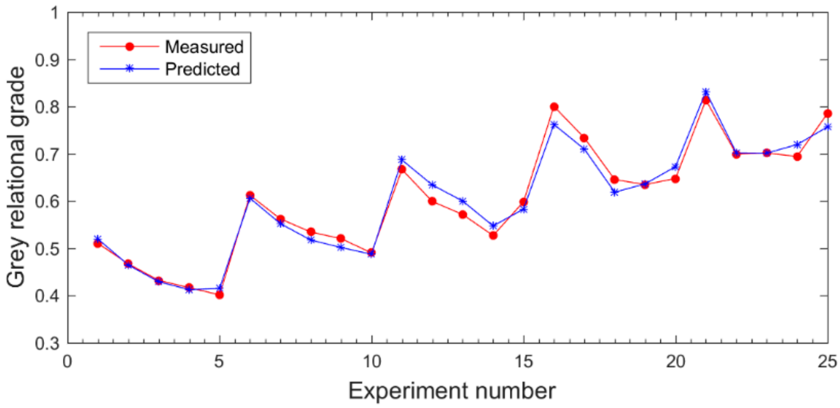

Figure 3. Comparisons of measured-predicted values for grey relation grade (GRG).

Table 7. ANOVA results for the GRG model.

Source	DF	SS	MS	F	P
Regression model	8	0.324835	0.040604	69.81	<0.001
Error	16	0.009307	0.000582	-	-
Total	24	0.334142	-	-	-
S = 0.0241181	R-sq = 97.21%			R-sq (adj) = 95.82%	

3.4. Optimization Results and Comparative Analysis

The optimization of the aforementioned regression model was solved with response optimizer in minitab17 software. The constraint was the value range of the independent variables *A*, *B*, and *C*. The solution goal was the maximum value of GRG. The optimization results are shown in Figure 4.

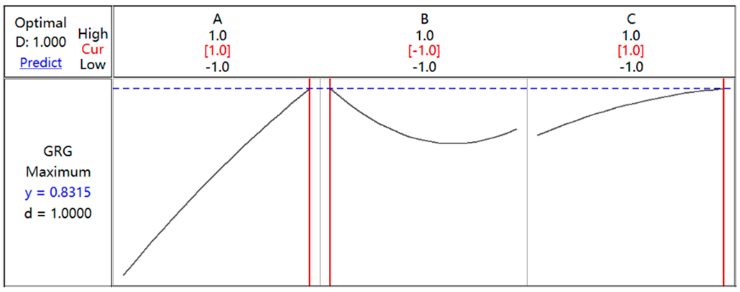

Figure 4. Multi-objective optimization results of cutting parameters.

As can be seen from Figure 4, the regression model obtains the maximum GRG of 0.8315 when $A = 1$, $B = -1$, and $C = 1$. The optimal solution corresponds to the following cutting parameters: $a_p = 2.2$ mm, $f = 0.15$ mm/rev, and $v = 90$ m/min, which are also consistent with experiment number 21.

The comparison of experimental results using the initial and the optimal turning parameters is listed in Table 8. The initial parameters are suggested by tool maker, and the optimal parameters are determined by the multi-objective optimization method developed. For the comparison between initial setting and the optimal solution, MRR increased from 433.9042 mm^3/s to 472.1559 mm^3/s, Ra decreased from 2.4110 μm to 0.7980 μm, and SEC decreased from 13.2391 J/mm^3 to 2.4545 J/mm^3, respectively. The optimization results show that a trade-off point can be drawn between the good cutting quality, high production rate, and low energy consumption with the proposed optimization method.

Table 8. Results with different cutting parameters.

Items	a_p (mm)	f (mm/rev)	v (m/min)	*Ra* (µm)	MRR (mm^3/s)	SEC (J/mm^3)
Initial parameters	1.2	0.25	90	2.4110	433.9042	13.2391
Optimal parameters	2.2	0.15	90	0.7980	472.1559	2.4545
Promotion	-	-	-	66.90%	8.82%	81.46%

4. Conclusions

In this research, the multi-objective optimization framework of turning parameters was investigated. The multi-objective optimization method based on grey relational analysis and RSM was proposed and verified in wet turning AISI 304 austenitic stainless steel. The main conclusions are as follows.

(1) In order to effectively balance the cutting quality, production rate, and energy consumption in turning process, Ra, MRR, and SEC are featured as optimization objectives of turning parameters for sustainable manufacturing.
(2) The complex multi-objective optimization problem can be transformed to a single objective optimization problem with grey relational analysis, which simplifies the optimization procedure.
(3) The coefficient of determination R-sq of the GRG model is 97.21%. This means that the regression model based on RSM can be used to predict the value of GRG with high accuracy.
(4) In this optimization example, the optimal combination of cutting parameters in turning AISI 304 austenitic stainless steel is: a_p = 2.2 mm, f = 0.15 mm/rev, and v = 90 m/s. Compared with the initial turning parameters, Ra decreases 66.90%, MRR increases 8.82%, and SEC decreases 81.46%.

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