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Optimization of Dry Turning Parameters for C45 Steel Using Simple Additive Weighting Method

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Abstract— *In the manufacturing industry, optimizing machining parameters is crucial for enhancing both the quality and efficiency of the production process. This study focuses on the dry turning of C45 steel, a commonly used medium carbon steel known for its good machinability and stable mechanical properties. The objective is to minimize surface roughness (R_t) and maximize the material removal rate (MRR) by identifying the optimal machining parameters: cutting speed (V_c), feed rate (f_z), and depth of cut (a_p). An experimental factorial design was employed to systematically vary the machining parameters and collect data on the resulting surface roughness and material removal rates. The Simple Additive Weighting (SAW) method, a Multi-Criteria Decision Making (MCDM) technique, was utilized to evaluate and rank the different machining conditions. The SAW method involves normalizing the decision matrix, applying weights to each criterion, and calculating composite scores for each alternative to determine the optimal set of parameters. The SAW optimization process, implemented using Python, utilized powerful libraries such as pandas for data manipulation, numpy for numerical operations, and openpyxl for writing results to an Excel file. The results indicate that the optimal machining parameters are a cutting speed of 240 m/min, a feed rate of 0.30 mm/tooth, and a depth of cut of 0.30 mm under dry conditions. These parameters provide a balanced trade-off between achieving low surface roughness and high material removal rate. This study demonstrates the effectiveness of the SAW method in managing trade-offs between competing objectives and highlights its applicability in real-world manufacturing environments. Future work could expand on this approach by considering additional machining conditions and integrating other MCDM methods to further enhance optimization outcomes. The findings provide valuable insights for manufacturers seeking to improve both the quality and efficiency of their machining processes.*

Keywords— *C45 Steel, Dry Turning, Material Removal Rate, Simple Additive Weighting, Surface Roughness.*

I. INTRODUCTION

In the manufacturing industry, the machining of high-durability and precision steel parts is essential, especially for C45 steel—a commonly used medium carbon steel prized for its good machinability and stable mechanical properties [1]. Turning is a primary method for shaping and finishing machine parts from C45 steel, where surface quality and machining efficiency are critical indicators of the final product quality [2].

The application of different machining conditions, such as dry machining and flood coolant machining, can significantly affect the machining outcomes. Dry machining, which does not utilize coolant, is valued for its cost reduction and environmental benefits; however, it can lead to rapid tool wear and poorer surface quality [3]. In contrast, flood coolant machining [4], [5] uses coolant to reduce temperature and wear, thereby improving tool life and the quality of the surface finish.

This study aims to analyze the impact of technological parameters such as cutting speed, feed rate, and depth of cut on surface quality (measured by surface roughness, R_t) and material removal rate (MRR) under dry machining conditions. An experimental factorial design was employed to provide a comprehensive view of the influencing factors.

To achieve the optimal machining parameters, the Simple Additive Weighting (SAW) method was used for multi-objective optimization [6]. This method allows for a balanced consideration of minimizing surface roughness and maximizing the material removal rate. Through this analysis, we hope to enhance the understanding of the C45 steel machining process and contribute to improving production efficiency in the manufacturing industry, thereby better meeting current technical and environmental requirements.

II. MATERIAL AND METHOD

A. Experimental Equipment and Setup

The experiments were conducted using a Mori-Seiki CNC lathe, renowned for its precision and reliability in metal machining. The surface roughness of each machined workpiece was measured using a JS-210 Mitutoyo surface roughness tester, which is capable of providing highly accurate and reliable surface texture measurements. The material removal rate (MRR) was calculated using the standard formula.

Fig. 1. Experimental workpiece and machine

The experimental design employed a factorial approach, detailed in the table below, specifying the range and categorization of factors influencing machining outcomes (Fig. 2).

Factor	Name	Units	Change	Type	SubType	Minimum	Maximum	Coded Low	Coded High	Mean	Std. Dev.
A	Vc		Hard	Numeric	Continuous	80.00	240.00	-1 ↔ 80.00	+1 ↔ 240.00	159.49	55.29
B	fz		Easy	Numeric	Continuous	0.1000	0.3000	-1 ↔ 0.10	+1 ↔ 0.30	0.2022	0.0829
C	ap		Easy	Numeric	Continuous	0.1000	0.3000	-1 ↔ 0.10	+1 ↔ 0.30	0.1970	0.0812
D	CL		Easy	Categoric	Nominal	Dry	Flood			**Levels:**	2.00

Fig. 2. Factorial Design using Design Expert software.

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The experimentation with C45 steel workpieces (Figure 1) was conducted on a Mori-Seiki CNC lathe (Figure 2), following the experimental matrix outlined earlier. The compiled results are presented in Table 1.

B. *Data Collection*

Each workpiece was machined under controlled conditions, and immediately after machining, the surface roughness was measured. The roughness measurements, along with the machining parameters—cutting speed (V_c), feed rate per tooth (f_z), and depth of cut (a_p)—were systematically recorded in a data compilation sheet for further analysis.

TABLE I. Experimental Design Matrix for machining of C45 Steel

Group	Run	V_c	f_z	a_p	CL	R_t	MRR
1	1	240	0.145	0.105	Dry	10.908	23.329
1	2	240	0.3	0.3	Dry	11.221	137.58
1	3	240	0.1	0.25	Flood	4.407	38.217
1	4	240	0.3	0.11	Flood	16.288	50.446
2	5	80	0.12	0.1	Dry	14.529	6.115
2	6	80	0.3	0.12	Flood	8.888	18.344
2	7	80	0.261	0.295	Dry	10.946	39.233
2	8	80	0.1	0.26	Flood	13.291	13.248
3	9	160	0.1	0.3	Dry	5.633	30.573
3	10	160	0.197	0.194	Flood	9.588	38.948
3	11	160	0.3	0.1	Dry	15.743	30.573
3	12	160	0.3	0.21	Flood	7.591	64.204
4	13	185.6	0.196	0.3	Flood	7.499	69.511
4	14	185.6	0.21	0.203	Dry	12.857	50.396
4	15	185.6	0.1	0.1	Flood	5.69	11.822
5	16	138.39	0.19	0.1	Flood	7.958	16.748
5	17	138.39	0.3	0.3	Flood	15.817	79.332
5	18	138.39	0.1	0.197	Dry	10.789	17.365
5	19	138.39	0.222	0.199	Dry	9.226	38.957

C. *Multi-Objective Optimization*

The Simple Additive Weighting (SAW) method is a popular Multi-Criteria Decision Making (MCDM) technique used for evaluating and ranking multiple alternatives based on multiple criteria. SAW involves normalizing the decision matrix, applying weights to each criterion, and calculating a composite for each alternative. This score is used to rank the alternatives from the most to the least preferred.

The calculation process with SAW is carried out as shown in the flowchart in Figure 3, where:

- *Normalization*: Transforming the original data into a comparable scale. For criteria to be minimized (e.g., surface roughness, R_t), normalization involves dividing the minimum value by each value in the criterion. For criteria to be maximized (e.g., material removal rate, MRR), normalization involves dividing each value by the maximum value.
- *Weighting*: Assigning a weight to each criterion to reflect its importance. The normalized values are then multiplied by these weights.
- *Scoring*: Summing the weighted normalized values for each alternative to obtain a composite score.
- *Ranking*: Sorting the alternatives based on their composite scores to determine the optimal set of machining parameters.

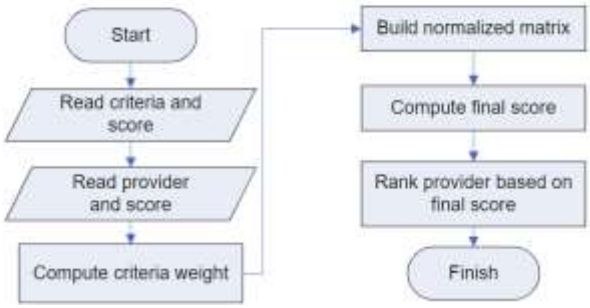

Fig. 3. Flowchart of Simple Additive Weighting Method

III. Result and Disscusion

In this study, the SAW method was implemented using Python, leveraging several powerful libraries for data manipulation and analysis. The following libraries were used: *pandas* for data manipulation and analysis; *numpy f*or numerical operations; *openpyxl* for writing the results to an Excel file. The calculation results and rankings are summarized in Table 2.

TABLE 2: Calculation Results and Rankings Using the SAW Method

Group	Run	V=	f_z	a_p	CL	R_t	MRR	Rt_ normalized	MRR_ normalized	Rt_ weighted	MRR_ weighted	Score	Rank
1	**2**	**240**	**0.30**	**0.30**	**Dry**	**11.22**	**137.58**	**0.39**	**1.00**	**0.20**	**0.50**	**0.70**	**1**
1	3	240	0.10	0.25	Flood	4.41	38.22	1.00	0.28	0.50	0.14	0.64	2
4	13	186	0.20	0.30	Flood	7.50	69.51	0.59	0.51	0.29	0.25	0.55	3
3	12	160	0.30	0.21	Flood	7.59	64.20	0.58	0.47	0.29	0.23	0.52	4
3	9	160	0.10	0.30	Dry	5.63	30.57	0.78	0.22	0.39	0.11	0.50	5
4	15	186	0.10	0.10	Flood	5.69	11.82	0.77	0.09	0.39	0.04	0.43	6
5	17	138	0.30	0.30	Flood	15.82	79.33	0.28	0.58	0.14	0.29	0.43	7
5	19	138	0.22	0.20	Dry	9.23	38.96	0.48	0.28	0.24	0.14	0.38	8
3	10	160	0.20	0.19	Flood	9.59	38.95	0.46	0.28	0.23	0.14	0.37	9
4	14	186	0.21	0.20	Dry	12.86	50.40	0.34	0.37	0.17	0.18	0.35	10
2	7	80	0.26	0.30	Dry	10.95	39.23	0.40	0.29	0.20	0.14	0.34	11
5	16	138	0.19	0.10	Flood	7.96	16.75	0.55	0.12	0.28	0.06	0.34	12
1	4	240	0.30	0.11	Flood	16.29	50.45	0.27	0.37	0.14	0.18	0.32	13
2	6	80	0.30	0.12	Flood	8.89	18.34	0.50	0.13	0.25	0.07	0.31	14
1	1	240	0.15	0.11	Dry	10.91	23.33	0.40	0.17	0.20	0.08	0.29	15
5	18	138	0.10	0.20	Dry	10.79	17.37	0.41	0.13	0.20	0.06	0.27	16
3	11	160	0.30	0.10	Dry	15.74	30.57	0.28	0.22	0.14	0.11	0.25	17
2	8	80	0.10	0.26	Flood	13.29	13.25	0.33	0.10	0.17	0.05	0.21	18
2	5	80	0.12	0.10	Dry	14.53	6.12	0.30	0.04	0.15	0.02	0.17	19

The optimal machining parameters were determined to be a cutting speed (V_c) of 240 m/min, a feed rate (f_z) of 0.30 mm/tooth, and a depth of cut (a_p) of 0.30 mm under dry conditions. This set of parameters achieved the highest composite score, providing a balanced trade-off between minimizing surface roughness (R_t) and maximizing the material removal rate (MRR).

IV. CONCLUSION

The multi-objective optimization using the Simple Additive Weighting (SAW) method has identified the optimal set of machining parameters for the dry turning of C45 steel. Based on the composite scores and rankings, the most favorable machining condition was found to be a cutting speed (V_c) of 240 m/min, a feed rate (f_z) of 0.30 mm/tooth, and a depth of cut (ap) of 0.30 mm under dry conditions. This set of parameters, which achieved the highest composite score, provides a balanced trade-off between minimizing the surface roughness (R_t) and maximizing the material removal rate (MRR).

The optimal parameters indicate that higher cutting speed, feed rate, and depth of cut under dry conditions result in a more favorable machining performance. Specifically, these conditions provide a significant material removal rate while maintaining acceptable surface quality. The results demonstrate that increasing the cutting speed and feed rate can enhance the material removal rate, which is critical for improving productivity in manufacturing processes. However, these parameters must be carefully balanced to avoid compromising the surface finish.

While a lower surface roughness is desired, the normalization and weighting process ensures that it does not overly dominate the decision-making process. This balanced approach allows for a more practical and efficient optimization, acknowledging that some level of surface roughness may be acceptable if it leads to significantly higher productivity. The SAW method effectively manages the trade-offs between competing objectives, providing a comprehensive view of the impacts of different parameter settings. This approach is beneficial for manufacturers aiming to optimize their processes without sacrificing too much on either performance measure.

The use of Python for implementing the SAW method demonstrates its practicality and efficiency. The ability to automate the optimization process and output the results in a user-friendly format (Excel) underscores the method's applicability in real-world manufacturing environments. Future studies could expand upon this work by considering additional machining conditions, such as different tool materials and cooling methods, to further refine the optimization process. Moreover, integrating other MCDM methods alongside SAW could provide comparative insights and potentially more robust optimization outcomes. By systematically applying the SAW method, manufacturers can make informed decisions that enhance both the quality and efficiency of their machining processes, ultimately leading to improved production outcomes and reduced operational costs.

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