Multi-Objective Optimization of the Turning Process using the Probability Method

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ABSTRACT

This research aims to determine the optimal values of the cutting parameters when solving the turning process multi-objective problem. Three cutting parameters are considered in this study: spindle speed (n_w), feed rate (f), and depth of cut (a_p). A turning experiment series was conducted on a conventional lathe, with nine experiments having been designed according to the Taguchi experimental design matrix. In each experiment, the values of the three parameters changed and the material Removal Rate (Q) was measured. The Probability method was used to solve the multi-objective optimization problem. The Method based on the Removal Effects of Criteria (MEREC) technique was employed to calculate the weights of the criteria. The results of the optimization problem using the Probability method were also compared with those obtained using other methods, including the Simple Additive Weighting (SAW), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), VIsekriterijumska optimizacijaI KOmpromisno Resenje (VIKOR), Multi-Atributive Ideal-Real Comparative Analysis (MAIRCA), Evaluation by an Area-based Method for Ranking (EAMR), Complex Proportional Assessment (COPRAS), Measurement Alternatives and Ranking according to Compromise Solution (MARCOS), Proximity Indexed Value (PIV), and Combined Compromise Solution (COCOSO). All the methods converged on the same unique solution to the multi-objective optimization problem. The optimal values for the parameters were: n_w = 1350 rev/min, corresponding to a feed rate of 0.13 mm/rev, and a depth of cut of 0.4 mm. When machining with these optimal cutting parameters, the resulting values for Ra, RE, and Q were 1.057 µm, 0.03 mm, and 13225.68 mm²/min, respectively.

Keywords-turning; multi-objective optimization; probability method; MEREC method; MCDM

I. INTRODUCTION

Turning is considered one of the most common machining methods in the machining processes [1]. Therefore, the optimization of the turning process has been extensively studied. Many studies have solved the multi-objective optimization problem in turning by using algorithms to solve the regression equations [2-4]. The regression models are built based on experimental data, and then the equations (systems of equations) are solved through the employment of various algorithms to find the optimal solution. However, in some cases, it is difficult to use the optimal values found if the experimental machines are conventional lathes. It must be also emphasized that although CNC lathes have become very popular and offer many advantages, such as flexibility and high automation, the role of conventional lathes is still extremely important in the industry. Conventional lathes are still preferred for their high reliability and ability to handle traditional machining tasks efficiently [5]. However, they cannot continuously adjust the technological parameters. For example, after solving the optimization problem, a certain value is determined as the optimal spindle speed value, but the conventional lathe cannot be adjusted to operate at that value. For the machine to operate at that value, significant improvements are necessary, such as installing an inverter. Therefore, applying conventional lathes to machining at optimal values encounters certain obstacles. An effective approach to solving multi-objective optimization problems in the turning process is the use of Multi-Criteria Decision Making (MCDM) methods [6-8]. MCDM involves ranking alternatives to identify and select the best option [9, 10]. Numerous studies have applied MCDM methods to optimize the turning processes for various materials, demonstrating their versatility and effectiveness. For instance, the Preference Index Value (PIV) method was deployed to optimize the turning process of the AISI-1040 steel [11]. The Complex Proportional Assessment (CORPAS) method was applied to optimize the turning process of OHNS steel [12]. The Weighted Aggregates Sum-Product Assessment (WASPAS) method was utilized to optimize the turning process of AISI D3 steel [13]. A combination of the TOPSIS and PIV methods was used to optimize the turning process of 9XC steel [14]. Four methods, SAW, VIKOR, TOPSIS, and Elimination and Choice Expressing Reality (ELECTRE), were simultaneously implemented to optimize the turning process of Ti6Al4V alloy [15]. Three methods, Pareto Edgeworth Grierson (PEG), Preference Selection Index (PSI), and Collaborative Unbiased Rank List Integration (CURLI), were deployed to optimize the turning process of SB410 steel [16]. These studies demonstrate the broad applicability of the MCDM techniques in addressing the challenges of multi-objective optimization in machining processes. Thus, MCDM methods have been widely used to solve the multi-objective optimization problem in the turning process. However, some recent studies have shown that most MCDM methods use "additive" algorithms, and subjective or artificial factors, which make users less confident in their decision about the alternative considered to be the most optimal [17-19]. Multi-objective optimization using Probability is an MCDM method that is characterized by not containing subjective or artificial elements, thus ensuring the accuracy of the final decision on the considered optimal solution. This advantage of the Probability method has been used in a few recent studies, such as optimizing the selection of building materials [17], selecting materials in the microelectronics industry [18], selecting materials in the pharmaceutical extraction industry [19], optimizing the choice of university to study logistics [20], and optimizing the design of a conveyor belt mesh [21]. Despite its advantages, the number of studies applying the Probability method is still very small. This limited research has motivated the present study to apply the Probability method to optimize the multi-objective turning process materials and methods.

A. Experimental Procedure

The material used in the experiment was the 3X13 steel, a type of martensitic stainless steel, notable for its high carbon content. This type of steel possesses very good hardness and wear resistance, so, it is often applied in harsh working environments, such as when cutting blades, engine parts, valves, springs, and while working at high temperatures [22]. The 3X13 is a steel designation/designated according to the GOST standard of the Russian Federation. This type of steel is equivalent to several other steel types complying with the standards of their origin country, such as 420 steel under the SAE standard, USA, 1.4028 steel under the DIN standard, Germany, SUS420J2 steel under the JIS standard, Japan, 410F21 steel under the AFNOR standard, France, 420S45 steel under the BS standard, United Kingdom, GX30Cr13 steel under the UNI standard, Italy, and 3Cr13 steel under the GB standard, China. The main element composition of this steel includes C 0.42%, Si 1%, Mn 1%, Cr 13%, and S 0.05%. The initial steel billet had a diameter of ∅28, and then a rough turning process was performed to prepare the test specimens. The test specimens had a diameter and length of 24 mm and 300 mm, respectively. The used machine was a conventional lathe of the ECOCA brand that was manufactured in Taiwan, and constitutes a universal lathe. It is worth emphasizing that although CNC lathes have become very popular and offer many outstanding advantages, including high flexibility and automation, the role of conventional lathes is still extremely important in the industry. Universal lathes are still preferred for their high reliability and ability to efficiently handle traditional machining tasks [23].

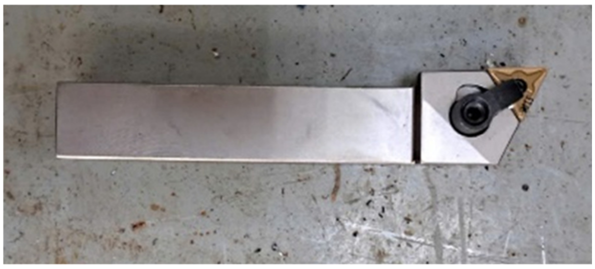

Fig. 1. Cutting tool.

Kyocera, Korea, titanium nitride-coated cutting tools were used. In Figure 1, it is observed that the tool nose radius was 0.4 mm, while the rake angle and the clearance angle were both 7 degrees. This type of cutting tool has high hardness and oxidation temperature, commonly used in milling and turning to machine workpieces with high hardness and heat resistance [24]. To eliminate the influence of the tool wear on the responses of each experiment, each cutting tool was utilized only once, meaning that the number of cutting tools employed was equal to the number of the experiments which were to be conducted. The Ra was measured using an SJ-201 roughness tester, and the RE was measured deploying a dial gauge with an accuracy of 1/100. To ensure accuracy and minimize measurement errors, the values of Ra and RE were measured at least three times during each experiment. The final Ra and RE values were then determined by calculating the average of these repeated measurements. Figure 2 illustrates some of the main components of the experimental system. The cutting speed Q is calculated as:

$$Q = \pi \times d_w \times f \times a_p \quad \left(\frac{mm^2}{min}\right) \qquad (1)$$

where d_w, f, and a_p represent the workpiece diameter, feed rate, and depth of cut, respectively.

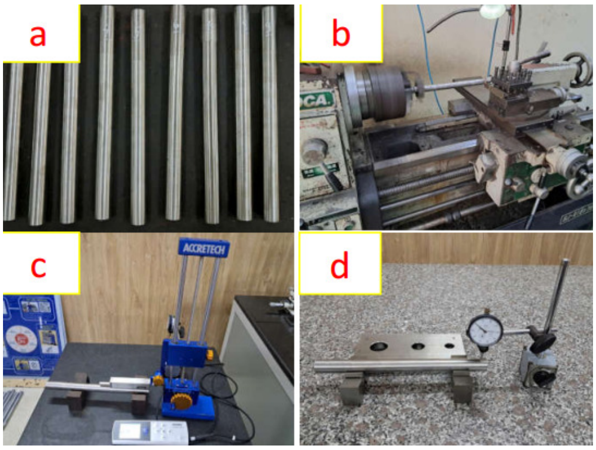

Fig. 2. Experimental systems. (a) Workpiece, (b) lathe, (c) Ra roughness test, (d) RE roundness test.

A sequence of nine experiments was carried out, designed according to the Taguchi method, which ensures that the minimum number of experiments is conducted while obtaining all the necessary information about the output parameters. Taguchi's experimental design is considered very suitable when experiments are conducted on conventional lathes rather than CNC machines [25]. Each of the three cutting parameters, i.e. spindle speed, feed rate, and depth of cut, was selected at three levels, as displayed in Table I. The data in this table were selected according to [22], and based on their ability to be adjusted. The values used for the lathe are outlined in Table I. The experimental design matrix of the nine experiments was designed according to the Taguchi form, as shown in Table II.

TABLE I. VALUES AT LEVELS OF THE CUTTING PARAMETERS

Parameters	Symbol	Unit	Value at level		
			1	2	3
Workpiece speed	n_w	rev/mi	530	880	1350
Feed rate	f	mm/re	0.05	0.08	0.13
Depth of cut	a_p	mm	0.25	0.4	0.55

TABLE II. EXPERIMENTAL DESIGN MATRIX

Exp.	Code value			Real value		
	nw	f	ap	nw (v/ph)	f (mm/vg)	ap (mm)
1	1	1	1	530	0.05	0.25
2	1	2	2	530	0.08	0.4
3	1	3	3	530	0.13	0.55
4	2	1	2	880	0.05	0.4
5	2	2	3	880	0.08	0.55
6	2	3	1	880	0.13	0.25
7	3	1	3	1350	0.05	0.55
8	3	2	1	1350	0.08	0.25
9	3	3	2	1350	0.13	0.4

B. Probability Method

The following procedure is employed to solve the multi-objective optimization problem using the Probability method [17]:

1. Constructing a decision matrix, as demonstrated in (2), where x_{ij} is the value of the criterion j at the alternative i, with i = 1 / m, and j = 1 / n. Let w_j be the weight of criterion j:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \ddots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \qquad (2)$$

2. By letting BC be the benefit criterion and NC be the cost criterion, the probability of achieving a favorable outcome in the decision-making process is calculated according to:

$$\begin{cases} \alpha_j = \frac{1}{\sum_{i=1}^{m} x_{ij}} \quad \text{if} \quad j \in BC \\ P_{ij} \propto X_{ij}, \quad P_{ij} = \alpha_j X_{ij,} i = 1, 2, \ldots, m, \quad j = 1,2,..n \end{cases} \qquad (3)$$

$$\begin{cases} \beta_j = \frac{1}{m\left(x_{jmax} + x_{jmin} - \frac{\sum_{i=1}^{m} x_{ij}}{m}\right)} \quad \text{if} \quad j \in NC \\ P_{ij} \propto \left(x_{jmax} + x_{jmin} - x_{ij}\right), \\ P_{ij} = \beta_j\left(x_{jmax} + x_{jmin} - x_{ij}\right) \\ i = 1, 2, \ldots, m, \quad j = 1,2,..n \end{cases} \qquad (4)$$

3. Considering the weight w_j of the criterion j, the overall favorable probability of the alternative i is calculated according to (5). The optimal alternative is the one with the highest overall favorable probability:

$$P_i = \prod_{j=1}^{n} \left(P_{ij}\right)^{w_j} \qquad (5)$$

C. MEREC Method

The MEREC method has been employed to calculate the weights of the criteria, offering high accuracy and being widely recommended for use. The former has been widely deployed across various fields to determine the criteria weights, such as in selecting sustainable materials [26], choosing the best option for the metal milling processes, evaluating options for the metal grinding processes [27], identifying the optimal choice for the metal turning processes [28], and electing the best alternative in the Powder Mixed Electric Discharge Machining (PEDM) processes [29]. The implementation of the MEREC method involves the following steps [6]:

1. Constructing a decision matrix as in the Probability method.

2. Calculating the normalized values according to:

$$n_{ij} = \frac{min x_{ij}}{x_{ij}} \quad \text{if} \quad j \in BC \qquad (6)$$

$$n_{ij} = \frac{x_{ij}}{max\, x_{ij}} \quad \text{if} \quad j \in NC \qquad (7)$$

3. Calculating the overall performance of the alternatives:

$$S_i = Ln\left[1 + \left(\frac{1}{n}\sum_j^n \left|ln\left(n_{ij}\right)\right|\right)\right] \qquad (8)$$

4. Calculating the performance of the alternatives:

$$S'_{ij} = \mathrm{Ln}\left[1 + \left(\frac{1}{n}\sum_{k,k\neq j}^{n}\left|\ln\left(n_{ij}\right)\right|\right)\right] \quad (9)$$

5. Calculating the absolute value of the deviations according to:

$$E_j = \sum_{i}^{m}\left|S'_{ij} - S_i\right| \quad (10)$$

6. Calculating the weights of the criteria:

$$w_j = \frac{E_j}{\sum_{k}^{n} E_k} \quad (11)$$

II. RESULTS AND DISCUSSION

The results of the turning experiment are summarized in Table III. Based on the data, the following key findings are observed: the minimum Ra value is 0.691 mm, recorded in experiment 1; the minimum RE value is 0.01 mm, obtained in experiments 2 and 7; the maximum material Q is 13225.68 mm²/min, recorded in experiment 9. However, no single experiment simultaneously achieves the minimum Ra, minimum RE, and maximum Q values. As a result, identifying an experiment that balances these criteria, minimizing Ra and RE while maximizing Q, requires a systematic approach. This cannot be accomplished merely by observing the data in Table III. Instead, an MCDM method is required to be employed. To address this issue, the Probability method was implemented to determine the optimal solution among the nine experimental results, evidenced in Table III. Calculating the criteria weights is a crucial step in this process. Using (6)-(11), the weights of the criteria Ra, RE, and Q, calculated via the MEREC method, are 0.2833, 0.2381, and 0.4786, respectively. For the Non-Complementary (NC) criteria Ra and RE, the normalized coefficients were computed using (4). The resulting values are β_j for Ra: 0.07928 and β_j for RE: 4.761905. These calculations and their respective results are summarized in Table IV. This systematic approach ensures a balanced evaluation of the experiments and enables the identification of the optimal solution.

TABLE III. EXPERIMENTAL RESULTS

Exp.	Ra (μm)	RE (μm)	Q (mm²/min)
1	0.691	0.04	1997.04
2	0.769	0.01	3195.264
3	1.748	0.04	5192.304
4	0.940	0.02	3315.84
5	0.901	0.04	5305.344
6	1.440	0.01	8621.184
7	0.846	0.03	5086.80
8	0.946	0.02	8138.88
9	1.057	0.03	13225.68

TABLE IV. P_{IJ} VALUES OF CRITERIA Ra AND RE IN THE EXPERIMENTS

Exp.	1	2	3	4	5	6	7	8	9
Ra	0.1386	0.1324	0.0548	0.1188	0.1219	0.0792	0.1263	0.1184	0.1096
RE	0.0476	0.1905	0.0476	0.1429	0.0476	0.1905	0.0952	0.1429	0.0952

For Q, which is a BC criterion, by applying (3), the normalized coefficient α_j of this parameter was calculated as 1.8492×10^{-5}, and by applying (4), the values of the probability of achieving a favorable outcome of this criterion were calculated, as summarized in Table V. Applying (5), the P_i values of each experiment were calculated, as shown in Table VI. The ranking of the experiments is also displayed in the last row of this table. Accordingly, experiment 9 is determined to be the optimal and experiment 8 is ranked second. Conversely, experiment 1 is determined to be the worst experiment, and experiment 3 is ranked eighth. To ensure the accuracy of the assessment and to provide greater confidence in solving the multi-objective optimization problem, it is essential to compare the rankings of the experiments obtained using the Probability method with those derived from other methods. This comparison validates the consistency and reliability of the results, ensuring that the chosen method effectively balances the objectives, and aligns with alternative approaches. SAW, TOPSIS, VIKOR, MAIRCA, EAMR, COPRAS, MARCOS, PIV, and COCOSO are the nine methods simultaneously used to rank the experiments and the ranking results were compared with those obtained when using the Probability method. The ranking results of the experiments using the Probability method and the experimental findings attained by deploying the nine methods are summarized in Table VII.

TABLE V. . P_{IJ} VALUES OF CRITERION Q IN EXPERIMENTS

Exp.	1	2	3	4	5	6	7	8	9
Q	0.0369	0.0591	0.0960	0.0613	0.0981	0.1594	0.0941	0.1505	0.2446

TABLE VI. P_I VALUE OF EACH EXPERIMENT AND RANKING OF THE EXPERIMENTS

Exp.	1	2	3	4	5	6	7	8	9
P_i	0.0571	0.0981	0.0693	0.0905	0.0878	0.1364	0.1026	0.1389	0.1556
Rank	9	5	8	6	7	3	4	2	1

It is observed that the ranking of the experiments performed when using the Probability method does not completely coincide with that when utilizing other methods. Even the ranking order of the experiments deploying the SAW, TOPSIS, VIKOR, MAIRCA, EAMR, COPRAS, MARCOS, PIV, and COCOSO methods is not completely consistent with each other. This is a normal occurrence when using MCDM methods [30-32]. It is also noted that the ranking of the alternatives when deploying the Probability method has a very high level of similarity to the one when using the other nine methods. It is worth mentioning that all the employed methods have identified Experiment 9 as the optimal one, confirming its status as the best experiment. To compare the ranking results of the experiments using different methods more comprehensively, the Spearman rank correlation coefficient was calculated as:

$$S = 1 - \frac{6\sum_{i=1}^{m} D_i^2}{m(m^2-1)} \quad (12)$$

where D_i is the difference in the ranking of experiment i when using different methods [33-35]. Table VIII summarizes the Spearman coefficient between each method and the Probability method.

TABLE VII. EXPERIMENT RANKING

Exp.	1	2	3	4	5	6	7	8	9
Probability	9	5	8	6	7	3	4	2	1
SAW	8	4	9	7	6	2	5	3	1
TOPSIS	8	6	9	7	5	2	4	3	1
VIKOR	9	5	8	7	6	3	4	2	1
MAIRCA	8	4	9	6	7	3	5	2	1
EAMR	9	4	8	7	6	3	5	2	1
COPRAS	9	4	7	8	6	2	5	3	1
MARCOS	8	4	9	7	6	2	5	3	1
PIV	8	4	9	6	7	3	5	2	1
COCOSO	8	4	9	6	7	3	5	2	1

TABLE VIII. SPEARMAN COEFFICIENT

Method	**Probability**
SAW	0.93333
TOPSIS	0.91667
VIKOR	0.98333
MAIRCA	0.96667
EAMR	0.96667
COPRAS	0.91667
MARCOS	0.93333
PIV	0.96667
COCOSO	0.96667

III. CONCLUSIONS

The use of the Probability method to solve the multi-objective optimization problem has the advantage of not containing subjective or artificial factors, thereby ensuring the accuracy of the final decision regarding the optimal alternative. This study applied the Probability method to optimize the multi-objective turning process of 3X13 steel when its machining is performed on a conventional lathe with input parameters, including spindle speed (n_w), feed rate (f), and depth of cut (a_p). The three criteria for evaluating the turning process involve the Surface Roughness (Ra), Roundness Error (RE), and material Removal Rate (Q). The following conclusions were drawn:

- The ranking of the experiments using the Probability method has a very high level of similarity compared to the one when employing other MCDM methods. The Spearman coefficient between the Probability method and other methods is very large, with the smallest being 0.91667. Notably, all the utilized methods have consistently identified the same optimal experiment.
- The optimal value of the spindle speed (n_w) is 1350 rev/min, corresponding to 101.78 m/min, the optimal value of the feed rate (f) is 0.13 mm/rev, and the optimal value of the depth of cut (a_p) is 0.4 mm. Currently, the values of the output parameters Ra, RE, and Q are 1.057 mm, 0.03 mm, and 13225.68 mm²/min, respectively.
- This study has only determined the optimal values of spindle speed (n_w), feed rate (f), and depth of cut (a_p), and has solely investigated three output parameters of the turning process: Ra, RE, and Q. Determining the optimal values for other parameters, such as the tool type and clamping method, as well as investigating additional output factors, like the tool wear rate and tool life, are important tasks for future research to further optimize the cutting process when machining 3X13 steel. Moreover, this study has only used the MEREC method to calculate the weights of the criteria, which is an objective weighting method. Thus the opinions of experts on the importance of the criteria were ignored. The use of a weighting method that combines both subjective and objective factors to calculate the weights of the criteria will overcome this limitation and needs to be implemented in the future.
- The application of the Probability method has successfully identified the optimal machining parameters, significantly improved the surface quality of the product, and increased the productivity of the turning process. This research has provided a solid foundation for applying the Probability method to optimize other manufacturing processes. In the future, combining the Probability method with machine learning techniques could help build intelligent decision support systems, automate the optimization process, and enhance production efficiency.

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