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Assessment of Turning process using the WSM Method

J. Arivudainambi, *P. Muthusamy, G. Suresh
Adhiyamaan College of Engineering Hosur, Tamilnadu, India.
*Corresponding author Email: *muthuap69@gmail.com*

Abstract. *Metal turning is a form of machining. It is used to create circular areas by cutting objects. The turning process requires a machine or lathe, a working tool, a fixture, and a cutting tool. A preformed piece of metal is secured to a device. A common process for turning a part includes rotating it while moving a single-point cutting tool parallel to the axis of rotation. This cutting tool works on both the outer and inner surfaces of the part. Factors such as cutting speed, cutting tool, depth of cut, and work-piece are considered in the turning process. In the assessment, the options are Cu, Si, Mn, Mg, and Zn. The results show that Zn ranks first, while Si has the lowest rank. The dataset's value for the Range of Turning process in the WSM (Weighted Sum Model) Method indicates that zinc (Zn) achieves the top ranking.*
Keywords: *MCDM.*

1. Introduction

A common process for turning a part includes rotating a single-point cutting tool parallel to the axis. It works on both the outer and inner surfaces of the part to remove material. Turning is a form of machining that requires a turning machine or lathe, a work piece, a device, and a cutting tool. It is used to create cylindrical parts, where the cutting tool moves linearly while the work piece rotates, reducing the diameter of the work piece to a specific dimension and creating a smooth surface finish. Metal turning is a machining process that involves removing unwanted material to create circular sections. It requires a machine or lathe, tooling, a fixture, and a cutting tool. The work piece is a preformed piece of metal secured to a fixture. Turning achieves the desired shape of the object by removing material, resulting in high machining accuracy with controlled axis movement. However, the production cost is high, and the processing speed is slow. Additionally, the task often follows a conservative design approach, disregarding the variation of loads and resulting in more affected water tanks. The water level in the tank varies continuously, causing a variation in the pressure inside. Based on the design results, the study concluded that LSM (likely referring to a specific method) offers a 13% economic advantage over WSM (likely referring to another method) in terms of material cost savings. It also confirmed that LSM is currently the only method used in the design of major structures worldwide.

2. Turning Process

The cost per part, production time per part, and tool life, as well as cutting parameters and surface quality issues, are discussed in the context of the multi-pass turning process aimed at achieving minimum unit production costs. An optimization problem approach is utilized through simulation to solve this problem [1]. The optimization of the turning process involves the use of various numerical methods, analytical techniques, and testing investigations. The accuracy of cutting parameter limits is defined to enhance surface quality [2]. The Taguchi technique and the application of response surface methods have been proven effective in optimizing the turning process for machining titanium materials [3]. This technological advancement in cutting tools for machining hard materials allows for improved process performance in metal cutting industries [4]. To prepare the semi-standard compression test specimen, a 6 mm diameter and 7 mm length is achieved through a low-speed turning process, followed by manual grinding to reduce the hardness of the affected layer [5]. The turning process involves converting raw materials into products using a traditional method, but CNC machining improves efficiency, and both manual and semi-automatic modes are compared as parameters [6]. Although the advantages of micro-textured tools have been studied in terms of cutting forces, cutting temperature, and tool wear, a performance study on surface roughening tools has not yet been conducted [7]. The turning process induces vibrations due to variations in machine structure, cutting tools, and steel samples. The interaction between the vibrating tool and the steel specimen results in wear and tear, leading to a reduction in surface quality [8]. When studying the effect of cutting tool nose radius on the cutting process, it is essential to consider the impact of the radius. Therefore, at least two methods of cutting metal are processed to determine the uncut chip thickness: plowing or shearing [9]. Further research is needed to optimize parameters in turning processes to thoroughly analyze the trade-off between quality and performance improvement, including reduced processing time and carbon emissions associated with surface roughness reduction [10]. Twisting, as a machining procedure, is one of the various production methods that can benefit significantly from the Fourth Industrial Revolution. In various manufacturing processes, twisting is commonly used as one of the four metal cutting processes [11]. Further research proposes a comparison of genetic algorithms with other optimization methods, such as etc. However, before proceeding, the objective function and all controls must be established to utilize a real example of the process [12]. In the dry turning process, cutting parameters depend on various factors, including the selection of steel materials, different heat processes, the type of cutting tool, and machining conditions [13]. The ability to suppress chatter at different spindle speeds varies due to fluctuations in the conversational frequency during the turning process. Future work will investigate the effectiveness of specific speed regions in suppressing chatter or enhancing performance [14]. A significant focus of research has been on predicting measurements. Sensors, such as strain gauges, are utilized to measure shear forces during twisting operations [15]. The aim is to test cooling strategies and determine the most effective fluid flow direction for improving tool life and workpiece surface roughness [16]. In this study, a detailed 3-degree-of-freedom model of the turning process is established, considering the feed speed factor [17]. To explore how Bayesian optimization can enhance the process, controlled and unconstrained Bayesian optimization mechanisms are compared in terms of turning process parameters [18]. The presence of multiple-volatile partial co-rotational processes has revealed that these processes are spread across the depth area, both in low-cut and high-cut regions. Accurately identifying the model parameters or machining dynamics can lead to predictable outcomes and help suppress chatter during the turning process [19]. Interestingly, their model does not include feed speed, which is considered to be the most important factor affecting the turning process. Additionally, the effect of feed rate on cutting dynamics and process properties should be explored [20]. Considering the advantages of vibration machining, such as improved dimensional precision and surface roughness of workpieces, it is scientifically and experimentally recommended to incorporate vibration machining in the turning process [21].

3. Wight Sum Method

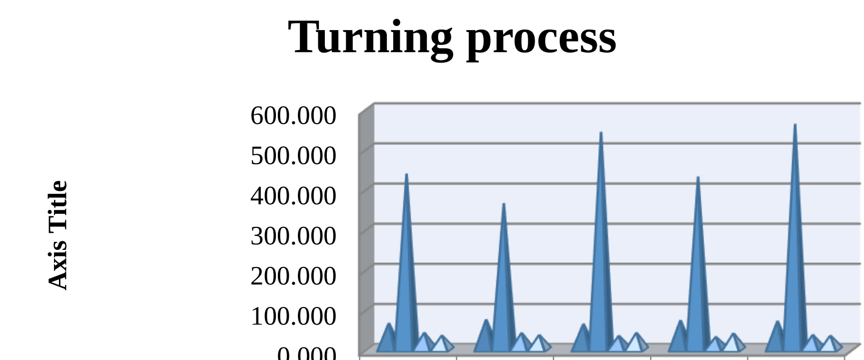
WSM scenes application enables independent static monitoring capabilities from different angle observation ranges. A universal and robust method is essential, especially for activity monitoring applications where intense observations will be made from various angles also used [22]. WSM is one of the suppliers selected by VTC and included in this plan. Currently, WSM adheres to very high VTC quality standards [23]. The algorithm was programmed using a system model multi-objective DE to achieve the desired simulation results. A multi-objective optimization is developed as an expressed weighted sum model, with two objective functions and 'w' representing the weighting function [24]. A study of the weighted sum ratio scaling problem is conducted for interference power control in a perceptual multiple access channel, where each SU communicates with a base station having a single transmit antenna and multiple receive antennas [25]. It will be shown later that a weighted sum is not unusual. Intuitively, the importance for both attributes follows the Pareto border by successively changing the weights from one end to the other [26]. The problem is constructed by adding objectives of objective function, two in the case of two criteria and three in the case of three objectives, with one of them multiplied by the parameter β [27]. The objective of reducing the sum of weighted completion times when the machine is not available is to minimize the global cost of stocking [28]. This is a valid objective because it calculates the stocking cost per unit time of the product, and the weighted sum represents the overall cost of stocking Due to the high computational effort associated with band models, the Weighted Ash Gases (WSGG) model with multiple global correlations has been developed [29]. This model allows for the weighted estimation of stocking costs, as gases such as CO_2 and H_2O are replaced with equivalently limited ash gases, simplifying the calculations [30]. In order to improve awareness of investment risks and reduce risk through hedging, we solve the multi-objective model empirically based on portfolio VAR by conducting research sampling under the assumption of a normal distribution, and then compare the results [31]. The use of various contextual information is essential in these models [32]. However, the computational tasks involved in performing the weighted sum or multiplication and accumulation functions are technically intensive. Therefore, efforts are made to achieve low power consumption in these computational tasks [33]. Two MCDM (Multiple Criteria Decision Making) methods were employed: the weighted sum method, chosen for its simplicity despite containing inaccurate and vague information, and the fuzzy logic method, used for performance assessment. The assessment includes five vehicle types, each with different modes of stock displays [34]. Inverse problems under distance have also received attention. The weighty sum-type is a count that indicates weighted transitions. It focuses on whether a parameter of an arc is changed, which corresponds to a situation of concern [35]. In our approach, we account for type mismatch or incomplete channel sum-rate loss due to prediction and other factors. We derive sum-ratio expressions for weighted sum-ratio to address mismatches and ensure robustness in the design [36]. From a user-centered perspective, the NOMA (Non-Orthogonal Multiple Access) system does not have PC (Personal Computer) functions. Two proposed methods are used to solve this problem. The first method involves the Dinkelbach ellipsoidal pattern, and the second method follows an epigraphical pattern combined with a convex approximation [37].

4. Analysis And Discussion

TABLE 1. Turning process in Data Set

	Cutting speed	Cutting tool	Depth of cut	Work-piece
Cu	67.080	439.530	43.150	36.050
Si	76.120	365.970	42.690	37.300
Mn	65.080	543.580	35.180	43.100
Mg	74.170	432.280	32.600	41.590
Zn	72.330	563.410	37.960	35.890

Table 1 show the Turning process shows the Cutting speed it is seen that Si the highest value for Mn is showing the lowest value. Cutting tool, it is seen that Zn is showing the highest value for Si is showing the lowest value. Depth of cut it is seen that Cu is showing the highest value for Mg is showing the lowest value. Work-piece it is seen that the Mn is showing the highest value for Zn is showing the lowest value. Alternative: Cutting speed, cutting tool, depth of cut, work-piece. Assessment Option: Cu, Si, Mn, Mg, Zn. It is solved by using the WSM method. It is the data set of this paper.



	Cu	Si	Mn	Mg	Zn
DATA SET Cutting speed	67.080	76.120	65.080	74.170	72.330
DATA SET Cutting tool	439.530	365.970	543.580	432.280	563.410
DATA SET Depth of cut	43.150	42.690	35.180	32.600	37.960
DATA SET Work-piece	36.050	37.300	43.100	41.590	35.890

FIGURE 1. Turning process in Data Set

Figure 1 shows the graphical representation turning process Data Set value of Alternative: Cutting speed, cutting tool, depth of cut, work-piece. Assessment Option: Cu, Si, Mn, Mg, Zn.

TABLE 2. Turning process in Normalized Data

	Normalized			
Cu	0.88124	0.78012	0.75550	0.99556
Si	1.00000	0.64956	0.76364	0.96220
Mn	0.85497	0.96480	0.92666	0.83271
Mg	0.97438	0.76726	1.00000	0.86295
Zn	0.95021	1.00000	0.85880	1.00000

Table 2 Shows the Normalized Data Matrix of Alternative: Cutting speed, cutting tool, depth of cut, work-piece. Assessment Option: Cu, Si, Mn, Mg, Zn.

TABLE 3. Turning process in Weight age

Weight			
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25

Table 3 Shows the Turning process in Weight age of Alternative: Cutting speed, cutting tool, depth of cut, work-piece. Assessment Option: Cu, Si, Mn, Mg, Zn.

TABLE 4. Turning process in weighted normalized decision matrix

	Weighted normalized decision matrix			
Cu	0.22031	0.19503	0.18888	0.24889
Si	0.25000	0.16239	0.19091	0.24055
Mn	0.21374	0.24120	0.23167	0.20818
Mg	0.24360	0.19181	0.25000	0.21574
Zn	0.23755	0.25000	0.21470	0.25000

Table 4 Shows the Turning process in weighted normalized decision matrix of Alternative: Cutting speed, cutting tool, depth of cut, work-piece. Assessment Option: Cu, Si, Mn, Mg, Zn.

TABLE 5. Turning process in Preference Score

	Preference Score
Cu	0.85311
Si	0.84385
Mn	0.89479
Mg	0.90115
Zn	0.95225

Table 5 shows the Turning process in Preference Score value of the Cu 4th value 0.85311, Si 5th value 0.84385, Mn 3rd value 0.89479, Mg 2nd value 0.90115, and Zn 1st value 0.95225.

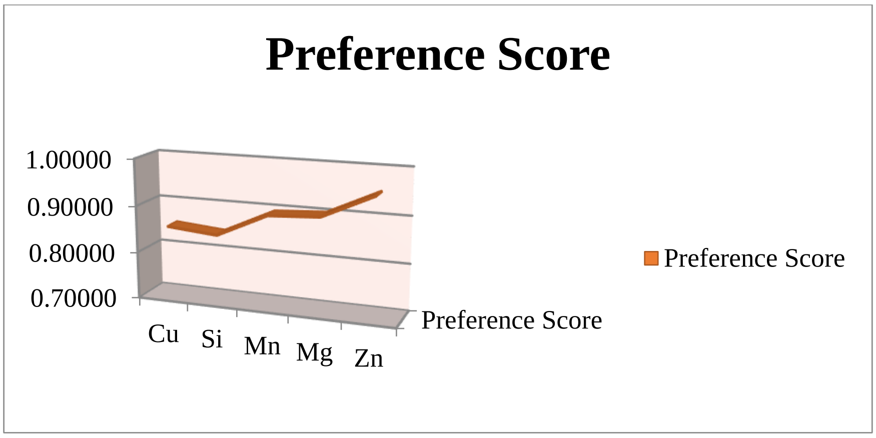


FIGURE 2. Turning process in Preference Score

Figure 2 shows the graphical representation Discordance Turning process in Preference Score value of the Cu 4th value 0.85311, Si 5th value 0.84385, Mn 3rd value 0.89479, Mg 2nd value 0.90115, and Zn 1st value 0.95225.

TABLE 6. Turning process in Rank

	Rank
Cu	4
Si	5
Mn	3
Mg	2
Zn	1

This table 6 shows that from the result it is seen that Cu 4th rank 0.85311, Si 5th rank 0.84385, Mn 3rd rank 0.89479, Mg 2nd rank 0.90115, and Zn 1st rank 0.95225.

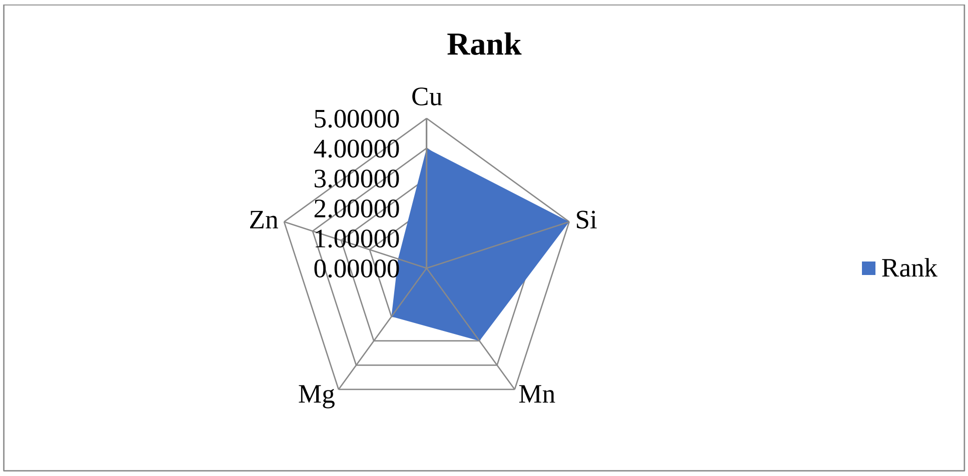


FIGURE 3. Turning process in Rank

Figure 3 shows the graphical representation Discordance Turning process in that from the result it is seen that Cu 4th rank 0.85311, Si 5th rank 0.84385, Mn 3rd rank 0.89479, Mg 2nd rank 0.90115, and Zn 1st rank 0.95225.

5. Conclusion

The optimization of the turning process involved research that utilized several numerical methods, analytical techniques, and testing investigations. The Taguchi technique and the application of response surface methods were employed to improve accuracy and increase the quality of the surface. This optimization process focused on turning machining of titanium material, and the effect of the cutting tool's nose radius on the process was studied. In order to analyze the effect, at least two methods of cutting metal were considered in relation to the uncut chip thickness: plowing and among other common product gases such as CO2 and H2O, ash gas. The weighted sum method was used, where non-ash gases were replaced with equally limited ash gases, simplifying the analysis. The functionality of weighted sum, multiplication, and accumulation was found to be essential but computationally intensive in these models, requiring technical expertise. Significant efforts were made to achieve low power consumption in these computational tasks, aiming to optimize energy consumption functions. Based on the results, Zn received the highest rank, whereas Si obtained the lowest rank.

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