Investigation and optimization of machining responses in CNC turning of aluminium 6061 T6

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ABSTRACT

This study investigates and optimizes the machining responses during CNC turning of aluminium 6061-T6, a material favored in industries like aerospace and automotive for its machinability and strength. The research specifically examines the influence of cutting speed, feed rate, and depth of cut on key performance metrics such as surface roughness. Using the Taguchi method, an L9 orthogonal array was employed to design the experiments, reducing the number of trials while ensuring comprehensive analysis. The experimental results indicated that feed rate was the most significant factor affecting surface roughness, with higher feed rates leading to an increase in roughness. For example, at a cutting speed of 370 m/min, feed rate of 0.25 mm/rev, and depth of cut of 1.0 mm, the surface roughness reached 9.48 µm. Conversely, the best surface finish of 0.85 µm was achieved at a cutting speed of 370 m/min, feed rate of 0.05 mm/rev, and depth of cut of 1.5 mm. Further optimization using Teaching-Learning-Based Optimization (TLBO) identified the optimal parameters for minimizing surface roughness: a cutting speed of 370 m/min, feed rate of 0.05 mm/rev, and depth of cut of 0.5 mm, resulting in a surface roughness of 0.7785 µm. This combination of Taguchi method and TLBO effectively enhances the precision and cost-efficiency of CNC turning operations, providing actionable insights for manufacturing industries seeking to optimize machining processes.

Keyword: - *Teaching-Learning-Based Optimization (TLBO), Al 6061 T6, Taguchi, SN ratios, Regression, Optimization, CNC turning, machining responses.*

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1. Introduction

Machining is primarily used to shape metals, particularly in industries where precision and durability are essential. It involves a complex interplay of various factors, including cutting speed, feed rate, and tool geometry, which the operator controls to achieve desired results. Turning is a key machining technique used to create cylindrical shapes. It involves rotating a workpiece against a cutting tool, resulting in a precise and smooth surface. This process is commonly used in industries such as automotive, aerospace, and manufacturing.

A lathe is a machine specifically designed for turning operations. It consists of a bed, headstock, tailstock, and carriage, each with its own functions. The headstock holds the workpiece, the tailstock supports the workpiece during turning, and the carriage holds the cutting tool and moves along the bed to create the desired shape. Aluminium alloys are a popular choice for machining due to their excellent machinability and lightweight properties. They are widely used in industries where weight reduction is crucial, such as aerospace and automotive. While pure aluminium is also machinable, aluminium alloys often exhibit superior properties due to the presence of alloying elements.

Mahamani (2014) investigated the impact of process parameters on cutting force and surface roughness during the turning of AA2219-TiB2/ZrB2 MMC using the Taguchi method. The study found that higher cutting speeds, lower feed rates, and smaller depths of cut resulted in reduced cutting forces and improved surface finishes. Feed rate was identified as having the greatest effect on cutting force and surface roughness. Mohamad et al. (2013) employed the

Taguchi method to explore the effect of lubrication conditions on surface roughness, as well as the influence of cutting speed, feed rate, and depth of cut on surface roughness individually. Their results showed that minimum quantity lubrication (MQL) produced better surface roughness compared to wet machines, with feed rate being the most significant factor affecting surface roughness, followed by cutting speed and depth of cut. Ersan Aslan et al. (2007) used the Taguchi method to study the combined effects of cutting speed, feed rate, and depth of cut on surface roughness and flank wear while turning hardened AISI 4140 steels with an Al_2O_3+TiCN blended ceramic tool. They found that cutting speed was the primary factor affecting tool wear, and the interactions between feed rate-depth of cut and cutting speed-feed rate had significant effects on surface roughness. Mahesh Babu et al. (2012) applied the Taguchi method to examine the impact of machining parameters on surface roughness in turning hybrid metal matrix composites (Al-SiC-B_4C). They observed that feed rate was the most influential parameter on surface roughness, followed by cutting speed.

Yang and Tarng (1998) used the Taguchi method to find optimal cutting parameters for minimizing surface roughness and maximizing tool life when turning S45 steel bars. They discovered that cutting speed had the most significant impact on tool life, while feed rate was crucial for surface roughness, followed by depth of cut and cutting speed. Rajasekaran et al. (2012) applied the Taguchi method to optimize cutting parameters for surface roughness in turning CFRP composites. Their results indicated that feed rate was the most significant parameter affecting surface roughness, with cutting speed and depth of cut also playing roles. Abhang and Hameedullah (2012) studied the effects of feed rate, depth of cut, and lubricant temperature on surface roughness while turning EN31 steel using the Taguchi method. They found that lubricant temperature and feed rate were the main factors influencing surface roughness.

This research aims to establish a comprehensive understanding of the machining behavior of aluminum 6061 T6 under CNC turning conditions. Quantify the relationships between cutting parameters and machining responses. Develop a predictive model for predicting machining performance based on process parameters. Determine optimal machining conditions for achieving desired surface quality, cutting force, and tool life. Provide valuable insights for process optimization and cost reduction in the manufacturing industry.

2. Method and materials

2.1 Workpiece Material

The sample material for the research is Al 6061 T6 aluminium in the form of flat plate with 200 mm length, 150 mm width and 20 mm thickness. The chemical composition of the material is shown in following table.

Table 1: Chemical composition of Al606 T6

Element	Al	Mg	Si	Fe	Cu	Cr	Zn	Ti	Mn
Composition (%)	Balance	1.0	0.65	0.4	0.5	0.21	0.08	0.1	0.15

2.2 Selection of the cutting parameters and their levels

The choice of cutting input variables is made by taking into account the equipment precision, machining series, setup mode, limiting cutting conditions of the cutting tool manufacturer's catalogue and the values are taken by researchers in their work. The selection of machining process is strongly affected by the tolerance of the part to be machined.

Table 2: Machining process parameters along with their levels

Cutting parameter	Unit	Level 1	Level 2	Level 3
Cutting speed	m min^{-1}	130	200	370
Feed rate	mm rev^{-1}	0.05	0.15	0.25
Dept of cut	mm	0.5	1.0	1.5

2.3 Taguchi design of experiment

The Taguchi method is a statistical approach developed by Dr. Genichi Taguchi to improve the quality of manufactured goods and optimize industrial processes. It focuses on designing experiments that efficiently determine the impact of various factors on a process or product, with the aim of minimizing variability and improving performance. The Taguchi method is widely used in engineering and manufacturing to enhance quality while reducing costs.

Table 3: Chemical composition of Al606 T6

Trial No.	Cutting parameter level		
	Cutting speed	Feed rate	Depth of cut
1	130	0.05	0.5
2	130	0.15	1.0
3	130	0.25	1.5
4	200	0.05	1.0
5	200	0.15	1.5
6	200	0.25	0.5
7	370	0.05	1.5
8	370	0.15	0.5
9	370	0.25	1.0

3. Results and discussion

Surface roughness is a critical quality attribute in machining and manufacturing processes, reflecting the texture of a surface at a micro-scale level. Experimental results on surface roughness typically involve assessing the impact of various machining parameters, such as cutting speed, feed rate, depth of cut, and tool geometry, on the roughness of the finished surface. The machined surface roughness was measured by a 3D-Hommelewerk profile meter. The average surface roughness Ra, which is the most widely used surface finish parameter in industry, was selected for this study, being the arithmetic average of the absolute value of the heights of roughness irregularities from the mean value measured within a sampling length of 5 mm. The surface roughness obtained from the experiments is summarized in the following table.

Table 4: Experimental results

Trial No.	Cutting parameter level			Surface roughness
	Cutting speed	Feed rate	Depth of cut	
1	130	0.05	0.5	1.19
2	130	0.15	1.0	2.15
3	130	0.25	1.5	8.5
4	200	0.05	1.0	2.53
5	200	0.15	1.5	4.40
6	200	0.25	0.5	7.38
7	370	0.05	1.5	0.85
8	370	0.15	0.5	3.92
9	370	0.25	1.0	9.48

3.1 Analysis of the S/N ratio

In the Taguchi method, the term `signal' represents the desirable value (mean) for the output characteristic and the term `noise' represents the undesirable value (S.D.) for the output characteristic. A detailed discussion has been added in the introduction section. Therefore, the S/N ratio is the ratio of the mean to the S.D. Taguchi uses the S/N ratio to measure the quality characteristic deviating from the desired value. In our case the surface roughness has been measured as the quality characteristic, so, for the S/N ratio lower is better category has been taken to analyze the process parameters.

Table 5: S/N ratio for each trial

Trial No.	Cutting parameter level			Surface roughness	S/N ratio (dB)
	Cutting speed	Feed rate	Depth of cut		
1	130	0.05	0.5	1.19	-1.5109
2	130	0.15	1.0	2.15	-6.6488
3	130	0.25	1.5	8.5	-18.5884
4	200	0.05	1.0	2.53	-8.0624
5	200	0.15	1.5	4.40	-12.8691
6	200	0.25	0.5	7.38	-17.3611
7	370	0.05	1.5	0.85	1.4116
8	370	0.15	0.5	3.92	-11.8657
9	370	0.25	1.0	9.48	-19.5362

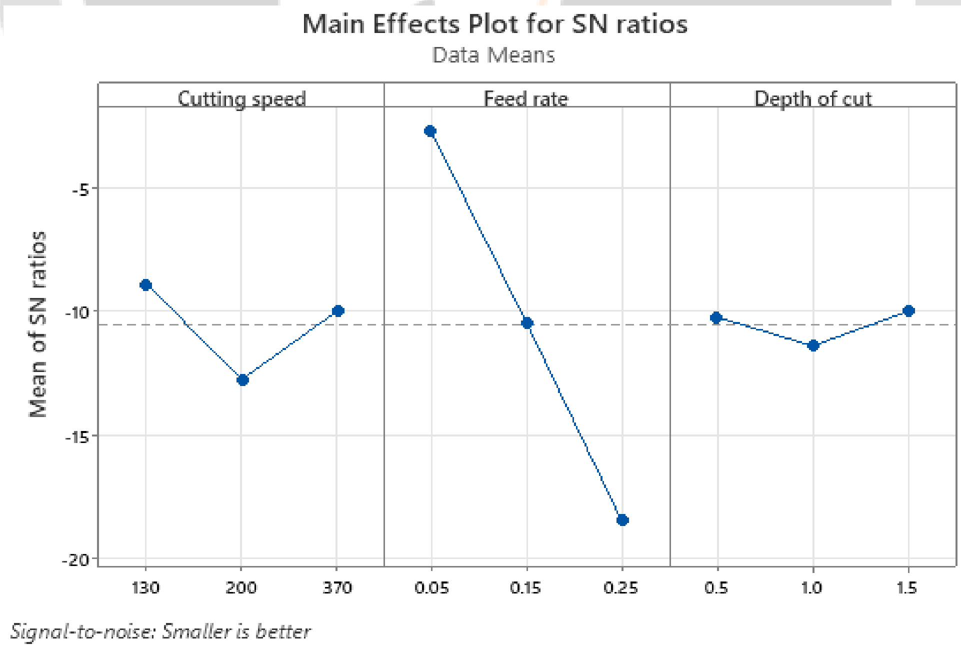

Figure 1. Main Effect plot for SN ratio of the parameters

The mean S/N ratio for each level of the cutting parameters is summarized and called the S/N response table for surface roughness (Table 5). In addition, the total mean S/N ratio for the nine experiments is also calculated and listed in the following table. As shown in the greater is the S/N ratio, the smaller is the variance of tool life around the desired (the-lower-the-better) value. However, the relative importance amongst the cutting parameters for tool life still needs to be known so that optimal combinations of the cutting parameter levels can be determined more accurately. This will be discussed in the next section using the analysis of variance.

3.2 Analysis of Variance for SN ratios

The following table shows the results of ANOVA for surface roughness. It can be found that cutting speed and feed rate are the significant cutting parameters for affecting surface roughness. The change of the depth of cut in the range given in table has an insignificant effect on surface roughness. Therefore, based on the S/N and ANOVA analyses, the optimal cutting parameters for surface roughness are the cutting speed at level 2, the feed rate at level 3, and the depth of cut at level 2.

Table 6: Response Table for Signal to Noise Ratios

Level	Cutting speed	Feed rate	Depth of cut
Cutting speed	-8.916	-2.721	-10.246
Feed rate	-12.764	-10.461	-11.416
Depth of cut	-9.997	-18.495	-10.015
Delta	3.848	15.775	1.401
Rank	2	1	3

3.3 Regression Equation

In the Taguchi method, regression equations are often used to model the relationship between the input factors (control variables) and the response variable (output). The Taguchi method focuses on optimizing the performance of a process by designing experiments that systematically vary input parameters to identify their effect on the output. The regression equation in the Taguchi method serves as a mathematical model that describes how the input variables influence the response. It is crucial for predicting outcomes, optimizing processes, and identifying the most influential factors. This approach helps in understanding the complex interactions between multiple factors, thereby enabling more informed decision-making in process optimization and quality improvement. The equation generated by the Taguchi design of experiment is given by the following equation. The R-square obtained for the above equation is 91.42%, which shows a quite good score.

Surface roughness= 1.66 - 0.0068 Cutting speed + 12.0 Feed rate - 1.96 Depth of cut+ 0.049 Cutting speed*Feed rate + 0.0043 Cutting speed*Depth of cut+ 12.5 Feed rate*Depth of cut

3.4 Optimization

Teaching-Learning-Based Optimization (TLBO) is a population-based optimization algorithm inspired by the teaching and learning process in a classroom. Proposed by Rao et al. in 2011, TLBO has gained attention due to its simplicity, efficiency, and ability to solve complex optimization problems without requiring algorithm-specific parameters like mutation rates or crossover probabilities commonly used in other evolutionary algorithms.

For single response optimization of surface roughness, the equation is generated using regression analysis and used individually as objective function in TLBO algorithm. The constrained values for TLBO are minimum and maximum values of process variables given in following table.

Table 7: Optimized values of the cutting parameters

	Cutting steed	Feed rate	Depth of cut
Minimum	130	0.05	0.5
Maximum	370	0.25	1.5

The graph generated by TLBO algorithm in MATLAB 2022a is shown in the following figure. The stars in graph figure shows the learning procedure of algorithm to reach the maximum value. In the graph where the stars line is constant for iteration no. shows minimum value of surface roughness.

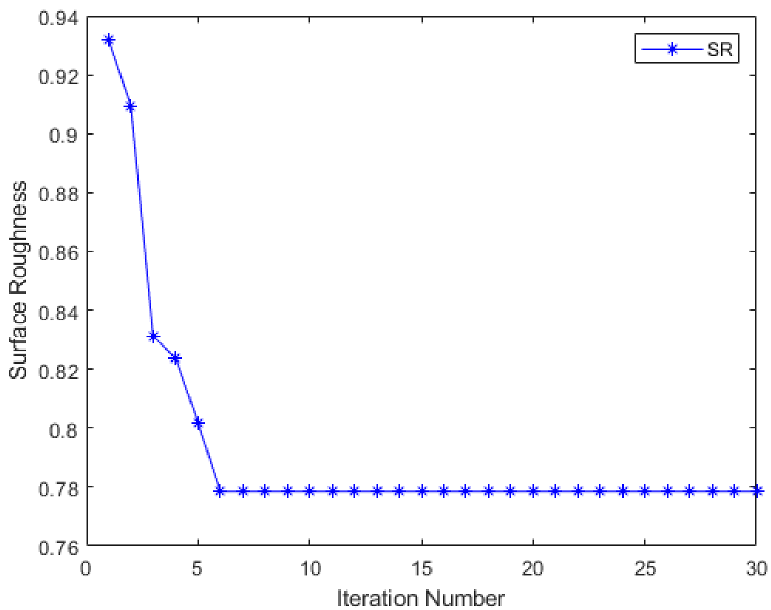

Figure 2: Convergence plot for surface roughness generated using TLBO.

Table 8: Optimized parameters from TLBO

Parameter	Cutting steed	Feed rate	Depth of cut	SR
Values	370	0.05	0.5	0.7785

4. CONCLUSION

This study effectively applied the Taguchi method and Teaching-Learning-Based Optimization (TLBO) to optimize the machining parameters for CNC turning of aluminium 6061-T6. The research highlighted the significant impact of cutting parameters—particularly feed rate—on machining outcomes like surface roughness, tool wear, and material removal rate. By using an L9 orthogonal array, the study efficiently determined the most influential factors, with results indicating that higher feed rates generally led to increased surface roughness, while optimal conditions were achieved through a careful balance of cutting speed and depth of cut. The optimization process revealed that precise control of machining parameters can significantly improve surface quality, with the best surface roughness recorded at 0.7785 µm using TLBO. These findings emphasize the importance of systematic experimentation and advanced optimization techniques in enhancing the performance and cost-effectiveness of CNC turning operations.
The insights gained from this research are directly applicable to manufacturing environments where surface finish and tool longevity are critical. The methodology established here provides a solid foundation for future studies and practical implementations in optimizing machining processes for aluminium alloys and other materials.

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