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(Research Article)

Optimizing Machining Quality and Production Efficiency Through a Taguchi-Based Six Sigma Framework

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Abstract

This study introduces a Taguchi-based Six Sigma Optimization Framework (TSSOF) to enhance machining performance by optimizing key parameters in the CNC turning of EN8 steel. Focused on improving surface finish and material removal rate (MRR), the research applies Taguchi's Design of Experiments (DOE) and Six Sigma principles to analyze the effects of cutting speed, feed rate, and depth of cut. Using the signal-to-noise (S/N) ratio approach, optimal parameters were found to be a cutting speed of 125 m/min, feed rate of 0.1 mm/rev, and depth of cut of 0.3 mm, yielding the best surface finish. ANOVA reveals that feed rate is the most significant factor affecting surface roughness while cutting speed and depth of cut have lesser impacts. A regression model is developed to quantify the relationship between machining parameters and surface roughness, providing a data-driven optimization strategy. The results demonstrate that TSSOF effectively reduces defects, enhances efficiency, and improves process capability, making it valuable for automotive, aerospace, and advanced manufacturing industries.

Keywords: Taguchi-Based Six Sigma (TSSOF); Design of Experiments (DOE); Signal-to-Noise Ratio (S/N Ratio); CNC Turning; Machining Optimization; Surface Roughness (Ra); Material Removal Rate (MRR); EN8 steel.

1. Introduction

In today's competitive manufacturing landscape, achieving high machining quality and maximizing production efficiency are essential for operational excellence. Manufacturers seek advanced methodologies to optimize processes, reduce variability, and improve product quality while minimizing costs. The Taguchi-Based Six Sigma Optimization Framework (TSSOF) combines Lean principles, Six Sigma, and Taguchi's design of experiments (DOE) strategy to enhance machining efficiency and minimize defects. It offers a structured approach to optimizing machining parameters, improving performance, reducing waste, and stabilizing processes [1].

Lean manufacturing eliminates non-value-added activities and streamlines workflows [2]. Six Sigma, through its DMAIC methodology, identifies process variations and drives continuous improvement [3]. The Taguchi method, using DOE, determines optimal process conditions to minimize variability and enhance robustness. By integrating these methodologies, TSSOF provides a data-driven approach to achieving superior machining quality and cost-effective manufacturing [4].

This study applies TSSOF to optimize machining parameters in CNC turning operations for EN8 steel, focusing on cutting speed, feed rate, and depth of cut to achieve a superior surface finish and maximize material removal rate (MRR). Taguchi's DOE and Analysis of Variance (ANOVA) are used to assess the significance of machining parameters, while a regression-based model correlates factors with performance outcomes.

The objective is to enhance machining performance by reducing surface roughness, improving accuracy, and maximizing MRR, leading to better productivity and reduced cycle times. The predictive model supports data-driven decision-making and provides a reliable tool for continuous improvement. This framework is particularly valuable for precision industries such as automotive, aerospace, and high-precision manufacturing, where accuracy and operational efficiency are crucial.

The paper is structured as follows: Section 2 reviews relevant literature, Section 3 presents the research gap, Section 4 outlines the methodology, Section 5 describes the experimental setup and findings, and Section 6 concludes with insights and future research directions.

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2. Literature Review

The Taguchi-Based Six Sigma (TSS) approach combines Six Sigma's data-driven problem-solving with Taguchi's robust experimental design to enhance manufacturing efficiency, reduce variability, and ensure product quality. Using the DMAIC (Define, Measure, Analyze, Improve, Control) methodology, Six Sigma identifies and eliminates defects, improving process capability and efficiency. Meanwhile, Taguchi's Design of Experiments (DOE) optimizes key factors while minimizing the impact of uncontrollable noise, ensuring reliable outcomes.

TSS provides a powerful framework for optimizing critical parameters, reducing waste, and maximizing resource utilization. It also supports predictive modeling for continuous improvement, aligning with Industry 4.0's data-driven manufacturing. Applied in precision industries like automotive and aerospace, TSS helps meet stringent quality standards, reduce defects, and optimize machining efficiency, driving cost-effectiveness and long-term operational excellence (Gomaa, 2024, [1]).

The integration of Lean Six Sigma (LSS) with the Taguchi method is a powerful strategy for optimizing manufacturing processes, reducing defects, and improving product quality. By combining Lean's waste reduction, Six Sigma's defect control, and Taguchi's experimental design, this framework enhances operational efficiency, process stability, and cost-effectiveness. Table 1 summarizes studies applying Taguchi-based LSS across industries, showcasing its impact on process optimization, quality improvement, and efficiency enhancement in sectors like machining, automotive, semiconductor, food processing, and telecommunications.

Several studies highlight the effectiveness of Taguchi-based LSS. Gomaa (2024) [1] developed an LSS framework for spare parts manufacturing using tools like process mapping, DOE, and OEE to optimize parameters and improve quality. Similarly, Gomaa (2023) [5] applied DMAIC to improve machining efficiency in automotive spare parts production. Chen et al. (2023) [6] used a DMAIC-Taguchi approach to optimize transistor gasket parameters, while Muraleedharan et al. (2023) [7] applied it to galvanized iron metal, enhancing process stability. Duc et al. (2023) [8] optimized oil immersion tank conditions in molybdenum processing, demonstrating the framework's versatility.

Research also shows the application of Taguchi-based LSS in diverse fields: Yusof and Lee (2022) [9] improved macaron production quality, while Erlangga and Wahyuni (2022) [10] demonstrated its impact on SMEs, improving efficiency and reducing defects in resource-constrained industries.

The Taguchi-based LSS methodology has proven effective in optimizing multi-characteristic products and complex industrial processes. Yu et al. (2022) [11] applied DMAIC with Taguchi to improve the quality of multi-characteristic products, managing multiple variables efficiently. Gerger and Firuzan (2021) [12] demonstrated its success in the automotive industry, enhancing process performance and reducing customer complaints.

In metal casting, Omprakas et al. (2021) [13] used Taguchi-Six Sigma DMAIC to reduce shrinkage defects in sand-casting, improving yield. Ketabforoush and Abdul Aziz (2021) [14] applied it to reduce variation in green construction materials, enhancing sustainability. Ganganallimath et al. (2019) [15] further validated its impact on reducing defects in green sand-casting.

Kaushik et al. (2016) [16] and Chen and Brahma (2014) [17] extended this approach to improve casting quality and reduce waste in green sand-casting. Their findings highlight the effectiveness of combining Six Sigma's defect reduction with Taguchi's robust design.

The approach also extends to high-precision industries. Ibrahim et al. (2019) [18] applied it for business process improvement in telecom, while Chou and Chen (2017) [19] optimized surface roughness in CNC milling, improving material removal rates. Lin and Wong (2014) [20] demonstrated its utility in precision manufacturing, optimizing quality and efficiency in hand tool drilling.

Research on Taguchi-based Lean Six Sigma highlights its effectiveness across industries, from manufacturing and metal casting to food production and precision machining, driving improvements in process optimization, defect reduction, and efficiency.

Table 1. Review of Taguchi-based lean six sigma

#	Study	Application	Key contributions
1	Gomaa, 2024 [1]	Spare parts manufacturing	Developed a comprehensive LSS framework integrating the Taguchi method. Utilized improvement tools such as SIPOC, KPI analysis, OEE, VSM, DOE, ANOVA, Takt time, and 7S to enhance efficiency and quality.
2	Gomaa, 2023 [5]	Machining processes in car spare parts manufacturing	Proposed a DMAIC-based framework to optimize machining efficiency and effectiveness using Lean Six Sigma principles.
3	Chen et al., 2023 [6]	Transistor gasket manufacturing	Implemented a DMAIC framework incorporating the Taguchi method to optimize process parameters and enhance product quality.

4	Muraleedharan et al., 2023 [7]	Galvanized iron metal processing	Applied a Taguchi-based DMAIC methodology to optimize process conditions, improving manufacturing efficiency and reducing variability.
5	Duc et al., 2023 [8]	Oil immersion tank production (Molybdenum materials)	Utilized LSS with Taguchi DOE to determine optimal process parameters, leading to defect reduction and efficiency improvements.
6	Yusof and Lee, 2022 [9]	Food industry (Macaron production)	Developed a Six Sigma DMAIC framework using the Taguchi approach to improve product quality and streamline the production process.
7	Erlangga and Wahyuni, 2022 [10]	Small and Medium-Sized Enterprises (SMEs)	Explored the application of LSS and Taguchi methods in SMEs to reduce defect rates and enhance production efficiency.
8	Yu et al., 2022 [11]	Multi-characteristic product manufacturing	Implemented a DMAIC-Taguchi approach to improve the quality of complex industrial products through process optimization.
9	Gerger and Firuzan,2021 [12]	Automotive industry	Applied a Taguchi-six sigma methodology to enhance process performance and reduce customer complaints.
10	Omprakas et al., 2021 [13]	Sand-casting industry	Used a Six Sigma DMAIC approach with Taguchi techniques to minimize shrinkage defects in sand-casting processes.
11	Ketabforoush and Abdul Aziz, 2021 [14]	Green construction materials production	Investigated the impact of Taguchi-based six sigma on variation reduction and process stability in sustainable material manufacturing.
12	Ganganallimath et al., 2019 [15]	Green sand-casting	Developed a Taguchi-based six sigma approach to minimize defects and improve overall casting quality.
13	Ibrahim et al., 2019 [18]	Telecommunications sector	Identified and analyzed critical process control factors for business process improvement using the Taguchi method.
14	Chou and Chen, 2017 [19]	CNC milling process	Applied a Taguchi-based six sigma framework to optimize surface roughness in CNC machining, enhancing precision and efficiency.
15	Kaushik et al., 2016 [16]	Green sand-casting	Utilized Taguchi-based Six Sigma principles to reduce product defects and enhance process performance in casting operations.
16	Chen and Brahma,2016 [14]	Green sand-casting	Proposed a Taguchi-based six sigma framework to minimize defects and improve the consistency of casting processes.
17	Lin and Wong, 2014 [20]	Hand tool drilling production	Implemented Taguchi-based six sigma techniques to improve drilling process efficiency and product quality.

Achieving high-quality machining outcomes while minimizing waste and enhancing efficiency requires a data-driven, systematic approach. The Taguchi method, known for its robust experimental design, optimizes machining parameters and embeds quality early in development [21]. Unlike trial-and-error methods, it identifies key parameters to improve stability and resource utilization. Table 2 summarizes key studies using Taguchi in machining optimization, highlighting advancements in efficiency and quality.

Studies applying Taguchi span industries to optimize machining. Antony et al. (2024) [22] demonstrated its effectiveness in improving food industry production. Bouhali et al. (2024) [23] developed models for aluminum alloy dry turning, optimizing surface roughness. Chauhan et al. (2018) [24] enhanced tool life and precision in EN9 steel turning.

Soori and Asmael (2022) [25] reviewed parameter optimization for precision, while Chelladurai et al. (2021) [26] used Taguchi and RSM for multi-objective optimization in casting and welding. Chauhan and Kumar (2022) [27] compared carbide insert types in EN9 turning, highlighting the advantages of coated tools.

Patil and Gavali (2019) [28] studied how cutting speed, depth of cut, and feed rate affect EN9 steel turning, showing that precise parameter selection improves productivity and reduces energy use. Irfan et al. (2019) [29] combined the Taguchi method with regression analysis to optimize CNC machining of EN-45 spring steel, aiding predictive modeling. Mir and Wani (2018) [30] explored EN24 alloy steel using PVD-coated TiAlN and carbide inserts, demonstrating Taguchi’s role in process refinement. Chauhan et al. (2018) [24] analyzed surface roughness, MRR, and tool wear, reinforcing robust parameter selection.

Deshpande and Pant (2017) [31] optimized CNC turning parameters for EN8 alloy steel, comparing coated and uncoated inserts for accuracy and tool life. Kumar et al. (2017) [32] applied Taguchi and regression analysis to optimize cutting parameters for EN45 spring steel. Jadhav and Shaikh (2016) [33] studied CNC machining of EN24 steel, comparing insert types for optimal surface finish, tool wear, and production rate.

Despite significant research on Taguchi-based machining optimization, few studies combine it with Lean Six Sigma, suggesting an opportunity for further research to enhance process excellence and efficiency.

Table 2. Machining process optimization using the Taguchi method

#	Study	Application	Key Contributions
1	Antony et al., 2024 [22]	Food industry	Reviewed and analyzed the application of Taguchi DOE in food processing for quality improvement.
2	Bouhali et al., 2024 [23]	Dry turning of aluminum alloys	Developed mathematical models to predict surface roughness and optimize machining conditions.
3	Chauhan et al., 2024 [24]	Turning of EN9 Steel	Investigated the performance of carbide inserts to enhance tool life and machining efficiency.
4	Soori & Asmael, 2022 [25]	Manufacturing Optimization	Reviewed advancements in machining parameter optimization to improve part accuracy and quality.
5	Chelladurai et al., 2021 [26]	Casting & welding	Applied response surface methodology (RSM) for multi-objective process optimization.
6	Chauhan & Kumar, 2022 [27]	Cutting performance of carbide tools	Compared plain and coated carbide inserts in turning operations for efficiency and tool wear analysis.
7	Patil & Gavali, 2019 [28]	Turning of EN9 steel	Examined the effects of cutting speed, feed rate, and depth of cut on machining performance.
8	Irfan et al., 2019 [29]	CNC machining of EN-45 spring steel	Applied Taguchi DOE with regression analysis to optimize machining parameters.
9	Mir & Wani, 2018 [30]	Turning of EN24 alloy steel	Investigated the effects of PVD-coated TiAlN and plain carbide inserts using the Taguchi method.
10	Deshpande & Pant, 2017 [31]	CNC turning of EN8 alloy steel	Optimized machining parameters using Taguchi DOE with coated/uncoated tool inserts.
11	Kumar et al., 2017 [32]	Machining of EN45 spring steel	Used Taguchi DOE and regression analysis to optimize cutting parameters.
12	Jadhav & Shaikh, 2016 [33]	CNC machining of EN24 alloy steel	Evaluated PVD-coated TiAlN and plain carbide inserts for improved machining efficiency.

3. Research Gap Analysis

Despite significant research on the Taguchi method for machining optimization, there are gaps in integrating it with Lean Six Sigma for a holistic process improvement framework. Most studies focus on optimizing individual metrics like surface roughness and MRR, with limited exploration of combining Taguchi with Lean Six Sigma. An integrated approach could enhance process stability, minimize defects, and drive continuous improvement.

Additionally, while the Taguchi method is effective in isolation, it often lacks the integration of Industry 4.0 technologies such as real-time monitoring and data analytics. The incorporation of machine learning and predictive analytics into Taguchi-based optimization could improve real-time control and maintenance.

Most research focuses on single metrics, with limited emphasis on multi-objective optimization, balancing trade-offs like tool wear, surface finish, and energy consumption. Sustainable manufacturing is also underexplored, with opportunities to integrate energy efficiency and environmental impact into the optimization process.

By combining Lean Six Sigma with the Taguchi method and integrating smart manufacturing principles, this study aims to create a more comprehensive, data-driven, and sustainable framework for machining optimization, improving quality, efficiency, and resource utilization.

4. Research Methodology

This study adopts a structured approach to optimize machining processes using a Taguchi-based Lean Six Sigma framework, as outlined in Table 3. The first phase identifies key challenges in machining, such as quality issues, inefficiencies, and high defect rates, forming the foundation for optimization.

A review of existing research and industry practices is conducted to identify gaps and compare methodologies, ensuring the study builds on proven strategies while addressing unexplored areas. The Taguchi method is applied to structure the experimental setup, selecting key parameters—cutting speed, feed rate, and depth of cut—and using an orthogonal array-based design to test various conditions.

The Define-Measure-Analyze-Improve-Control (DMAIC) framework is integrated to guide the optimization. The Define phase sets objectives and identifies inefficiencies, while the Measure phase gathers baseline data. In the Analyze phase, Design of Experiments (DOE) is used to evaluate the relationship between machining parameters and output quality, with insights guiding the Improve phase. Process optimizations are then tested through confirmation experiments, with control measures applied for sustained improvement.

Statistical methods like signal-to-noise (S/N) ratio analysis and ANOVA are used to identify optimal conditions, while regression analysis and hypothesis testing validate the results. The optimized parameters are implemented in real-world environments through case studies to assess productivity, defect reduction, and cost savings.

The final phase summarizes findings and proposes future research directions. By integrating DMAIC and Taguchi's DOE, this study demonstrates a systematic, data-driven approach to machining optimization, ensuring improved efficiency, reduced defects, and enhanced quality in industrial applications.

Table 3. Summary of research methodology

#	Step	Objective	Key activities	Expected outcomes
1	Problem identification	Define the research problem and scope	Identify machining challenges, review industry needs, and assess gaps in existing studies	Clear problem statement, research objectives, and scope
2	Literature review & benchmarking	Establish a theoretical foundation and best practices	Review past studies on the Taguchi method, six sigma, and machining optimization	Comprehensive insights into existing methodologies and research gaps
3	Experimental design	Develop a structured research framework	Define machining parameters, select materials and tools, and set up the Taguchi DOE framework	Well-structured experiment setup and research plan
4	Six sigma DMAIC implementation	Enhance process efficiency and quality	Apply define, measure, analyze, improve, and control (DMAIC) methodology	Systematic process improvements with data-driven decision-making
5	Parameter optimization	Determine optimal machining conditions	Conduct Taguchi-based experiments, analyze factor effects, and optimize cutting parameters	Improved machining efficiency, reduced variability, and enhanced quality
6	Statistical validation & analysis	Ensure reliability and accuracy of results	Perform ANOVA, regression analysis, and signal-to-noise ratio (S/N) validation	Statistically validated results ensuring robustness and reproducibility
7	Industrial application & case study	Demonstrate real-world feasibility	Implement optimized parameters in an industrial setting, compare performance with baseline data	Practical validation of improvements in machining operations
8	Conclusion & future research	Summarize key findings and propose future directions	Interpret results, discuss limitations, and recommend further research	Clear conclusions, industry insights, and suggestions for future studies

Table 4. DMAIC-based optimization approach

Phase	Objective	Key activities	Expected outcome
Define	Identify machining challenges and set goals	Define process inefficiencies, defects, and key improvement areas	Clearly defined problem statement and project scope
Measure	Collect baseline data for analysis	Develop a data collection plan, gather process performance data	Benchmark for process evaluation and comparison
Analyze	Investigate relationships between factors and outcomes	Conduct DOE, identify key factors and levels, execute experiments, analyze results	Identification of optimal machining conditions
Improve	Optimize process parameters and implement improvements	Apply optimized factor settings, verify process enhancements, implement control measures	Improved process efficiency and reduced defects

Control	Ensure long-term stability and continuous improvement	Set control limits, monitor performance, revisit DOE if deviations occur	Sustained process improvements and quality control

5. Case Study

This study was conducted in a spare parts manufacturing industry in Egypt, focusing on optimizing the CNC turning process for EN8 steel. EN8 is a widely used medium-carbon, medium-tensile steel commonly applied in various engineering applications. Given the critical role of machining parameters in determining product quality and efficiency.

5.1 Product defect analysis: This phase systematically identifies the root causes of defects and analyzes inefficiencies in the machining process. As shown in Figure 1, the Pareto chart highlights that the most prevalent defect in the CNC turning process is a poor surface finish. Since surface quality directly impacts product performance, durability, and customer satisfaction, addressing this issue is critical for improving overall manufacturing efficiency.

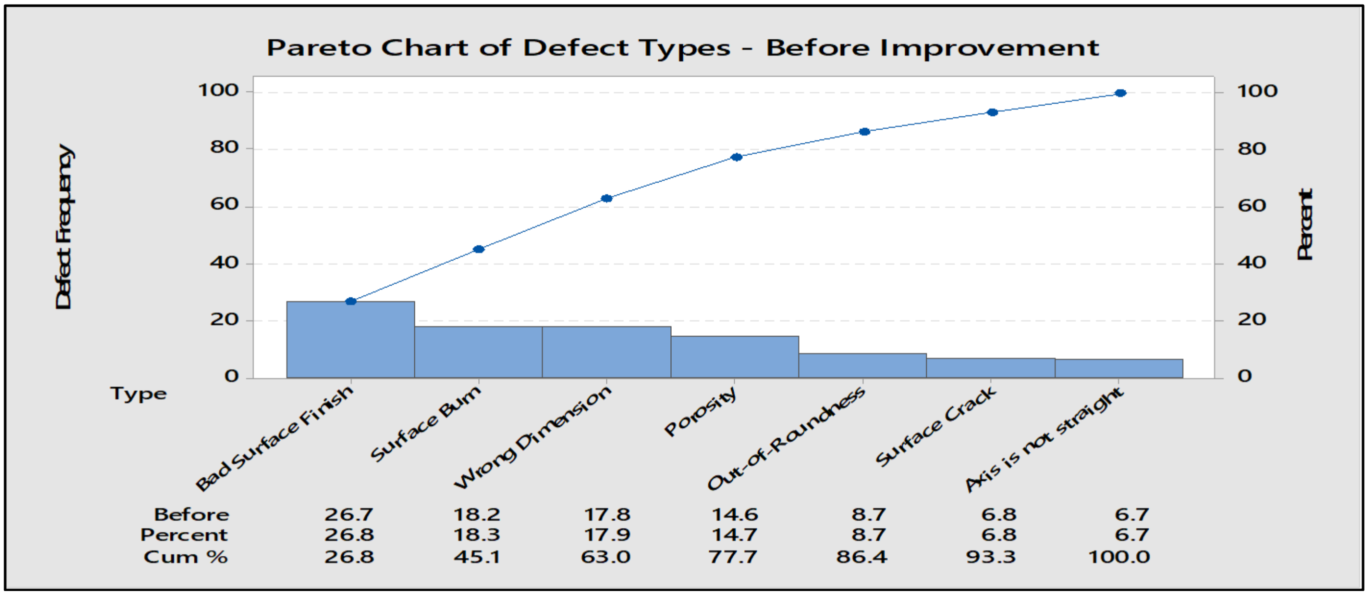

Figure 1. Pareto chart of defect types (before improvement)

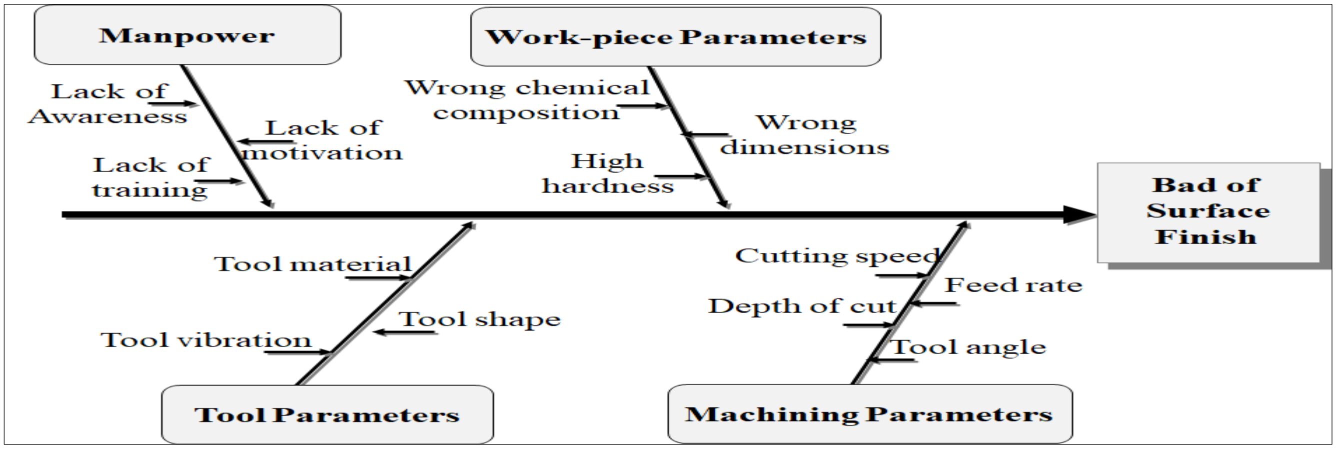

Figure 2. C&E diagram for bad surface finish

To gain deeper insights into the factors contributing to surface defects, a brainstorming session was conducted with engineers and machine operators. This session focused on identifying potential root causes related to machining conditions, tool performance, material properties, and environmental influences. As a structured approach to problem identification, an Ishikawa cause-and-effect diagram was developed, as illustrated in Figure 2. This diagram categorizes key factors affecting surface finish, including cutting speed, feed rate, tool wear, machine vibrations, and coolant application, providing a comprehensive view of process variations. To systematically enhance surface finish and optimize machining efficiency, experimental studies were conducted to refine process parameters. The Taguchi method was employed to design experiments that assess the impact of key machining variables on surface roughness. Using an orthogonal array, the study effectively analyzed various parameter combinations, minimizing the need for extensive trial-and-error experimentation.

The findings from this analysis form the foundation for process optimization, ensuring that machining operations are both efficient and capable of producing high-quality components. By leveraging a data-driven approach, this study aims to achieve consistent improvements in surface finish, reduce defect rates, and enhance overall manufacturing performance.

5.2 Optimization of machining process parameters: This section focuses on optimizing machining process parameters using the Taguchi method to enhance the surface roughness and material removal rate (MRR) of spare parts. The Taguchi method is employed to improve quality at the design phase by systematically identifying optimal process settings while minimizing process variability. A design of experiments (DOE) approach is utilized, and the signal-to-noise (S/N) ratio is calculated using Minitab 18. Additionally, analysis of variance (ANOVA) is performed to determine the most statistically significant factors influencing the machining process. The results provide insights into optimal machining conditions, ensuring a structured and data-driven approach to improving precision, efficiency, and consistency in manufacturing.

Turning is a widely used machining process in industrial applications, involving the removal of material from an external or internal cylindrical surface. The workpiece rotates at a specified cutting speed, while the cutting tool moves against it at a controlled feed rate and depth of cut. These machining parameters significantly impact surface finish, tool wear, material removal rate, and overall process efficiency. Optimizing these parameters is crucial for enhancing product quality, reducing costs, and improving productivity in machining operations.

To develop an effective optimization strategy, factors influencing the turning process are classified into control factors and noise factors, as presented in Table 5. Control factors are the parameters that can be adjusted to optimize machining performance, while noise factors represent external variables that introduce process variability but cannot be directly controlled. Identifying and categorizing these factors ensures a structured experimental approach, allowing for a comprehensive analysis of their impact on machining outcomes.

As shown in Table 6, three primary control factors—cutting speed, feed rate, and depth of cut—were selected for optimization due to their significant influence on surface roughness and material removal rate. Properly adjusting these parameters can lead to substantial improvements in machining accuracy, tool life, and process stability.

To experiment efficiently, an L9 orthogonal array was used, enabling the systematic analysis of three factors at three levels each. The Taguchi method minimizes the number of required experimental runs while maximizing the information gained, making it a cost-effective and time-efficient approach to process optimization. Figure 3 illustrates the process parameter diagram and the corresponding output objectives. The primary goal of the experiment is to evaluate the influence of turning parameters on the surface roughness (Ra) and material removal rate (MRR) of EN8 steel, a material commonly used in industrial applications due to its favorable mechanical properties and machinability. The experimental results, summarized in Table 7, highlight the effects of different machining conditions on the response variables. Table 8 presents a statistical analysis of the various runs, assessing data variability and consistency. The findings indicate that the coefficient of variation (CV%) is below 10%, confirming that the dataset is consistent and homogeneous, which enhances the reliability of the optimization study. The ANOVA results further pinpoint the most influential machining parameters affecting surface roughness and material removal rate, aiding in the selection of optimal machining conditions. Finally, Table 9 presents the average surface roughness (Ra), material removal rate (MRR), and signal-to-noise ratio (S/N %), validating the effectiveness of the optimized machining parameters. By leveraging the Taguchi-based DOE methodology, this study provides a structured, statistically validated framework for enhancing machining quality, increasing productivity, and reducing process variability. The optimized parameters can be effectively applied in industrial manufacturing to achieve greater process stability, cost efficiency, and operational excellence.

Table 5. Main factors affecting the turning process

Control Factors	Noise Factors
Machine Type	Machine vibration
Workpiece material	Machine conditions
Workpiece diameter	Workpiece variation
Cutting speed (m/min)	Workpiece temperature
Feed rate (mm/rev)	Tool vibration
Depth of cut (mm)	Manpower skill
Tool type	Environmental conditions
Tool nose radius, (mm)	
Coolant	

Table 6. CNC turning factors and their levels

Control Factors	Levels
Machine Type	CNC Turning
Workpiece material	EN8 steel
Workpiece diameter	Cylindrical rod φ 30 mm
Cutting speed (m/min)	75, 100, 125
Feed rate (mm/rev)	0.1, 0.2, 0.3
Depth of cut (mm)	0.3, 0.6, 0.9

Tool type	Carbide cutting tool
Tool nose radius, (mm)	0.8
Coolant	Water soluble oil

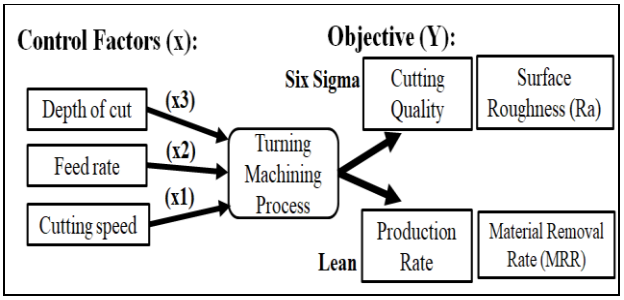

Figure 3. Process parameter diagram

Table 7. Taguchi L9 orthogonal array and experimental results

#	Cutting parameters			Surface finish (μ)		
	Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)	Run #1	Run #2	Run #3
	N	f	D	Ra1	Ra2	Ra3
1	75	0.1	0.3	1.13	0.95	1.01
2	75	0.2	0.6	2.21	2.65	2.37
3	75	0.3	0.9	3.47	4.16	3.71
4	100	0.1	0.6	1.10	0.92	0.98
5	100	0.2	0.9	2.61	2.17	2.33
6	100	0.3	0.3	3.09	3.71	3.31
7	125	0.1	0.9	1.07	0.89	0.95
8	125	0.2	0.3	1.79	2.16	1.93
9	125	0.3	0.6	3.67	3.07	3.28

Table 8. Basic statistical analysis of the different runs.

#	Surface finish (μ)			Statistical Analysis		
	Ra1	Ra2	Ra3	Average Ra	Standard Deviation	CV%
1	1.13	0.95	1.01	1.03	0.042	4.0%
2	2.21	2.65	2.37	2.41	0.151	6.3%
3	3.47	4.16	3.71	3.78	0.242	6.4%
4	1.10	0.92	0.98	1.00	0.042	4.2%
5	2.61	2.17	2.33	2.37	0.106	4.5%
6	3.09	3.71	3.31	3.37	0.216	6.4%
7	1.07	0.89	0.95	0.97	0.042	4.3%
8	1.79	2.16	1.93	1.96	0.125	6.4%
9	3.67	3.07	3.28	3.34	0.142	4.2%

Table 9. Average Ra, MRR, and signal to noise %.

#	N	f	D	Average Ra (μ)	Average MRR (mm3/sec.)	Signal to Noise % (Ra)
1	75	0.1	0.3	1.03	37.5	-0.257
2	75	0.2	0.6	2.41	150	-7.640
3	75	0.3	0.9	3.78	337.5	-11.550
4	100	0.1	0.6	1.00	100	0.000
5	100	0.2	0.9	2.37	300	-7.495
6	100	0.3	0.3	3.37	150	-10.553
7	125	0.1	0.9	0.97	187.5	0.265
8	125	0.2	0.3	1.96	125	-5.845
9	125	0.3	0.6	3.34	375	-10.475

Figure 4 illustrates the effect of cutting parameters on surface roughness, highlighting their critical influence on machining quality. The analysis shows that surface roughness is most significantly affected by cutting speed, feed rate, and depth of cut. It is observed that surface roughness improves (decreases) as cutting speed increases, feed rate decreases, and depth of cut reduces. Based on the signal-to-noise (S/N) ratio approach, the optimal surface finish (lowest Ra) is achieved with a cutting speed of 125 m/min, a feed rate of 0.1 mm/revolution, and a depth of cut of 0.3 mm. This combination of parameters results in the best surface quality, demonstrating the effectiveness of the optimization in enhancing machining performance and achieving high-quality finishes.

To assess the effectiveness and reliability of the developed model, the analysis of variance (ANOVA) approach was employed. ANOVA, along with the F-test, was utilized to identify the statistically significant cutting parameters and determine their contributions to the performance characteristics in turning operations. The results presented in Table 10 reveal that the 'Prob. > F' value is less than 0.05, indicating that the model is statistically significant and suitable for the analysis of the machining process. Further analysis of the contribution percentages of the cutting parameters revealed that feed rate is the most influential factor affecting surface roughness. This finding underscores the critical role of feed rate in determining the quality of the finished surface. In contrast, cutting speed and depth of cut were found to have relatively minor contributions to surface roughness, suggesting that changes in these parameters have a less pronounced effect. These insights emphasize the importance of optimizing feed rate to achieve better surface finish and offer valuable guidance for improving the turning process.

Using regression analysis with MINITAB 18 statistical software, the relationship between the turning factors and machining responses was modeled, as shown in the following equation. The model's goodness of fit was evaluated using the coefficient of determination (R^2), which was found to be 0.99 for surface roughness. This indicates an excellent fit, as the model accounts for 99% of the variance in the observed data. The R^2 value, which ranges from 0 to 1, serves as a measure of how well the model explains the variation in the response variable. An R^2 value greater than 0.8 is considered excellent, and in this case, the R^2 value of 0.99 demonstrates a very high level of accuracy in predicting the surface roughness. Therefore, this regression model can be considered highly reliable for predicting machining outcomes and optimizing turning process parameters to improve machining performance.

The interaction effects between machining parameters and surface roughness are illustrated in Figure 6. This figure clearly shows that significant interactions exist between the three factors, as indicated by the non-parallel lines. In experimental design, the degree of non-parallelism signifies the strength of the interaction, where greater non-parallelism suggests stronger interactions. The results demonstrate that the feed rate has the most substantial influence on surface roughness (Ra), followed by cutting speed and depth of cut. This finding suggests that variations in feed rate have the most direct impact on surface finish, with an increase in feed rate leading to rougher surfaces, and a decrease resulting in smoother finishes.

Figure 7 provides a three-dimensional surface plot that visualizes the relationship between the cutting parameters and surface roughness. It clearly shows that Ra increases when the cutting speed is reduced and the feed rate is increased, and conversely, it decreases when the cutting speed increases and the feed rate decreases. This further underscores the intricate relationship between the parameters and highlights the importance of carefully selecting optimal values to achieve the desired surface finish.

Finally, Table 12 offers proposed cutting conditions for different surface finish requirements and material removal rates (MRR). These conditions are derived from the experimental analysis and provide a practical guide for optimizing machining processes. By adjusting cutting parameters according to the table, operators can meet specific surface finish targets while ensuring high productivity and efficiency, thus minimizing waste and reducing the need for post-processing.

$$Ra = 0.13111 - 0.006333 * N + 12.4833 * f + 0.42222 * D \quad (1)$$

Where,
Ra - Surface finish (μ)
N - Cutting speed (m/min)
f - Feed rate (mm/rev)
D - Depth of cut (mm)

As shown in Table 11, the predicted values for the processes closely align with the measured data, demonstrating a strong correlation between the model's predictions and the actual outcomes. This level of agreement highlights the effectiveness of the optimization approach in accurately forecasting machining performance. To ensure the reliability and credibility of the statistical analyses for critical processes, the error values must remain below 5%. This threshold ensures minimal deviation between predicted and observed results, reinforcing the model's precision and the validity of the optimization strategy in real-world applications. Such low error values further validate the robustness and consistency of the proposed framework in improving machining performance.

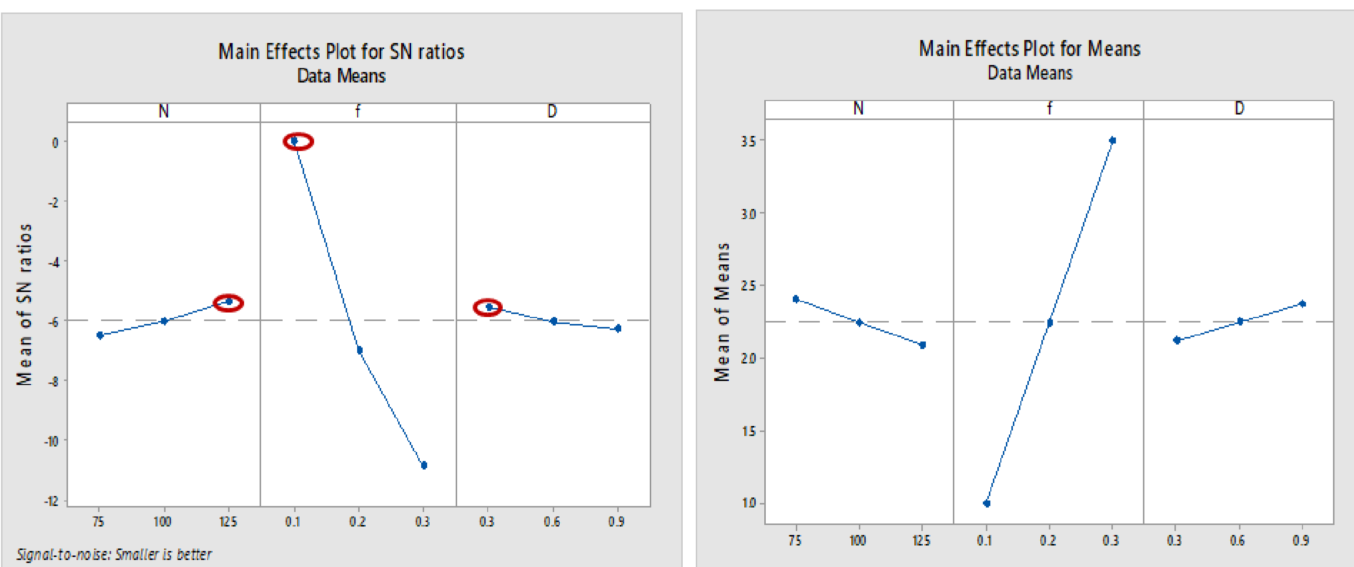

Figure 4. Influence of the cutting parameters on the surface roughness (Ra)

Table 10. Analysis of variance for surface finish (Ra).

Source of	DF	Seq SS	Adj SS	Adj MS	F	P	C%	Rank
N	2	0.15042	0.15042	0.07521	6769	< 0.001	1.57%	2
f	2	9.35002	9.35002	4.67501	420751	< 0.001	97.43%	1
D	2	0.09629	0.09629	0.04814	4333	< 0.001	1.00%	3
Error	2	0.00002	0.00002	0.00001			0.0%	
Total	8	9.59676					100.0%	

Table 11. Comparison between actual Ra and expected Ra.

#	N	f	D	Actual Ra	Predicted Ra	Error-values %
1	75	0.1	0.3	1.03	1.031	-0.13%
2	75	0.2	0.6	2.41	2.406	0.15%
3	75	0.3	0.9	3.78	3.781	-0.04%
4	100	0.1	0.6	1.00	1.000	0.02%
5	100	0.2	0.9	2.37	2.375	-0.20%
6	100	0.3	0.3	3.37	3.370	0.01%
7	125	0.1	0.9	0.97	0.968	0.19%
8	125	0.2	0.3	1.96	1.963	-0.16%
0	125	0.3	0.6	3.34	3.338	3.85%

The normality of the data was evaluated using a normal probability plot, a commonly used method to assess whether residuals follow a normal distribution. Additionally, the residual values were examined for normality, equal variance, and randomness through a (4 in 1) residual plot. Figure 5 presents these residual plots for surface roughness, providing a comprehensive overview of the data patterns. In the normal probability plot, most data points align closely with the straight line (mean line), indicating that the residuals generally follow a normal distribution. While there is some minor clumping observed in certain areas, this slight deviation does not significantly affect the overall normality, which is essential for valid regression analysis. These minor deviations suggest that randomization during data collection was conducted properly, with no significant bias in the residuals. The histogram shows the distribution of residual values, which are centered around the mean, in accordance with the normal distribution. This symmetry further supports the model's validity, as a normal distribution of residuals indicates that the model is capturing the underlying data patterns accurately. The "versus fit" graph illustrates the relationship between the residuals and their corresponding fitted values from the regression model. The residuals are scattered randomly around the zero line, indicating that surface roughness (Ra) data are not influenced by any unaccounted control factors. This randomness is a positive sign, suggesting that the regression model has appropriately considered all relevant input variables without introducing bias. Similarly, the "versus order" graph plots the residuals against the order of data collection. Here, the residuals are also randomly distributed around the zero line, confirming that the surface roughness (Ra) is not affected by the sequence in which the data were collected. This result eliminates any time-dependent effects as a potential source of bias. These residual plots collectively validate the regression model. They confirm that the model is robust and reliable for predicting surface roughness in the machining process, with no significant issues related to normality, variance, or randomness. Based on these findings, we can confidently conclude that the model is well-suited for optimizing surface roughness in this context.

6. Conclusion and Further Work

In this study, the Taguchi method was successfully applied to optimize the CNC turning process parameters for EN8 steel, showcasing its effectiveness in determining the optimal settings for improved process performance. The primary aim of this research was to use the Taguchi method to optimize cutting parameters for achieving an ideal balance between surface roughness and material removal rates. Through signal-to-noise (S/N) ratio analysis, the optimal surface finish (lowest Ra) was achieved with a cutting speed of 125 m/min, a feed rate of 0.1 mm/revolution, and a depth of cut of 0.3 mm. These results emphasize the significance of these parameters in enhancing surface quality and provide useful insights for manufacturers aiming to optimize their processes.

ANOVA results further confirmed that feed rate is the most significant parameter affecting surface roughness, with cutting speed and depth of cut playing a lesser role. These findings guide manufacturing engineers by highlighting the feed rate as the key parameter to adjust for the most substantial improvements in surface finish. The study reinforces the value of utilizing statistical techniques such as Taguchi's design of experiments and ANOVA to identify and optimize critical factors for improved manufacturing outcomes. The positive results from this study pave the way for future research and applications. The Taguchi-based Lean Six Sigma method can be adapted for a range of manufacturing processes, materials, and production environments, offering a versatile framework for ongoing optimization.

Table 12. Proposed cutting conditions according to the required surface finish

#	N	f	D	Expected Ra (μ)	Expected MRR (mm3/sec.)
1	125	0.1	0.3	0.71	62.50
2	125	0.1	0.6	0.84	125.00
3	125	0.1	0.9	0.97	187.50
4	125	0.2	0.3	1.96	125.00
5	125	0.2	0.6	2.09	250.00
6	125	0.2	0.9	2.22	375.00
7	125	0.3	0.3	3.21	187.50
8	125	0.3	0.6	3.34	375.00

9	125	0.3	0.9	3.46	562.50

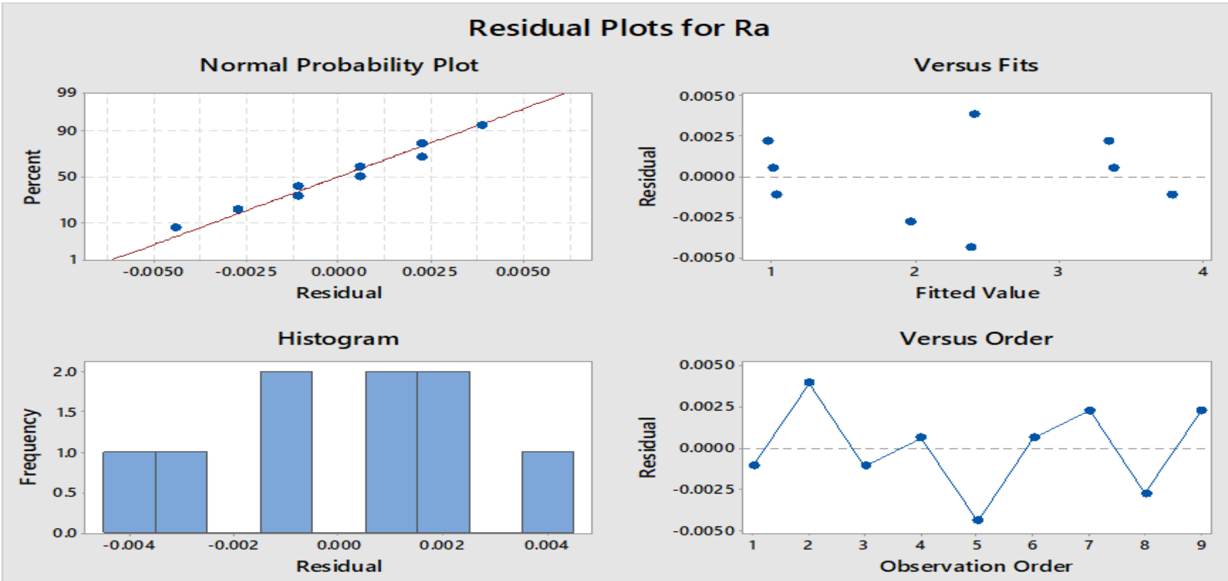

Figure 5. Residual plots for the surface roughness equation

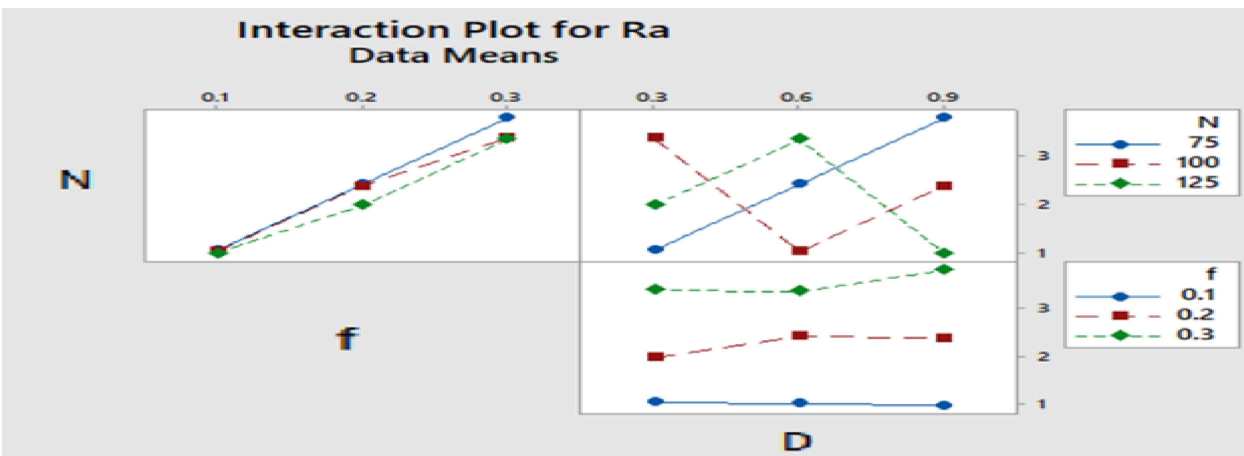

Figure 6. Interaction effect plots of surface roughness

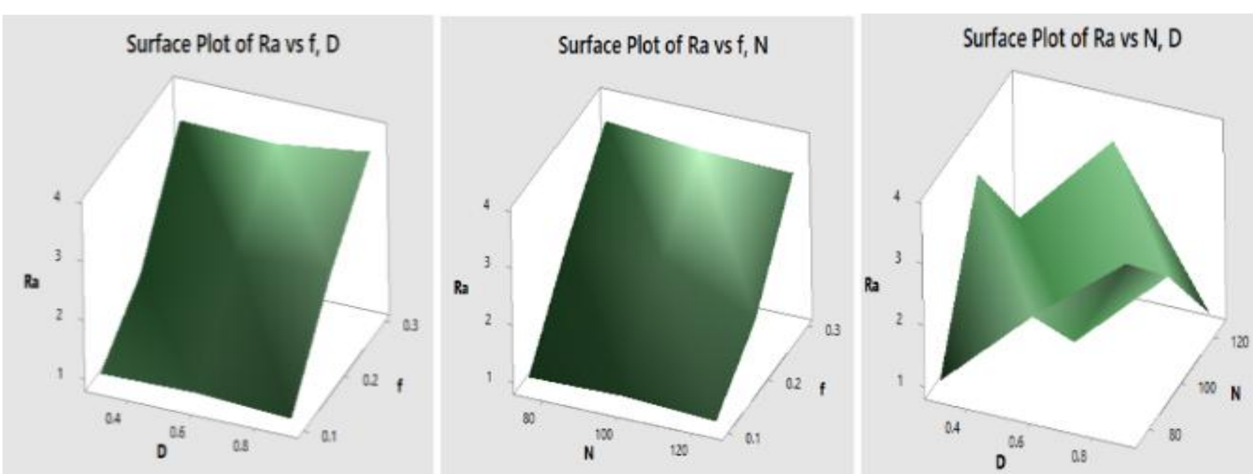

Figure 7. Three-dimensional surface plot for Ra

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