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Optimizing Machining Process Performance Using Lean Six Sigma: A Case Study

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KEYWORDS

lean six sigma (LSS)
DMAIC framework
machining process optimization
operational excellence
continuous improvement
problem solving methodology

ABSTRACT

To sustain competitiveness, companies continuously improve quality, productivity, and customer satisfaction, with Lean Six Sigma recognized as a key methodology for driving enduring operational excellence. This study examines the implementation of Lean Six Sigma (LSS) in machining operations, addressing key challenges such as (1) the lack of a unified, adaptable LSS framework tailored to machining processes, (2) limited empirical validation in industrial contexts, and (3) insufficient assessment of critical performance metrics, including quality, productivity, and customer satisfaction. To address these gaps, a structured, integrated LSS framework is proposed, combining Lean's waste-elimination principles with Six Sigma's data-driven methodologies for defect reduction and process variation control. The framework leverages robust measurement systems, statistical process analysis, and machining parameter optimization, providing a systematic, evidence-based approach to identify, prioritize, and implement process improvements.The framework was validated through a three-month case study in a leading spare parts manufacturing company in Egypt. Implementation resulted in notable improvements: product quality increased from 85% to 89%, sigma level rose from 2.5 to 2.7, processing time decreased from 645 to 370 hours/ton, overall equipment effectiveness (OEE) improved from 75% to 81%, value-added activities increased from 50% to 54%, and customer satisfaction rose from 87% to 89%. These results confirm the framework's effectiveness in enhancing process stability, operational efficiency, and product performance, providing actionable guidance for engineers, managers, and researchers seeking to institutionalize continuous improvement in machining operations.Ultimately, the proposed LSS framework serves as a comprehensive reference for production managers, organizational leaders, and researchers across diverse industrial sectors, offering structured and evidence-based guidance before initiating continuous process improvement initiatives.

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1. Introduction

In today's competitive manufacturing environment, organizations must deliver high-quality products efficiently while remaining agile in response to changing market demands. Achieving this requires systematic waste elimination, reduction of process variability, and the institutionalization of continuous improvement across production systems. Lean Six Sigma (LSS), which integrates Lean's waste-reduction principles with Six Sigma's data-driven methodologies, has emerged as a robust approach to enhance process performance, operational efficiency, and product quality [1,2].

Over the past two decades, LSS has been applied across various industries, including automotive, aerospace, electronics, and healthcare, yielding measurable improvements in productivity, quality, and cost efficiency. Lean emphasizes eliminating non-value-added activities, streamlining workflows, and optimizing resources, while Six Sigma applies statistical rigor to quantify, control, and reduce process variation. Together, LSS enables organizations to achieve both efficiency and quality objectives, align improvement initiatives with strategic goals, and enhance workforce engagement and customer satisfaction [3].

The DMAIC (Define–Measure–Analyze–Improve–Control) framework underpins LSS, providing a structured methodology for systematic improvement. Lean tools—including 5S, value stream mapping, Just-in-Time (JIT), Kaizen, and Total Productive Maintenance (TPM)—enhance workflow efficiency and standardization, while Six Sigma techniques—such as design of experiments (DOE), statistical process control, and process capability analysis—minimize defects and variability. Collectively, these tools optimize resources, improve productivity, and increase organizational agility [1,4].

Machining processes are critical in modern manufacturing, influencing product accuracy, surface quality, and production costs. They involve complex interactions among cutting parameters, tool wear, temperature, vibration, and material properties, where minor variations can lead to defects or premature tool failure. Traditional improvement tools provide insights but often fail to capture complex interactions. Integrating LSS with predictive analytics offers a systematic approach to optimize machining operations, enhance process stability, and sustain improvements [5].

Despite its potential, LSS adoption in machining faces challenges, including the absence of a unified, adaptable framework, limited empirical validation, insufficient evaluation of key performance metrics (e.g., quality, productivity, customer satisfaction), and underutilization of real-time data for predictive decision-making [6].

This study addresses these gaps by proposing an integrated LSS framework for machining operations, validated through a case study in a spare parts manufacturing company in Egypt. Results demonstrate significant improvements in product quality, sigma level, overall equipment effectiveness (OEE), and customer satisfaction. The research contributes by reviewing the current state of LSS, developing a context-specific framework for machining optimization, providing empirical evidence of its effectiveness, and offering practical guidance for engineers, managers, and researchers seeking to institutionalize continuous improvement.

The remainder of the paper is organized as follows: Section 2 reviews the theoretical background and literature on Lean Six Sigma. Section 3 identifies challenges and research gaps. Section 4 presents the research methodology and proposed framework. Section 5 details the case study and discusses results. Section 6 concludes and outlines directions for future research.

2. Literature Review and Conceptual Background

This study presents a systematic literature review (SLR) of LSS applications in machining processes, covering research published in specialized journals from 2015 to 2025. The review identifies critical trends, methodological approaches, success factors, and implementation gaps. Targeted keywords included *lean*, *six sigma*, *lean six sigma*, *lean sigma*, *total quality management*, *continuous improvement*, *manufacturing*, *production*, and *case study*, with the search limited to English-language publications [7]. By synthesizing evidence from both academic literature and industrial case studies, the review provides insights into how LSS has been applied to optimize machining operations and achieve operational excellence.

Lean Six Sigma (LSS), which integrates Lean's waste-elimination principles with Six Sigma's data-driven methodologies for variation and defect control, has emerged as a key approach for improving operational performance in manufacturing. Lean emphasizes process flow, value creation, and the elimination of non-value-added activities, while Six Sigma focuses on reducing variation, enhancing process capability, and achieving consistent quality. Together, LSS provides a systematic methodology that enhances efficiency, reduces costs, and improves product quality [2,8].

Gomaa (2023) [7] demonstrates that LSS improves product quality, increases sigma levels, reduces non-value-added activities, enhances productivity, lowers production costs, and improves customer satisfaction. A 40-step LSS framework tailored for manufacturing integrates tools such as process mapping, KPIs, OEE, seven quality control tools, process time analysis, value stream mapping, kaizen, 5S, brainstorming, and standard work within DMAIC phases, offering a structured roadmap for continuous improvement. LSS effectiveness depends on baseline performance, project scope, team expertise, and implementation strategy. By combining Lean for waste elimination and process optimization with Six Sigma for defect reduction and variation control, LSS provides a systematic and evidence-based approach to improving operational performance.

Empirical studies highlight LSS's versatility across industries. Irfan et al. (2025) [9] applied TPM and 5S in a cement plant, improving Overall Equipment Effectiveness (OEE) from 65.6% to 68%. Widiwati et al. (2025) [10] applied DMAIC to mooncake production, targeting five types of waste—transportation, waiting, overprocessing, defects, and inventory—improving production efficiency from 66.19% to 70.98% while reducing cycle time and lost products. Dara et al. (2024) [11] showed that Lean tools such as Just-in-Time (JIT), Continuous Improvement (CI), and Total Quality Management (TQM) significantly reduce non-value-added activities in construction projects ($\beta = 0.654$). Gomaa (2024a) implemented an LSS-DMAIC framework in a spare parts manufacturer, improving TEEP (58.4% → 67.6%), OEE (64.5% → 75.7%), sigma level (2.36 → 2.68), and process capability (0.38 → 1.01).

Additional studies further demonstrate LSS effectiveness. Mittal et al. (2023) [12] reduced rubber weather strip rejections, improving sigma from 3.9 to 4.45. Kulkarni et al. (2023) [13] optimized bearing production using DMAIC and Taguchi robust design, increasing Cp from 1.17 to 2.78 and Cpk from 0.976 to 2.23. Thakur et al. (2023) streamlined laboratory QC processes, reducing material and calibrator costs by 26% and 43%, respectively. Condé et al. (2023) [14] reduced defects in car parts, increasing sigma from 3.4 to 4.0. Saryatmo et al. (2023) improved brake lining efficiency from 26.85% to 35.33% and sigma from 4.91 to 5.12. Daniyan et al. (2022) [15] enhanced railcar bogie assembly efficiency by 46.8%, reduced lead time by 27.9%, and minimized non-value-added time by 71.9%. Adeodu et al. (2021) [16] improved process cycle efficiency and value-added activities in paper production. Jayanth et al. (2020) [17] increased productivity and quality in electronics manufacturing by 23%. Setyabudhi and Sipahutar (2019) [18] reduced coffee maker defects from 5.99% (sigma 3.1) by addressing operator errors and machine parameters. Adikorley et al. (2017) [19] demonstrated LSS success in textiles through changeover reduction and contamination control.

Collectively, these studies confirm that LSS delivers measurable operational improvements, though outcomes depend on baseline performance, project scope, implementation strategy, and team expertise.

Maximum benefits occur when both process efficiency and defect reduction are addressed concurrently. Despite its proven effectiveness, LSS applications in machining remain limited. Key gaps include the absence of context-specific, integrated frameworks, limited empirical validation, and insufficient evaluation of performance indicators such as first-pass yield, cycle time, OEE, and customer satisfaction. Furthermore, many frameworks underutilize digital technologies and real-time analytics, constraining predictive and proactive decision-making.

To address these gaps, this study proposes a structured, adaptable, and data-driven LSS framework for machining operations. The framework systematically reduces variation, eliminates waste, improves process stability, and leverages real-time data to support continuous improvement. By bridging theoretical insights and practical applications, it contributes to enhanced process capability, product quality, operational resilience, and long-term competitiveness in machining operations.

3. Challenges and Research Gaps

Lean Six Sigma (LSS) is widely recognized for enhancing operational efficiency, reducing waste, and improving quality. However, its effective application in machining operations remains limited due to the inherent complexity and precision requirements of these processes. Machining involves interdependent operations and is highly sensitive to cutting parameters, tool wear, material properties, and machine dynamics. While integrating Lean's waste-elimination focus with Six Sigma's data-driven problem-solving can stabilize processes and improve predictability, several critical challenges persist 2) [2,6-8,20-28].

1) Lack of a Unified, Adaptable Framework: Most studies treat Lean and Six Sigma separately, providing few integrated frameworks tailored to machining complexities, which often leads to fragmented improvements and inconsistent results.

2) Limited Integration and Empirical Validation: Lean and Six Sigma tools are frequently applied in isolation, reducing their synergistic potential. Empirical evidence from real-world machining environments is scarce, and comprehensive evaluation of key performance indicators—such as first-pass yield, cycle time, overall equipment effectiveness (OEE), and customer satisfaction—is limited.

3) Inadequate Performance Measurement: Few studies systematically assess LSS's impact across multiple operational metrics, and the absence of standardized benchmarks limits comparability and practical applicability.

4) Skills and Workforce Readiness: Effective LSS implementation requires personnel skilled in both Lean and Six Sigma methodologies and knowledgeable about machining operations. Lack of trained staff can hinder adoption and compromise the sustainability of improvements.

5) Organizational Culture and Change Management: Resistance to change, insufficient leadership support, and limited cross-functional collaboration often impede LSS initiatives, reducing the likelihood of sustained performance gains.

6) Cost and Resource Constraints: Implementing integrated LSS programs may require substantial investment in training, data infrastructure, and process redesign, which can be challenging for resource-limited organizations.

7) Sustainability and Environmental Considerations: Traditional LSS primarily focuses on efficiency and quality, often overlooking environmental objectives such as reducing energy consumption, tool wear, and material waste.

8) Scalability and Adaptability: Many LSS applications are process-specific or small-scale, with limited guidance for scaling improvements across machines, production lines, or facilities while maintaining effectiveness.

9) Underutilization of Digital Technologies and Data Analytics: Modern machining systems generate extensive real-time data, yet most LSS frameworks fail to fully exploit this information for predictive and proactive decision-making, constraining optimization in dynamic production settings.

10) Integration with Advanced Manufacturing Technologies: Although modern machining increasingly relies on CNC automation, IoT sensors, and Industry 4.0 systems, most LSS frameworks are not fully aligned with these technologies, limiting their capacity for real-time optimization.

Addressing these gaps requires a validated, context-specific LSS framework that integrates Lean and Six Sigma, accommodates machining-specific complexities, leverages real-time data and advanced technologies, fosters workforce readiness and cultural alignment, and incorporates sustainability objectives. The framework proposed in this study aims to bridge these gaps, delivering both theoretical rigor and practical relevance while enabling measurable improvements across key performance indicators in modern machining operations.

4. Research Methodology for Machining Process Optimization

The integration of Lean Six Sigma (LSS) principles with data-driven manufacturing provides a strategic and systematic foundation for achieving operational excellence. As machining systems evolve toward higher levels of complexity, automation, and conventional improvement methods are insufficient to meet the demands of precision, efficiency, and reliability. The proposed methodology combines the structured problem-solving logic of LSS with advanced analytics, reliability engineering, and continuous improvement techniques, enabling manufacturers to optimize machining processes systematically. Its primary objectives are to minimize process variation, improve process capability, enhance product quality, and increase equipment reliability through evidence-based decision-making.

Table 1 provides a comprehensive overview of key Lean Six Sigma (LSS) tools used to optimize machining process performance. These tools offer a systematic, data-driven framework for identifying inefficiencies, minimizing process variability, and enhancing product quality, reliability, and productivity [2,,8,23]. For clarity and practical application, the tools are organized into five functional categories, reflecting the progression from strategic alignment and process analysis to optimization, sustainment, and continuous improvement.

1) Group A – Strategic Alignment and Project Prioritization ensures that improvement initiatives are strategically focused and resource-efficient. Tools such as the Project Selection Matrix and Impact–Effort Matrix help prioritize high-impact projects, while SWOT Analysis and Hoshin Kanri align improvement objectives with organizational strategy. Key Performance Indicators (KPIs) establish measurable targets for performance monitoring and control.

2) Group B – Process Definition, Mapping, and Analysis provides a clear understanding of process flow, behavior, and variation. The DMAIC framework guides structured improvement, while SIPOC diagrams, Process Mapping, and CTQ Analysis define boundaries and critical quality requirements. Value Stream Mapping (VSM) identifies waste and inefficiencies, and SPC, Process Capability (Cp, Cpk), and Gage R&R ensure process control, stability, and data reliability.

3) Group C – Process Optimization and Quality Enhancement aims to achieve high precision, robustness, and defect prevention. Design of Experiments (DOE) and Response Surface Methodology (RSM) determine optimal process parameters, while the Taguchi Method enhances robustness by reducing sensitivity to variation. Failure Mode and Effects Analysis (FMEA) anticipates potential failures, and Root Cause Analysis (RCA) supported by Cause-and-Effect Diagrams identifies and eliminates the true sources of process defects.

4) Group D – Reliability, Equipment, and Maintenance Excellence strengthens equipment performance and operational reliability. Total Productive Maintenance (TPM) integrates preventive, predictive, and

autonomous maintenance to maximize uptime. Overall Equipment Effectiveness (OEE) measures losses across availability, performance, and quality dimensions, and Reliability-Centered Maintenance (RCM) prioritizes maintenance strategies based on criticality and risk.

5) Group E – Standardization, Sustainment, and Continuous Improvement focuses on stabilizing gains and fostering a culture of excellence. Standardized Work documents best practices for repeatability and safety, and 5S methodology improves workplace organization and discipline. Benchmarking identifies best practices and performance gaps, while Control Plans and Visual Management sustain process gains. Finally, Kaizen reinforces continuous improvement, collaboration, and learning across all levels.

Overall, the framework illustrates how the structured application of Lean Six Sigma (LSS) tools integrates strategic alignment, process optimization, and cultural transformation to improve machining performance, reliability, and competitiveness. By systematically reducing variability, optimizing process parameters, preventing failures, and enhancing equipment efficiency, these tools deliver measurable improvements in productivity, process capability, and operational reliability, supporting the shift toward adaptive, intelligent, and continuously improving manufacturing systems. The DMAIC framework underpins this approach by linking process analysis, root cause identification, solution implementation, and performance monitoring with strategic objectives, ensuring that improvements are evidence-based, sustainable, and continuously refined.

Table 2 provides a detailed overview of this framework, outlining objectives, key tools, and their practical applications in machining process optimization [24-28].

1) Define Phase: Process Definition and Mapping: In the Define phase, the machining process is clearly delineated to establish its scope, objectives, and boundaries. This ensures alignment with business strategy and customer requirements. Tools such as DMAIC, SIPOC (Suppliers, Inputs, Process, Outputs, Customers), Value Stream Mapping (VSM), Key Performance Indicators (KPIs), and SWOT Analysis are employed to visualize process flows, map value streams, and identify high-priority improvement areas. This phase establishes performance baselines, aligns stakeholders, and provides a structured roadmap for subsequent activities. In digitally connected environments, process mapping can leverage real-time sensor data and digital twins, offering deeper insights into process dynamics.

2) Measure Phase: Quantifying Process Performance: The Measure phase focuses on accurate data collection and performance evaluation, establishing a baseline of current process performance and assessing variability in critical parameters. Techniques such as Data Collection Plans, Statistical Process Control (SPC), process capability analysis (Cp/Cpk), and Gage Repeatability and Reproducibility (Gage R&R) ensure reliable and precise measurement. Integration of real-time data from CNC machines, IoT sensors, and smart monitoring systems enhances accuracy and supports predictive analysis. By quantifying performance systematically, manufacturers can identify deviations, prioritize improvement opportunities, and guide data-driven decision-making in subsequent phases.

3) Analyze Phase: Root Cause Identification and Process Optimization: The Analyze phase emphasizes identifying, validating, and prioritizing root causes of defects, variability, and inefficiencies. Tools such as Design of Experiments (DOE), Taguchi Method, Failure Mode and Effects Analysis (FMEA), and Root Cause Analysis (RCA) determine critical factors affecting performance, clarify parameter interactions, and quantify their impact on overall process outcomes. Statistical and experimental analyses reveal systemic issues and provide actionable insights for robust process improvement. Advanced techniques, including predictive analytics and machine learning, can further enhance root cause identification and process optimization using historical and real-time data.

4) Improve Phase: Solution Development and Implementation: The Improve phase is dedicated to developing and implementing solutions that enhance process performance, product quality, and equipment reliability. DOE and Taguchi Method identify optimal machining parameters, while Total Productive

Maintenance (TPM) and Reliability-Centered Maintenance (RCM) improve equipment availability and minimize downtime. Interventions reduce variability, prevent defects, and increase operational efficiency. Solutions are validated through pilot testing, iterative adjustments, and continuous performance monitoring, ensuring practicality, effectiveness, and sustainability. Integration of digital twin simulations allows virtual testing of parameter adjustments prior to physical implementation, reducing trial-and-error costs and improving confidence in results.

5) Control Phase: Sustaining Improvements: The Control phase ensures that improvements are sustained and processes remain stable over time. Tools such as Control Plans, Standardized Work, 5S, Benchmarking, KPIs, and SPC monitor performance, institutionalize best practices, and reinforce a culture of continuous improvement. Real-time dashboards and predictive analytics enable ongoing monitoring of key performance indicators, allowing rapid detection of deviations and continuous alignment with operational targets.

In conclusion, this methodology bridges Lean Six Sigma principles with data-driven manufacturing, offering a comprehensive and systematic approach to machining process optimization. By integrating analytical, quality, and maintenance-focused tools within the DMAIC framework, manufacturers can achieve measurable improvements in process capability, product quality, and equipment reliability.

Table 1. Lean Six Sigma Tools for Machining Process Performance Optimization.

Main Goals	#	Main Objectives	Main LSS Tools	Description
A. Strategic Alignment and Project Prioritization	1	Prioritize improvement projects	Project Selection Matrix / Impact–Effort Matrix	Evaluates opportunities based on impact, feasibility, and resources to focus on high-value initiatives.
	2	Align improvement initiatives with strategic objectives	SWOT Analysis / Hoshin Kanri	Assesses internal and external factors to ensure alignment with organizational goals.
	3	Define and monitor performance metrics	Key Performance Indicators (KPIs)	Establishes measurable indicators to track quality, productivity, and overall process performance.
	4	Implement a structured improvement methodology	DMAIC Framework	Guides systematic, data-driven improvement using Define–Measure–Analyze–Improve–Control.
B. Process Definition, Mapping, and Analysis	5	Define process scope, flow, and CTQ factors	SIPOC Diagram / Process Mapping / VoC and CTQ Analysis	Maps suppliers, inputs, processes, outputs, and customers to clarify boundaries and critical-to-quality parameters.
	6	Identify value streams and eliminate waste	Value Stream Mapping (VSM) / Takt & Lead Time Analysis	Visualizes material and information flows to uncover inefficiencies, balance workloads, and remove non-value-added activities.
	7	Monitor and control process variation	Statistical Process Control (SPC)	Uses control charts and statistical tools to detect and minimize variation, ensuring consistent performance.
	8	Assess process capability and compliance	Process Capability Analysis (Cp, Cpk)	Measures process capability relative to specification limits to verify quality consistency.
	9	Validate measurement system reliability	Gage Repeatability and Reproducibility (Gage R&R)	Evaluates measurement variation to ensure precision, repeatability, and data reliability.

Main Goals	#	Main Objectives	Main LSS Tools	Description
C. Process Optimization and Quality Enhancement	10	Optimize machining parameters and performance	Design of Experiments (DOE) / Response Surface Methodology (RSM)	Conducts structured experiments to determine optimal conditions for quality and efficiency.
	11	Enhance process robustness	Taguchi Method	Improves process stability by reducing sensitivity to uncontrolled variation and external noise.
	12	Identify and mitigate potential failure modes	Failure Mode and Effects Analysis (FMEA)	Detects, prioritizes, and mitigates potential failures to improve reliability and safety.
	13	Determine and eliminate root causes	Root Cause Analysis (RCA) / Cause-and-Effect Diagram / 5 Whys	Identifies and resolves underlying causes of defects and process issues.
D. Reliability, Equipment, and Maintenance Excellence	14	Improve equipment reliability and uptime	Total Productive Maintenance (TPM)	Integrates preventive, predictive, and autonomous maintenance to maximize availability and efficiency.
	15	Measure and enhance equipment utilization	Overall Equipment Effectiveness (OEE)	Quantifies losses across availability, performance, and quality to target improvements.
	16	Develop reliability-focused maintenance strategies	Reliability-Centered Maintenance (RCM)	Prioritizes maintenance tasks based on equipment criticality, function, and risk.
E. Standardization, Sustainment, and Continuous Improvement	17	Standardize and stabilize operations	Standardized Work	Documents best practices to ensure consistency, safety, and repeatability.
	18	Maintain workplace organization and discipline	5S Methodology	Promotes efficiency, safety, and visual order through Sort, Set in Order, Shine, Standardize, and Sustain.
	19	Benchmark and adopt best practices	Benchmarking	Compares performance with industry leaders to identify gaps and implement superior practices.
	20	Sustain and control process improvements	Control Plan / Visual Management	Establishes visual controls and monitoring systems to maintain gains and enable proactive corrections.
	21	Foster a culture of continuous improvement	Kaizen / PDCA Cycle	Embeds iterative learning, employee engagement, and incremental innovation to sustain operational excellence.

Table 2. DMAIC Framework for Machining Process Performance Optimization.

Phase	Purpose	Key Tools & Techniques	Machining Performance Deliverables
Define	Establish improvement scope, machining challenges, and stakeholder priorities	Project Selection, Project Charter, VoC, CTQ, Process Mapping, SIPOC, KPIs, and SWOT.	Clearly defines machining performance gaps (e.g., tolerance deviation, cycle time losses, tool cost escalation), aligns objectives with customer and operational requirements, and sets quantifiable targets.

Phase	Purpose	Key Tools & Techniques	Machining Performance Deliverables
Measure	Determine baseline process capability with reliable data	MSA/Gage R&R, Data Collection Plan, Time Study, Control Charts, Process Capability (Cp/Cpk), and sigma level.	Provides validated and repeatable measurements of dimensional accuracy, surface integrity, and tool wear behavior; establishes capability benchmarks and variation profiles.
Analyze	Verify root causes of variation and productivity losses	DOE Screening, Regression Modeling, Pareto Analysis, Waste Analysis, Brainstorming, RCA, 5 Whys, and Cause-and-Effect Diagram.	Identifies critical machining factors (cutting speed, feed rate, depth of cut, lubrication/cooling, tool geometry) that drive non-conformities, downtime, chatter, and thermal deviations.
Improve	Optimize process conditions and eliminate dominant causes	Improvement Plan, Brainstorming, Response-Surface DOE, Taguchi Robust Optimization, TPM/RCM, Poka-Yoke, and Condition-Based & Predictive Maintenance.	Implements optimized cutting regimes and reliability measures that enhance tool life, precision, machine availability, throughput, and energy efficiency while reducing scrap and rework.
Control	Sustain enhanced capability and ensure long-term process stability	Control Plan, Control Charts, Standardized Work, Standard Operating Procedure (SOP), Visual Management, Kaizen Events, Brainstorming, KPI Dashboards, and Performance Monitoring Systems.	Stabilizes machining performance, prevents regression, ensures consistent equipment health, and promotes continuous improvement in operations.

5. Case Study

To validate the proposed Lean Six Sigma (LSS) framework, a comprehensive case study was conducted in a leading Egyptian spare parts manufacturing company, a key supplier of precision-engineered components. The study aimed to reduce product defects, eliminate process waste, and minimize non-value-added time in machining operations, thereby enhancing productivity, quality, and operational efficiency. The focus was on EN8 steel components, critical high-precision items within the production line. The LSS–DMAIC (Define, Measure, Analyze, Improve, Control) methodology was systematically applied to optimize process performance, improve product quality, and embed continuous improvement practices (Gomaa, 2025) [8].

In the Define Phase, the project scope, objectives, and key performance indicators (KPIs) were clearly established. Critical machining processes were mapped, and a detailed project charter was developed to target improvements in first-pass yield, cycle time, and overall equipment effectiveness (OEE), ensuring alignment with strategic operational goals. During the Measure Phase, comprehensive data on defect rates, cycle times, machine utilization, and process performance were collected. Process mapping and Value Stream Analysis (VSA) identified bottlenecks, waste, and non-value-added activities, providing baseline metrics to guide targeted improvement efforts. The Analyze Phase used statistical analyses, Pareto charts, and cause-and-effect diagrams to identify root causes of defects and process variability. Key factors—including tool wear, suboptimal cutting parameters, material inconsistencies, and operator handling variability—were prioritized for corrective actions to improve reliability and process consistency. In the Improve Phase, interventions were implemented to address the identified issues. Lean tools, such as 5S, standardized work, and Kanban systems, streamlined workflows and reduced motion waste. Simultaneously, Six Sigma techniques, including Design of Experiments (DOE) and process capability analysis, optimized machining parameters and minimized variation. Operator training, equipment calibration, and setup optimization further reinforced process stability and performance gains. The Control Phase established sustainable monitoring and control systems, including real-time performance dashboards, standard operating procedures (SOPs), and statistical process control (SPC) charts. Combined with continuous improvement practices, these measures ensured long-term process stability, consistent quality, and sustained operational excellence.

The case study was structured into eight key steps for a comprehensive evaluation of LSS implementation:

1) Current Situation Analysis Before Improvement – Assessing baseline performance and identifying operational gaps.
2) Process Defect Analysis Before Improvement – Evaluating defect patterns and root causes affecting machining quality.
3) Process Capability Analysis Before Improvement – Measuring process stability, variation, and capability indices.
4) Process Value-Added Time Analysis Before Improvement – Distinguishing value-added from non-value -added activities to assess workflow efficiency.
5) Measurement System Analysis and Improvement – Ensuring the accuracy, precision, and reliability of measurement systems.
6) Optimization of Machining Process Parameters Using Taguchi DOE – Applying Taguchi experimental design to optimize parameters and reduce variability.
7) Results Discussion After Improvement – Interpreting gains in process performance, quality, and productivity.
8) Lessons Learned and Implications – Highlighting key success factors, managerial insights, and strategies for sustaining continuous improvement.

In conclusion, the case study confirmed the effectiveness of the proposed Lean Six Sigma framework. Integrating Lean principles with Six Sigma's statistical rigor under the DMAIC methodology led to measurable reductions in defects and process variability, improved process capability, and enhanced overall equipment effectiveness. The findings demonstrate that a structured, data-driven, and employee-engaged LSS framework can substantially improve manufacturing performance and operational excellence.

5.1. Current Situation Analysis Before Improvement

A comprehensive assessment of the company's operational performance established a baseline for LSS application. Historical production data, process observations, and operational records were analyzed to identify key challenges, objectives, and KPIs, summarized in Table 3. Performance gaps were identified across three critical dimensions: Product Quality, Operations, and Critical Resources.

Regarding Product Quality, the current quality level (85.7%) and sigma level (2.57) were below targets of 90% and 2.8, indicating variability and defects that compromise product consistency. Production inefficiencies were evident in Operations, where the production rate was 0.9 ton/hour versus a target of 1.1 ton/hour, OEE was 75.1% against 80%, and time utilization was 41.7% versus 60%. These metrics revealed workflow bottlenecks, underutilized equipment, and suboptimal process coordination. Critical Resources, including labor and machine productivity, were also below target, highlighting underutilized resources and the need for workforce optimization and better equipment management.

Overall, Table 3 illustrates significant gaps across quality, operations, and resources. This baseline assessment provided a structured foundation for applying LSS-DMAIC, enabling systematic waste reduction, process optimization, and variation control. To monitor process stability, a 25-day survey collected average quality ratios and process lead times (hours/ton). Figure 1 presents the quality control chart, highlighting variability and improvement opportunities, while Figure 2 illustrates the process lead time control chart, identifying bottlenecks and cycle time fluctuations. These tools provided benchmarks for evaluating the effectiveness of LSS interventions.

In conclusion, the current situation analysis established a data-driven foundation for Lean Six Sigma implementation, enabling targeted improvements in product quality, operational efficiency, and resource utilization, and ensuring sustainable gains in machining processes.

Table 3. Current Situation Analysis: Key Problems, Objectives, and KPIs.

Area	Main Problems	Objectives	KPI	Unit	Target	Actual
Product Quality	Low product quality	Enhance product quality	Quality %	%	≥ 90	85.7
	Low sigma level	Increase sigma level	Sigma level	–	≥ 2.8	2.57
Operations	Low production rate	Increase production rate	Production rate	ton/hour	≥ 1.1	0.9
	Low overall equipment effectiveness (OEE)	Improve OEE	OEE	%	≥ 80	75.1
	Low time utilization	Improve time utilization	Time utilization	%	≥ 60	41.7
Critical Resources	Low labor productivity	Improve labor productivity	Labor productivity	ton/man-hour	≥ 0.5	0.227
	Low machine productivity	Improve machine productivity	Machine productivity	ton/machine-hour	≥ 2.0	1.6

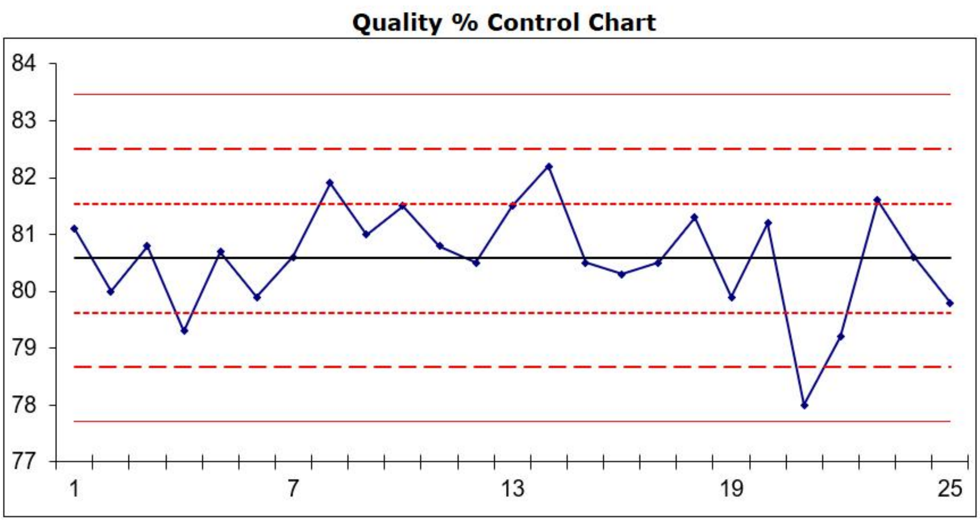

Figure 1. Quality control chart over 25 working days (Before improvement).

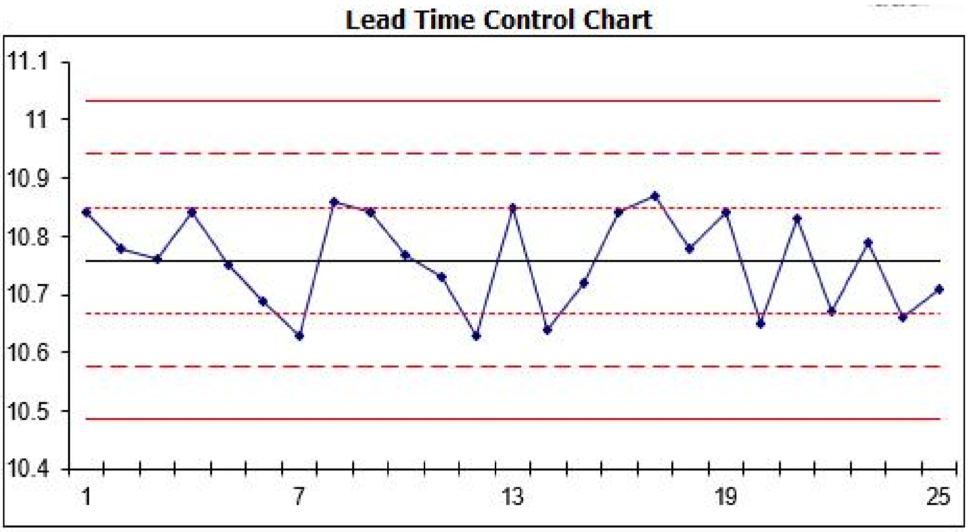

Figure 2. Lead time control chart over 25 working days (Before improvement).

5.2. Process Defect Analysis Before Improvement

This phase aimed to systematically identify the root causes of defects, analyze process inefficiencies, and address the key factors affecting machining performance. Pareto analysis (Figure 3) revealed that poor surface finish was the most frequent and critical defect, accounting for the majority of quality issues on the production line. In addition, seven other major defect types were identified: wrong dimension, surface burn, axis misalignment, porosity, out-of-roundness, surface cracks, and uneven surface texture. These defects were prioritized based on their impact on product functionality, adherence to customer specifications, and overall process reliability. Each defect was further examined in relation to machining parameters, tool conditions, and operational practices. Dimensional inaccuracies and axis misalignment were primarily linked to setup errors, tool wear, or operator variability, while surface burns and cracks were associated with excessive cutting speeds, insufficient cooling, or material inconsistencies. Quantifying both defect frequency and severity enabled focused corrective actions on the most critical factors, enhancing product quality, process stability, and operational efficiency.

To identify potential root causes systematically, a structured brainstorming session was conducted with process engineers, operators, and quality personnel. The results were organized into an Ishikawa (cause-and-effect) diagram (Figure 4), classifying contributing factors under Materials, Methods, Machinery, Manpower, Measurement, and Environment. This approach provided a holistic view of how each factor influenced defect occurrence and process variation. A detailed analysis was then performed specifically for poor surface finish, the most critical defect. Figure 5 presents the root cause assessment, considering cutting parameters (speed, feed rate, depth of cut), tool condition (wear and sharpness), machine settings (alignment and vibration), material properties (composition and hardness), and operator practices (skill level and adherence to procedures). This evaluation identified the most influential factors and prioritized them for corrective actions. Following the root cause analysis, experimental studies were conducted to optimize machining parameters for improved surface finish and reduced processing time. The Taguchi Design of Experiments (DOE) method was applied to determine the optimal combination of cutting parameters, ensuring consistent high-quality finishes and enhanced process stability.

Overall, this phase provided actionable insights for targeted process improvements, reduced variability, and improved product quality. The findings established a solid, data-driven foundation for the subsequent optimization of machining process parameters, ensuring that improvements were systematic, measurable, and sustainable.

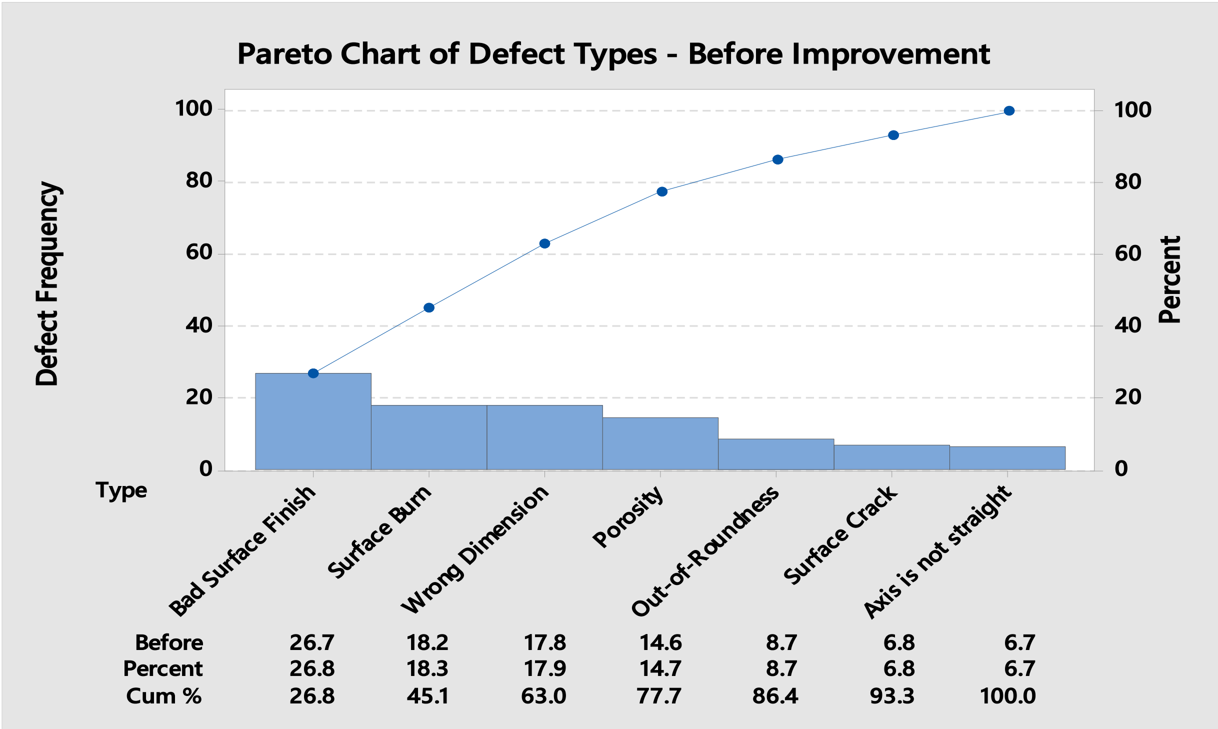

Figure 3. Pareto chart of defect types (Before improvement).

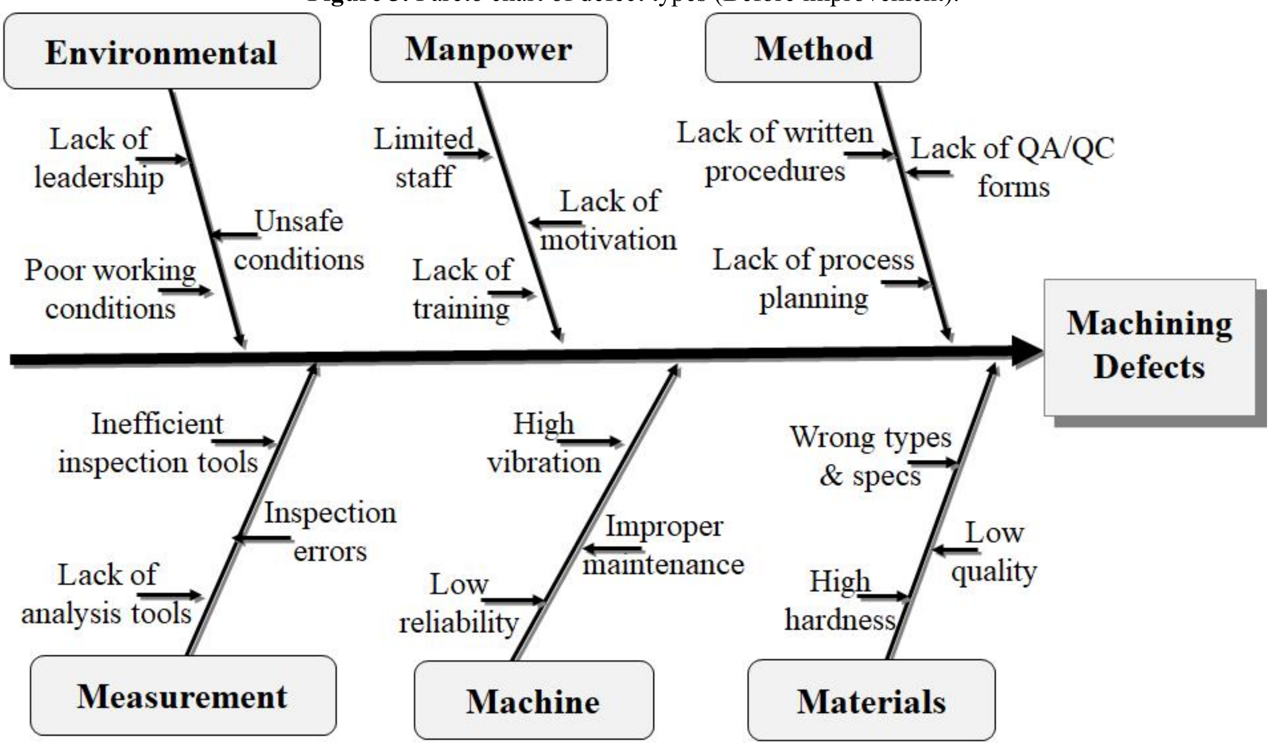

Figure 4. Cause-and-effect diagram for Machining Defects.

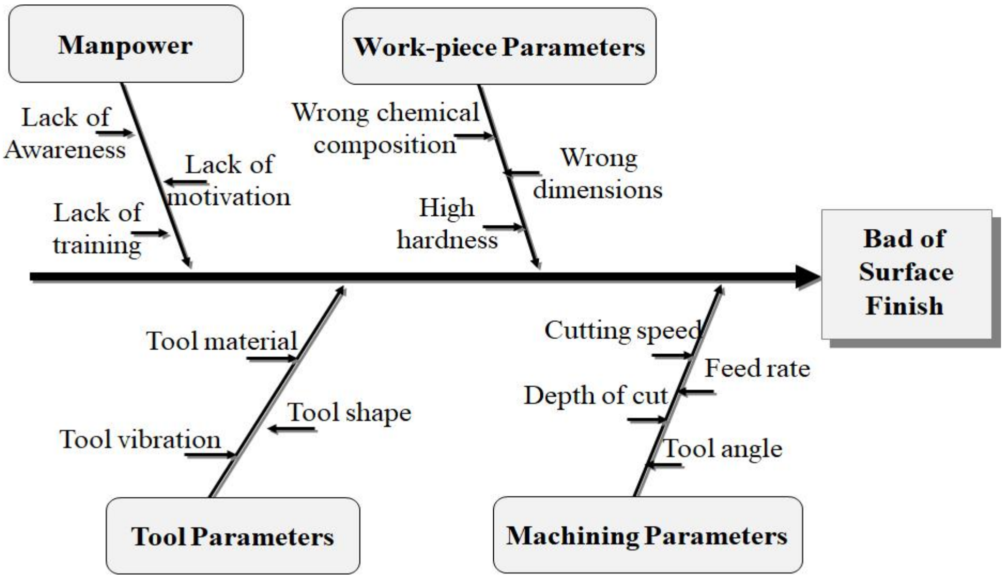

Figure 5. Cause-and-effect diagram for bad surface finish.

5.3. Process Capability Analysis Before Improvement

This section presents the process capability analysis conducted prior to implementing the Lean Six Sigma (LSS) framework in machining operations. As illustrated in Figure 6, the process showed a low capability index (Cpk = 0.30), indicating it was unable to consistently meet the required specifications. Such a low Cpk reflects high process variability and a significant risk of producing nonconforming parts, emphasizing the need for targeted improvements. The corresponding X-R control charts (Figure 7) further highlight process instability, with frequent excursions beyond control limits, confirming inconsistent performance and inadequate process control. These results underscore the necessity of systematic interventions to enhance process stability, reduce variation, and improve overall capability. This analysis provided a clear quantitative baseline for the subsequent DMAIC improvement efforts, enabling the identification of critical areas for corrective action and establishing a benchmark to evaluate the effectiveness of LSS implementation.

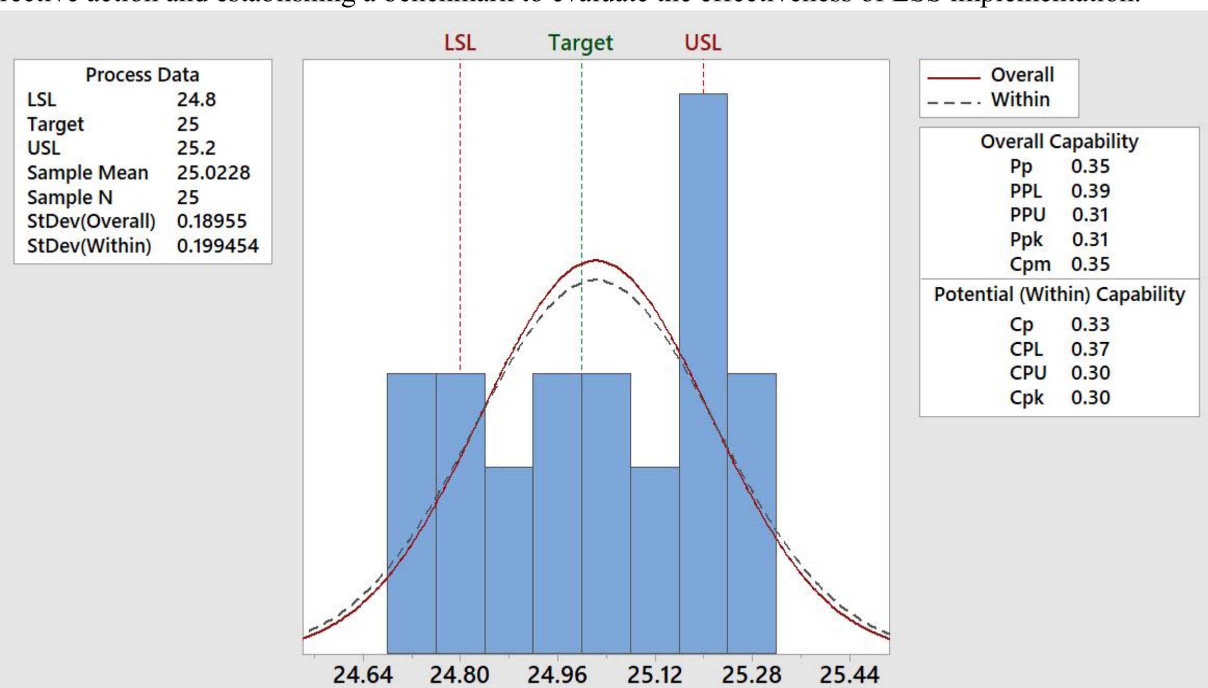

Figure 6. Process capability analysis (before improvement).

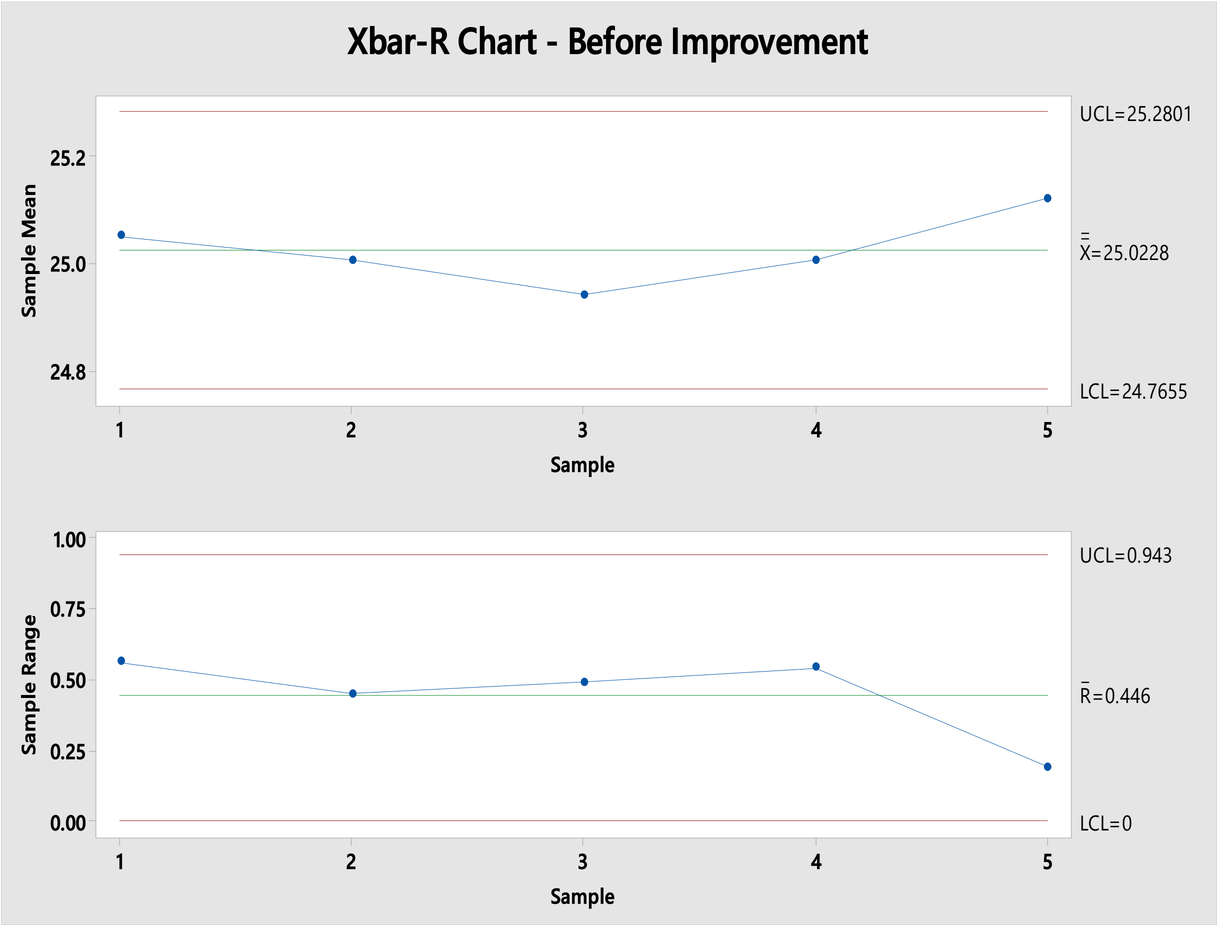

Figure 7. Process control charts (before improvement).

5.4. Process Value-Added Time Analysis Before Improvement

A detailed Value Stream Mapping (VSM) analysis was conducted to document the flow of materials, information, and lead times within the machining process. As illustrated in Figure 8, the value-added efficiency was approximately **37.2%**, indicating significant potential for performance improvement. The analysis also revealed multiple non-value-added activities and sources of waste, which are summarized in Figure 9.

Figures 10 and 11, together with Table 4, provide the order lead-time analysis and demonstrate how integrating Takt Time, Process Time, Cycle Time, and Lead Time forms a unified, time-based performance framework for Lean manufacturing. Aligning these interdependent metrics enhances production flow, reduces variability, eliminates inefficiencies, and improves responsiveness to customer demand. This time-oriented perspective increases process transparency, supports data-driven decision-making, and drives continuous improvement and sustainable value creation across the value stream.

To identify the root causes of inefficiencies, a structured brainstorming session was carried out with process engineers, operators, and quality personnel. The consolidated results were visualized using a cause-and-effect diagram (Figure 12), highlighting key contributors to process losses and guiding the prioritization of improvement efforts.

This analytical phase provided a strong, data-driven foundation for targeted actions aimed at increasing value-added time, minimizing waste, and optimizing overall operational performance.

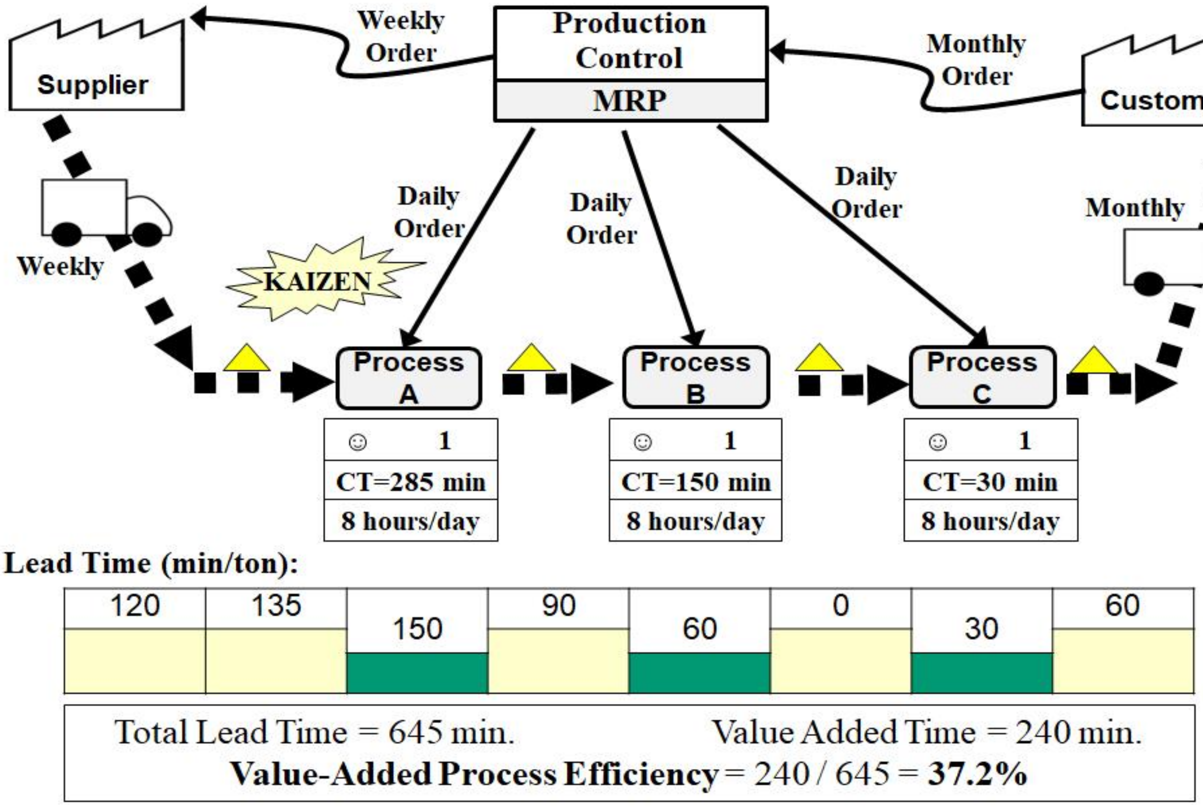

Figure 8. Value stream mapping (before improvement).

Figure 9. Value-added time elements for one shift (before improvement).

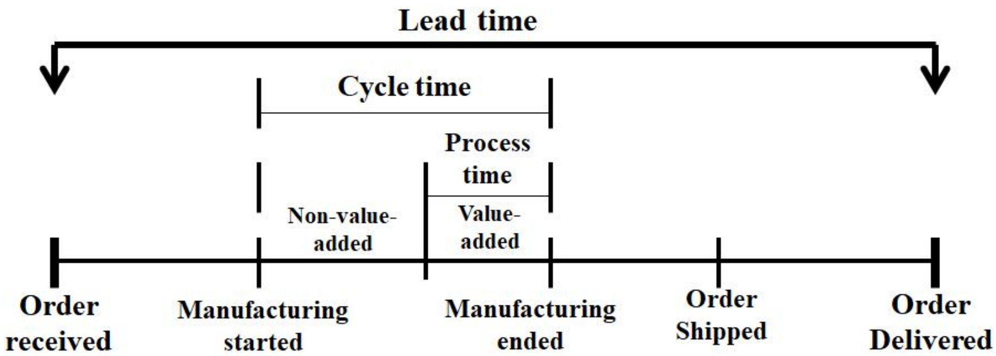

Figure 10. Order lead time elements.

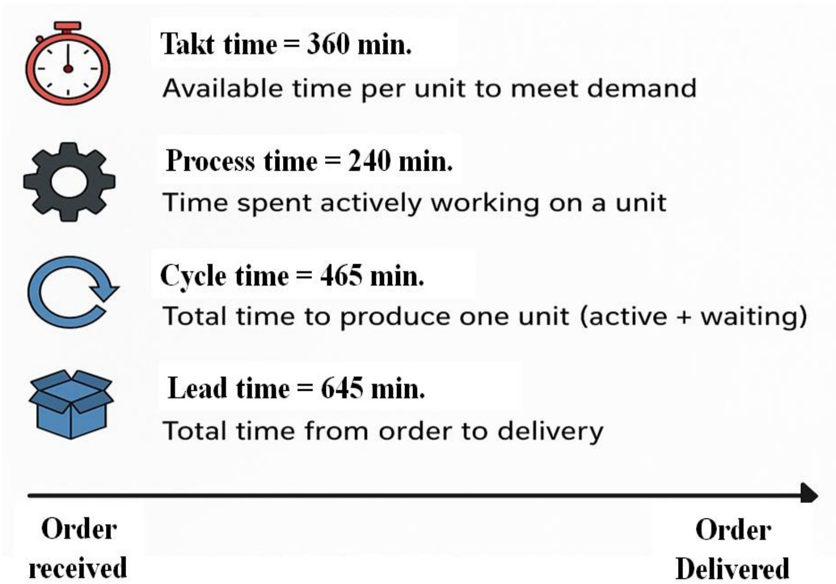

Figure 11. Order lead time analysis (before improvement).

Table 4. Key Time Metrics in Lean Systems.

Term	Definition	Includes Waiting?	Primary Focus	Value
Takt Time	Allowable time per unit to match the pace of customer demand	No	Aligning production with demand	360 min/unit
Process Time	Time spent performing direct, value-added work on the product or service	No	Value-added operations	240 min/unit
Cycle Time	Total time to complete one production cycle, including delays and idle time	Yes	Process performance	465 min/unit
Lead Time	The entire duration from customer order to final delivery across the value stream	Yes (all activities)	Customer responsiveness	645 min/unit

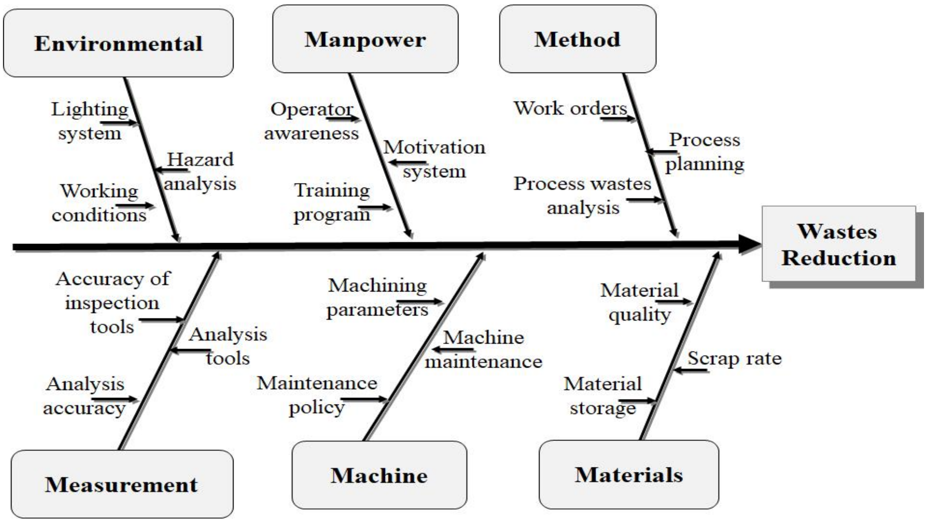

Figure 12. Cause-and-effect diagram for non-value-added reduction.

5.5. Measurement System Analysis and Improvement

Measurement System Analysis (MSA) is crucial for evaluating the accuracy, precision, and reliability of measurement systems, ensuring that observed process variation reflects true differences among parts rather than inconsistencies in measurement procedures. In this study, a crossed Gauge Repeatability and Reproducibility (R&R) analysis was conducted for each operator using a vernier caliper with a least count of 0.05 mm. Each part was measured multiple times by different operators, and the data were analyzed in Minitab to quantify the measurement system's contribution to overall process variation, including repeatability (device-related variation) and reproducibility (operator-related variation). According to standard criteria, %Study Variance below 10% indicates a highly reliable system, 10–30% is conditionally acceptable, and above 30% is inadequate (Sumasto et al., 2025; Kumar et al., 2023).

As shown in Figure 13, the initial analysis revealed a %Study Variance of 35.67%, exceeding acceptable thresholds. The R Chart by Operators highlighted higher variability for Operator C, while the $\bar{X}$ Chart indicated that the measurement system itself contributed substantially to overall variance. The Parts × Operators Interaction revealed strong interaction effects, confirming that both operator practices and part characteristics contributed to inconsistencies. Root cause analysis using brainstorming and an Ishikawa diagram (Figure 14) identified key factors across Methods, Machines, Operators, Materials, Environment, and Measurement. Major issues included inconsistent measurement procedures, insufficient operator training, calibration deficiencies, and environmental effects. Corrective actions were implemented, including recalibration of instruments, standardization of measurement procedures, operator retraining, and improved environmental controls. Post-improvement analysis, shown in Figure 15, demonstrated a marked reduction in variability, with %Study Variance decreasing to 15.38%. The R Chart confirmed all measurements were within control limits, operator effects were minimal, and part-to-part variation predominated. The Parts × Operators Interaction displayed parallel lines, indicating a reliable and consistent measurement system. These improvements enhanced measurement accuracy, reduced variability, and strengthened process control, providing a robust foundation for quality assurance, process optimization, and data-driven decision-making in the manufacturing environment.

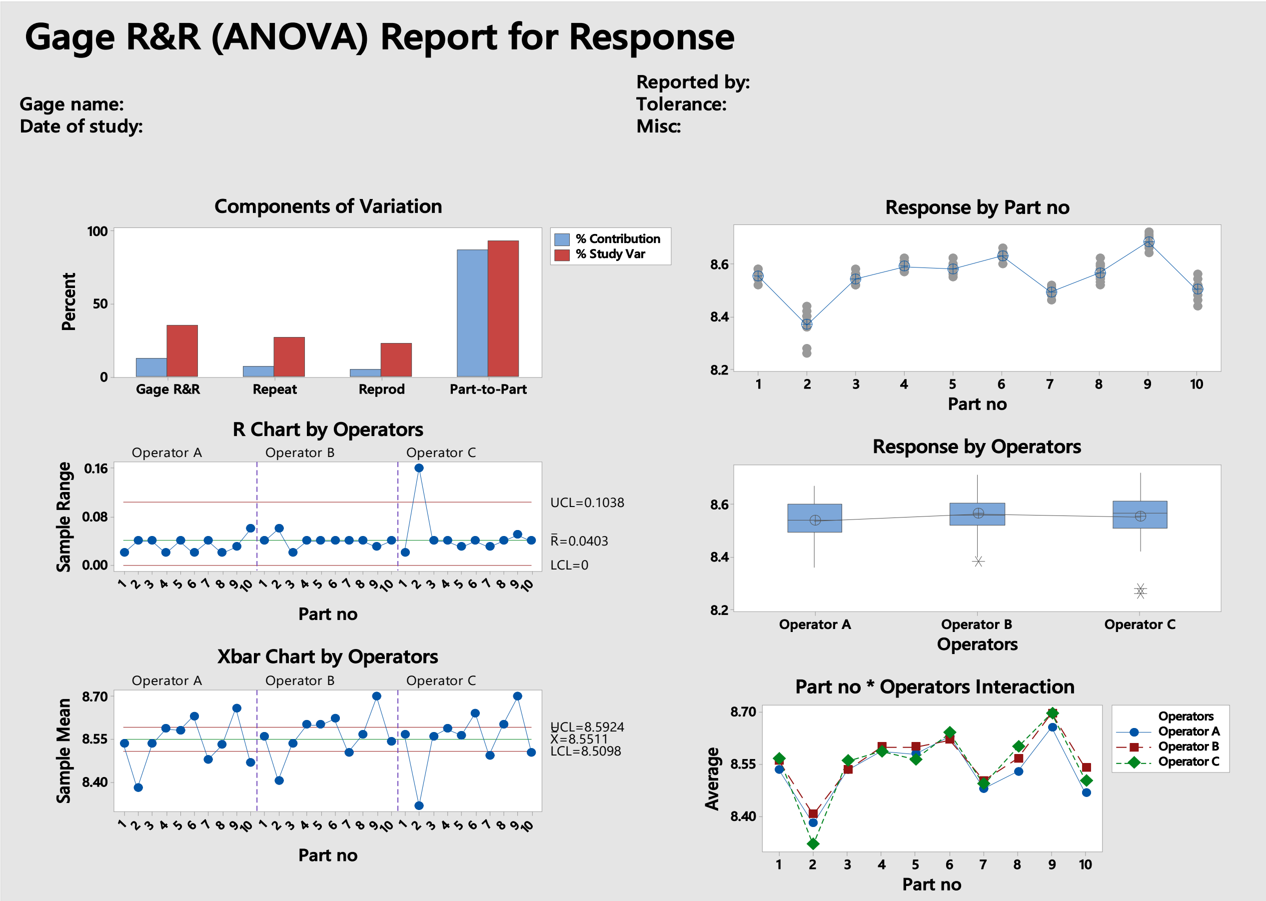

Figure 13. Gage R&R analysis results before measurement system improvement.

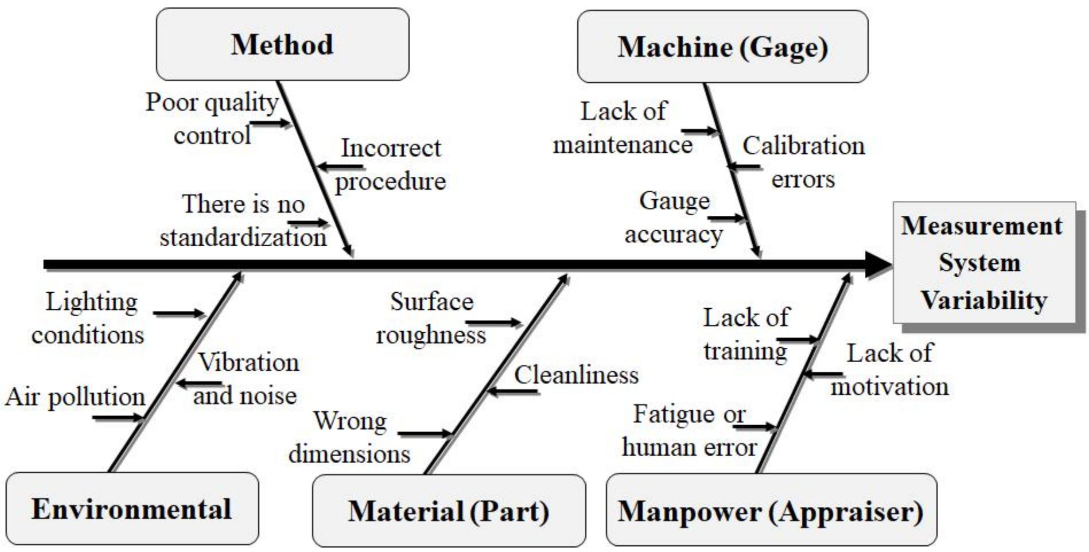

Figure 14. Cause-and-effect diagram of the measurement system errors.

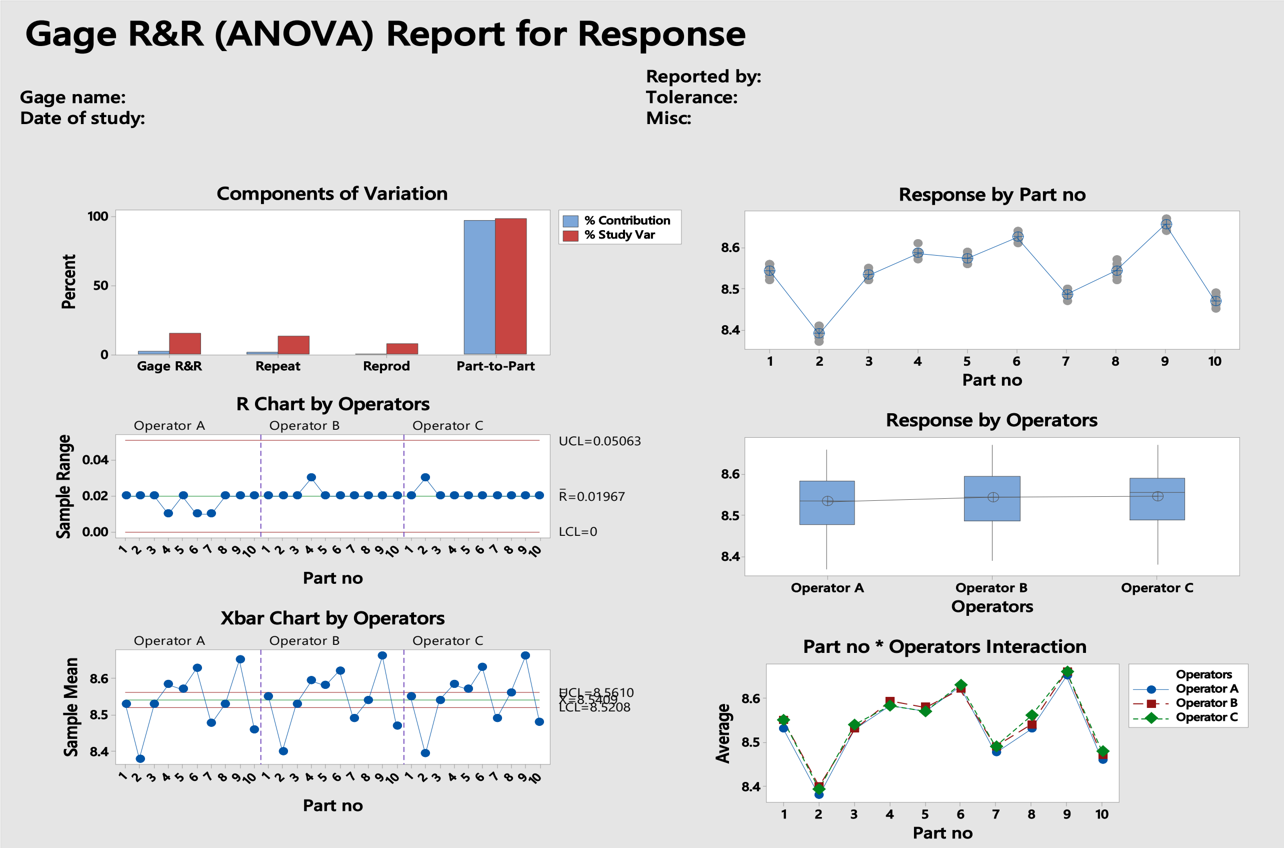

Figure 15. Gage R&R analysis results after measurement system improvement.

5.6. Optimization of Machining Process Parameters Using Taguchi DOE

This phase focused on optimizing machining parameters using the Taguchi method to improve the surface finish of spare parts. The Taguchi approach emphasizes quality optimization during the design phase, allowing systematic evaluation of process parameters and their effects on performance. A Design of Experiments (DOE) was developed, and Signal-to-Noise (S/N) ratios were calculated using Minitab 18. Analysis of Variance (ANOVA) was applied to determine the most influential factors, guiding the selection of optimal parameter settings (Gomaa, 2024) [24].

Turning, a commonly used machining process, was employed to remove material from external or internal cylindrical surfaces. The workpiece rotates at a specified cutting speed, while the cutting tool advances with a defined feed rate and depth of cut. Factors influencing the process were classified as control or noise factors. As shown in Table 5, cutting speed, feed rate, and depth of cut were selected as control factors. An L9 orthogonal array was used to study three parameters at three levels each. Figure 16 presents the process parameter diagram and output objectives. The experiment evaluated the effect of these parameters on surface roughness (Ra) and material removal rate (MRR) for EN8 steel. Figure 17 shows that surface finish improves with higher cutting speed, lower feed rate, and shallower depth of cut. S/N ratio analysis identified the optimal combination: cutting speed 125 m/min, feed rate 0.1 mm/rev, and depth of cut 0.3 mm.

ANOVA confirmed the statistical significance of the model (Prob. > F < 0.05, Table 6). Feed rate had the greatest impact on surface roughness, while cutting speed and depth of cut had smaller, though significant, effects. A regression model was developed to predict Ra:

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

where Ra represents surface roughness, N is cutting speed, f is feed rate, and D is depth of cut. The model achieved an R^2 of 0.99, demonstrating high predictive accuracy. Table 7 shows strong agreement between predicted and measured values, with errors below 5%, confirming model reliability.

Residual analysis validated the model. Normal probability, histogram, versus fit, and versus order plots (Figure 18) confirmed normality, randomness, and uniform variance of residuals, indicating no uncontrolled factors affected the process. Interaction plots (Figure 19) highlighted significant interactions among parameters, with feed rate exerting the strongest influence on Ra.

Table 5. 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

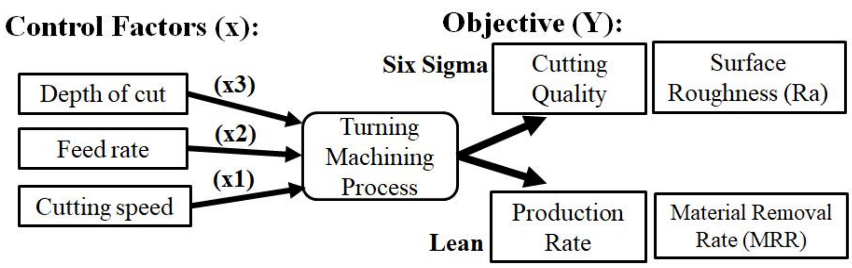

Figure 16. Process parameter diagram.

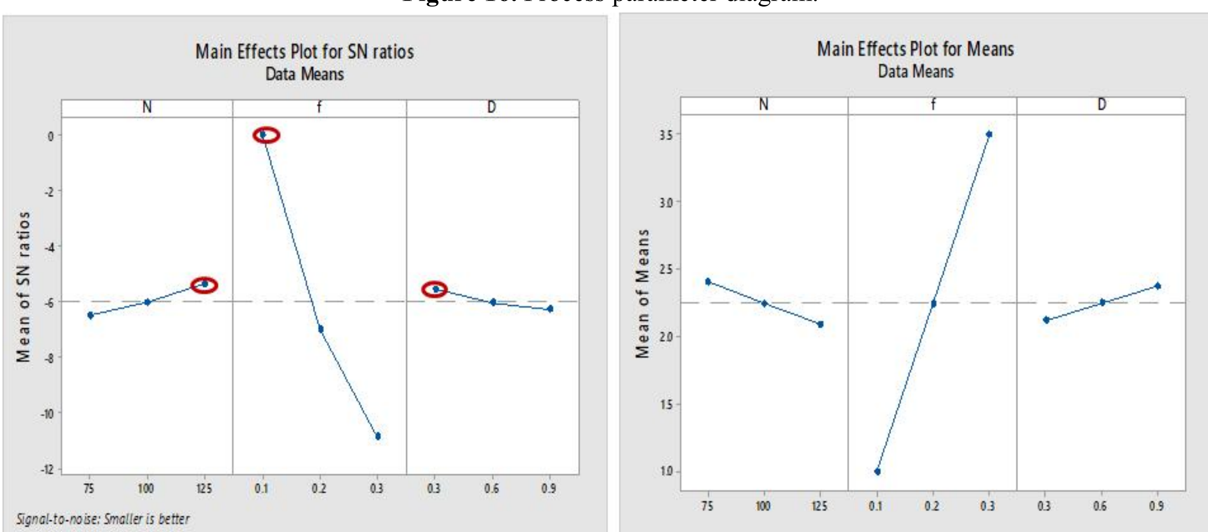

Figure 17. Influence of the cutting parameters on the surface roughness (Ra).

Table 6. 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 7. 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%

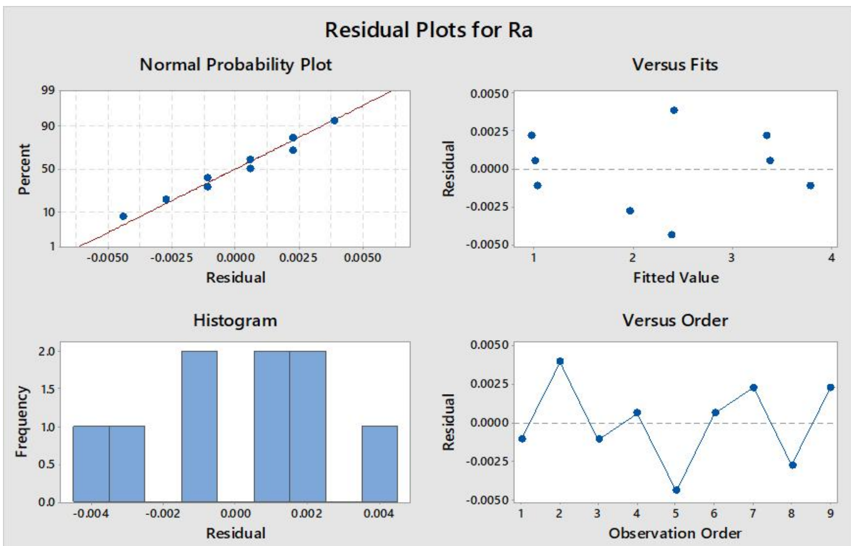

Figure 18. Residual plots for the surface roughness equation.

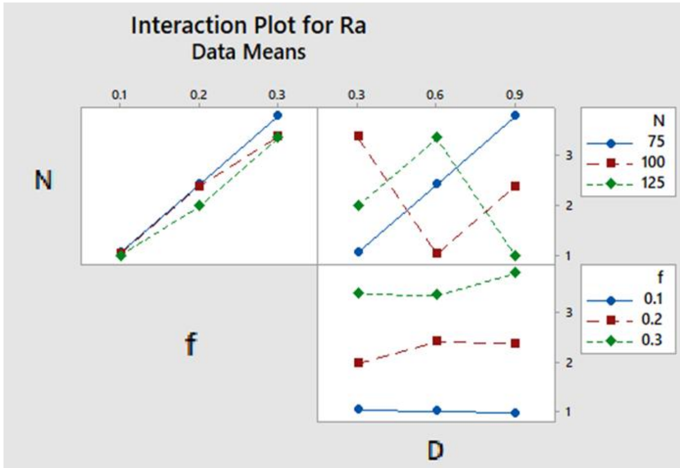

Figure 19. Interaction effect plots of surface roughness.

5.7. Results Discussion After Improvement

After implementing the Lean Six Sigma improvement plan, the project team systematically developed, tested, and sustained enhancements in the machining process. The 7S principle (5S + Safety + Sustainability) was applied to organize workspaces, streamline workflows, and reduce safety risks. A control plan was established to monitor improvements, standardize procedures, document best practices, and ensure long-term process stability. The project concluded with a formal closure report. The post-improvement results demonstrate notable gains in process performance. Figure 20 shows the quality control chart over 25 working days, highlighting reduced variability and defect rates. Figure 21 presents the improved process capability, reflecting enhanced stability, consistency, and adherence to specifications.

Value Stream Mapping (VSM) analysis (Figure 22) indicated an increase in value-added efficiency to 54.1%, representing a significant improvement over the pre-improvement baseline. Analysis of non-value-added activities and process waste (Figure 23) identified residual inefficiencies, guiding further optimization and continuous improvement initiatives.

Overall, the findings confirm that the structured application of Lean Six Sigma, supported by systematic monitoring, standardization, and active employee engagement, led to measurable and sustainable improvements in product quality, operational efficiency, and process stability. The results highlight the effectiveness of the LSS framework in fostering operational excellence and a culture of continuous improvement.

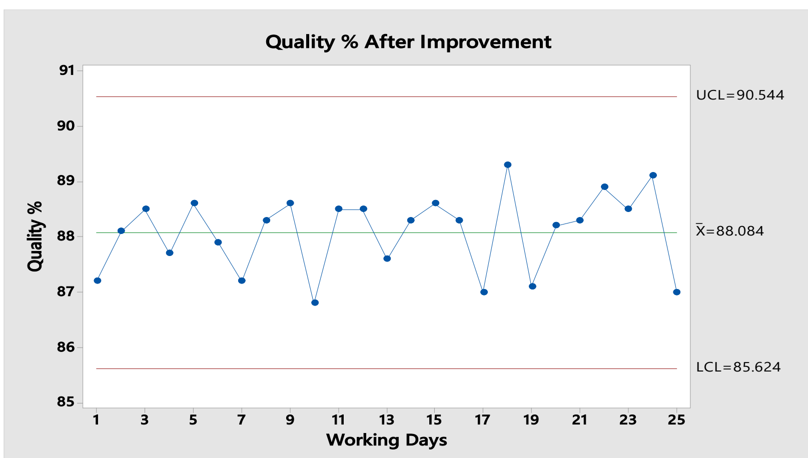

Figure 20. Quality control chart over 25 working days (After improvement).

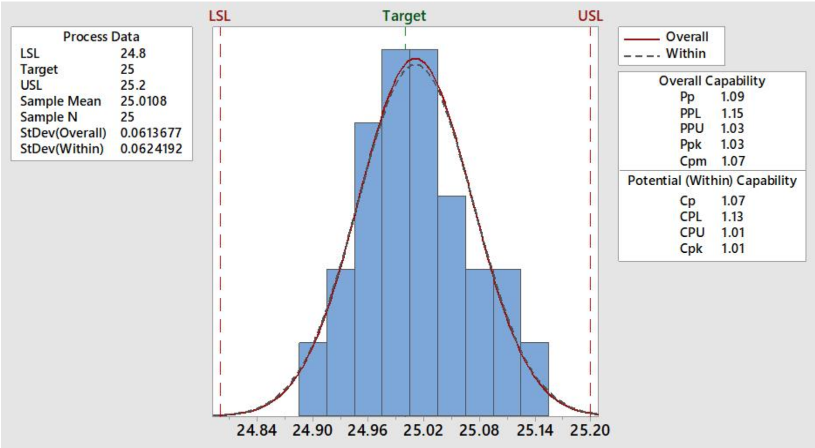

Figure 21. Process capability analysis (After improvement).

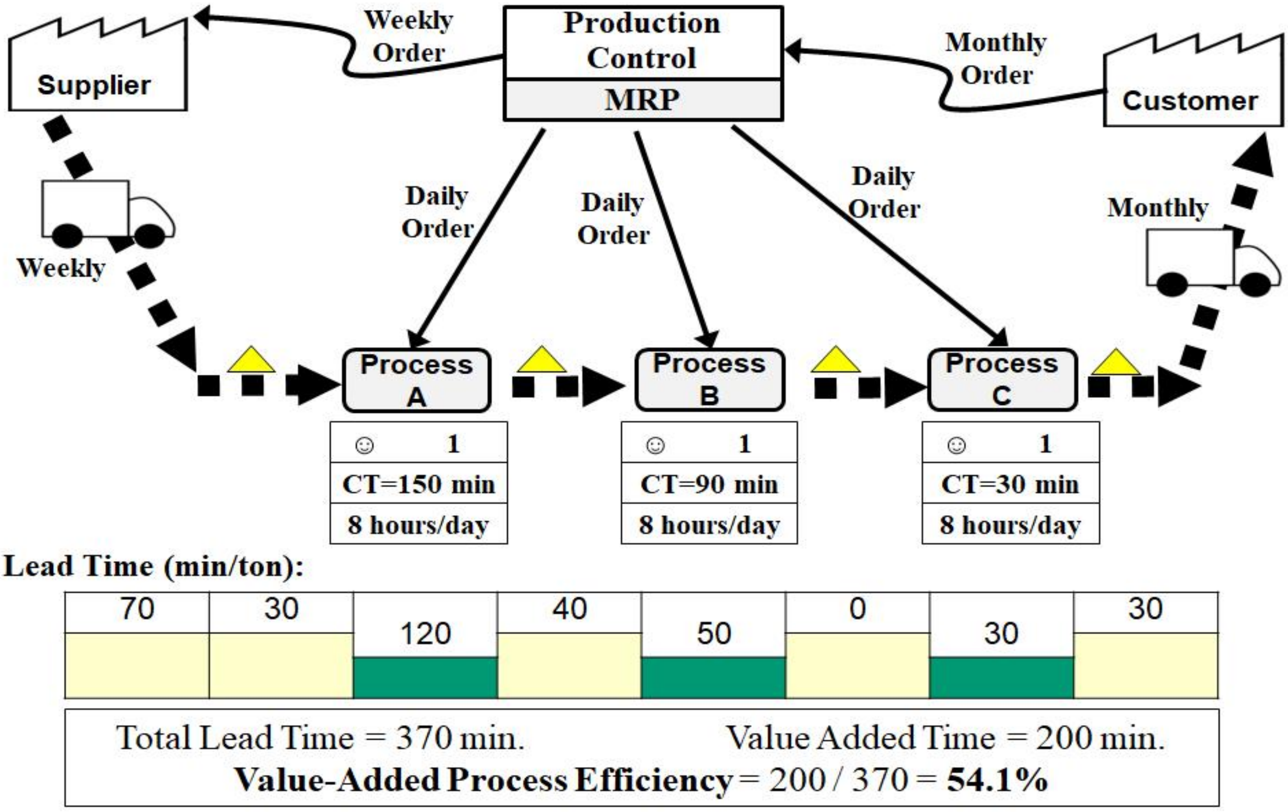

Figure 22. Value stream mapping (After improvement).

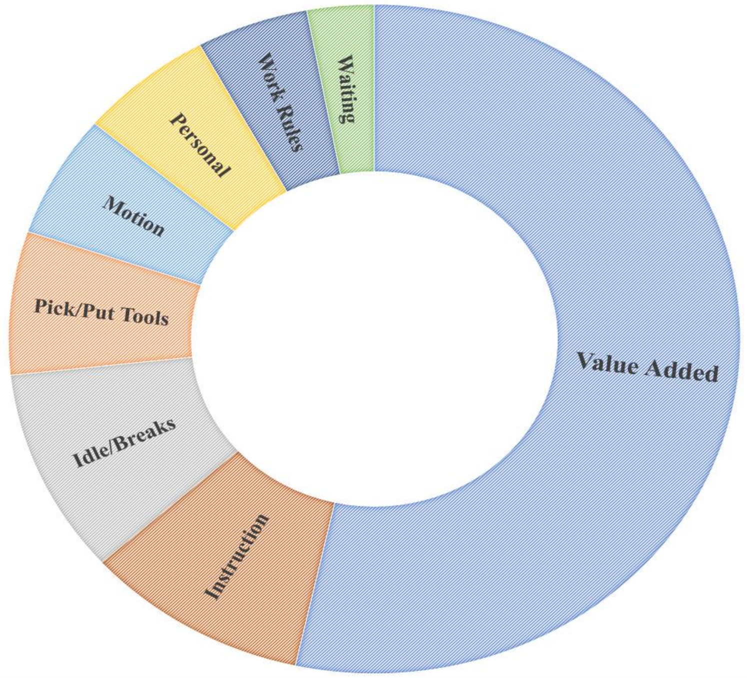

Figure 23. Value added analysis for one shift (After improvement).

5.8. Lessons Learned and Implications

The case study demonstrates that the proposed Lean Six Sigma (LSS) methodology significantly improves supply chain efficiency, operational performance, and product quality. As summarized in Table 8 and Figure 24, key improvements over three months include: product quality increasing from 85% to 89%, sigma level rising from 2.5 to 2.7, processing time reducing from 645 to 370 hours/ton, overall equipment effectiveness (OEE) improving from 75% to 81%, value-added efficiency increasing from 50% to 54%, and customer satisfaction improving from 87% to 89%. These outcomes highlight the measurable impact of a structured LSS approach on both operational performance and customer-focused results.

Several lessons emerged from the implementation process. First, structured, data-driven deployment ensures that improvement efforts focus on the most critical process inefficiencies, yielding measurable gains in quality, productivity, and operational stability. Second, integrating Lean and Six Sigma tools—including waste elimination, 5S, workflow standardization, Design of Experiments (DOE), and process capability analysis—effectively reduces variability, optimizes machining parameters, and enhances overall process performance. Third, employee engagement is essential: involving operators, engineers, and quality personnel in root cause analysis, process monitoring, and standardization fosters ownership, reinforces best practices, and sustains long-term improvements.

The study also emphasizes the value of continuous monitoring and control mechanisms. Implementing real-time dashboards, standardized operating procedures, and control charts ensures that performance gains are maintained, deviations are promptly detected, and corrective actions are implemented efficiently. Measurement system analysis further guarantees that observed improvements reflect true process performance rather than inconsistencies in measurement practices. From a managerial perspective, the methodology offers several strategic insights. The demonstrated improvements in quality, efficiency, and customer satisfaction confirm that LSS serves as a powerful enabler of operational excellence. Its scalable and adaptable framework makes it suitable for other machining processes, production lines, and manufacturing environments, supporting broader initiatives in process standardization, waste reduction, and quality assurance. Finally, the case study highlights that sustainable improvement requires a holistic approach combining technical interventions with organizational and cultural change. Standardized procedures, operator training, documentation of best practices, and a culture of continuous improvement are as critical as technical optimization. Together, these elements create a resilient, high-performance operational environment capable of consistently delivering quality, efficiency, and value.

In conclusion, the study confirms that a structured, systematic, and employee-engaged Lean Six Sigma framework delivers substantial, sustainable, and measurable improvements in product quality, operational efficiency, and customer satisfaction. Beyond operational gains, it fosters a culture of continuous improvement, data-driven decision-making, and long-term operational excellence, providing a practical and strategic reference for practitioners and researchers seeking to implement LSS in complex manufacturing systems.

Table 8. A summary of process performance indicators (Before and after improvement).

Indicators	Unit	Target	Before	After
Product quality (first time)	%	≥ 90	80.6	85.1
Product quality (after rework)	%	≥ 95	85.7	89.0
Sigma level (first time)	#	≥ 2.8	2.36	2.54
Sigma level (after rework)	#	≥ 3.14	2.57	2.73
Process lead time	min./ton	≤ 360	645	370
Process Efficiency	%	≥ 60	37.2	54.1
OEE	%	≥ 80	75	81
Value added	%	≥ 55	50	54
Customer satisfaction	%	≥ 92	87	89

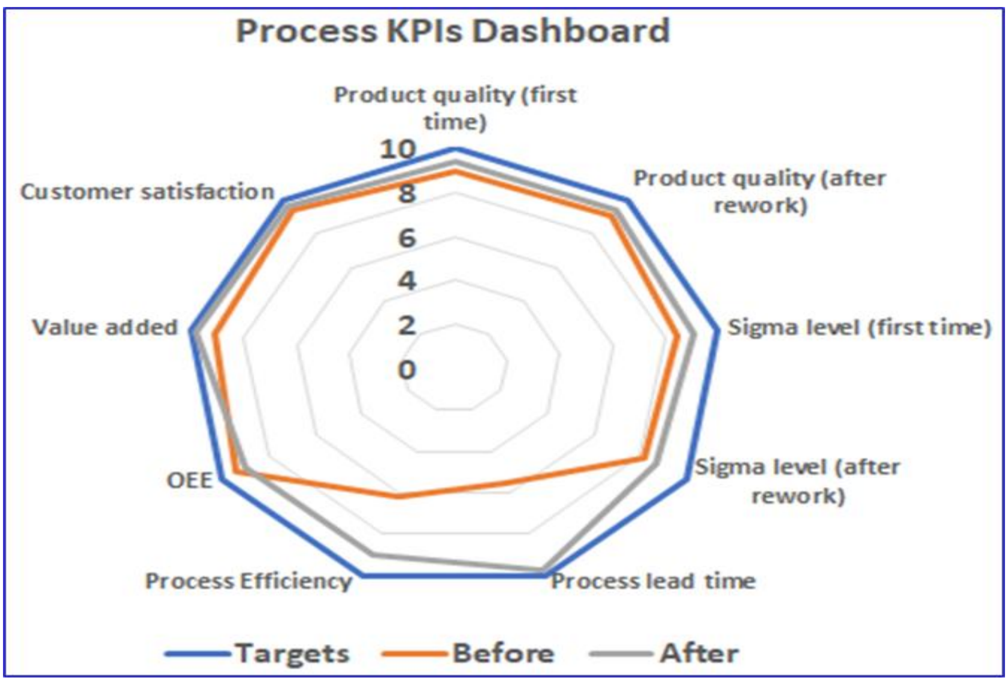

Figure 24. A summary of process performance indicators (Before and after improvement).

6. Conclusion and Future Work

This study investigates Lean Six Sigma (LSS) implementation in machining operations, identifying key challenges such as (1) the lack of a unified, adaptable LSS framework for machining processes, (2) limited empirical validation in industrial environments, and (3) insufficient evaluation of critical performance metrics such as quality, productivity, and customer satisfaction. To address these challenges, a structured, integrated LSS framework is proposed, combining Lean's waste-elimination principles with Six Sigma's data-driven methods for defect reduction and process variation control. The framework provides a comprehensive methodology for process optimization, quality improvement, and informed, evidence-based decision-making.

The framework was validated through a case study in a leading spare parts manufacturing company in Egypt. Implementation yielded substantial improvements: product quality increased from 85% to 89%, sigma level rose from 2.5 to 2.7, processing time decreased from 645 to 370 hours/ton, overall equipment effectiveness (OEE) improved from 75% to 81%, value-added activities increased from 50% to 54%, and customer satisfaction improved from 87% to 89%. These results confirm the framework's effectiveness in enhancing process stability, operational efficiency, and product performance.

The study demonstrates the synergistic benefits of integrating Lean and Six Sigma. Key components—including robust measurement systems, statistical process analysis, and machining parameter optimization—enabled consistent high-quality outputs and operational excellence. The framework provides a structured, evidence-based approach for identifying and prioritizing improvement opportunities, offering practical guidance for engineers, managers, and researchers aiming to institutionalize continuous improvement in machining operations.

Theoretical Implications: The framework fills critical research gaps by providing a unified, adaptable methodology that integrates Lean and Six Sigma specifically for machining processes, offering a basis for further studies in process optimization and continuous improvement.

Practical Implications: Practitioners can apply the framework to systematically reduce defects, optimize workflows, improve resource utilization, and enhance productivity.

Managerial Implications: Managers can leverage the framework to align operations with strategic objectives, implement data-driven decision-making, and cultivate a culture of continuous improvement, supporting sustainable operational performance.

Study Limitations: The research was conducted in a single manufacturing facility focusing on EN8 steel components, limiting generalizability across different industries, products, or organizational contexts.

Future Research Directions: Future studies can extend the framework to diverse manufacturing environments, integrate advanced digital technologies such as real-time analytics, predictive maintenance, and AI-based decision support, and explore the role of workforce training and human factors in sustaining performance. Including environmental and energy-efficiency metrics could further align the framework with sustainable manufacturing and Industry 4.0/5.0 objectives.

Conflicts of Interest: The authors declare no conflicts of interest.

Generative Artificial Intelligence Statement: The authors used the free version of ChatGPT to refine the writing quality of some paragraphs. No generative artificial intelligence (GenAI) was used in creating the manuscript content.

Data Availability Statement: Data supporting this study are included within the article.

Abbreviations:

Abbreviation	Full Term	Definition
5S	Sort, Set in Order, Shine, Standardize, Sustain	Workplace organization and visual management to enhance efficiency, safety, and discipline
CI	Continuous Improvement	Ongoing, incremental enhancements to eliminate waste and reduce variation
CTQ	Critical to Quality	Customer-defined characteristics that directly impact satisfaction and performance
DMADV	Define, Measure, Analyze, Design, Verify	Six Sigma methodology for designing or redesigning processes/products
DMAIC	Define, Measure, Analyze, Improve, Control	Data-driven improvement framework for optimizing existing processes
DOE	Design of Experiments	Structured statistical method to evaluate process variables and achieve optimal conditions
FMEA	Failure Mode and Effects Analysis	Proactive assessment to identify, evaluate, and reduce potential failure risks
Gage R&R	Gage Repeatability and Reproducibility	Statistical evaluation of measurement system accuracy and consistency across operators and equipment
JIT	Just-In-Time	Lean production method delivers materials only when needed to eliminate inventory waste
KPIs	Key Performance Indicators	Quantitative measures evaluating operational and strategic performance
LSS	Lean Six Sigma	Integrated methodology combining Lean waste elimination and Six Sigma variation reduction
OEE	Overall Equipment Effectiveness	Key metric of equipment productivity based on availability, performance, and quality
PDCA	Plan-Do-Check-Act	An iterative learning and improvement cycle for systematic problem -solving
PPM	Parts Per Million	Defect rate measurement per one million opportunities
RCA	Root Cause Analysis	Structured investigation to determine the underlying causes of deviations or defects
RCM	Reliability-Centered Maintenance	Maintenance strategy focusing on preserving equipment function through optimal preventive tasks
SIPOC	Suppliers, Inputs, Process, Outputs, Customers	High-level process mapping tool to define boundaries, stakeholders, and key flows
SOP	Standard Operating Procedure	Documented standardized work instructions ensuring consistency and compliance
SPC	Statistical Process Control	Monitoring process performance and variation using statistical techniques and control charts
SWOT	Strengths, Weaknesses, Opportunities, Threats	Strategic planning tool analyzing internal and external organizational factors
Takt	Takt Time	The rate at which a product must be completed to meet customer demand
TPM	Total Productive Maintenance	Holistic maintenance approach to eliminate failures and maximize asset productivity
TQM	Total Quality Management	Organization-wide philosophy focused on continuous quality improvement and customer satisfaction
VOC	Voice of Customer	Systematic collection of customer needs, expectations, and feedback
VSM	Value Stream Mapping	Visualization of process flows to distinguish value-added vs. non-value-added activities

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The authors declare no conflicts of interest.

Data Availability

Data supporting reported results can be found in the links to publicly archived datasets analyzed.

Conflicts of Interest

The authors declare no conflict of interest.

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