

Critical Studies on Cycle Time Reduction Using Lean Tools in Aerospace Components Manufacturing Industries

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Article

Keywords: Aerospace Manufacturing, Lean Manufacturing, Cycle Time Reduction, Artificial Intelligence, Industry 4.0, Predictive Analytics

Posted Date: October 20th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11059802/v1>

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Additional Declarations: No competing interests reported.

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Abstract

The production environment in the aerospace industry for component manufacturing was very complex, with high-precision machining, low-volume and high-mix production, and long production lead times. Having reduced cycle time has emerged as a key goal in order to be more productive, cost-effective, and faster to deliver whilst adhering to aerospace standards. This research provides an extensive analysis of cycle time reduction techniques using Lean Manufacturing concepts and Artificial Intelligence (AI) based predictive methods. The study identifies and assesses critical success factors affecting cycle time optimization that were identified as management commitment, machine reliability, employee capability, production scheduling, setup time reduction, and digital technology adoption. The effectiveness of Lean tools in reducing manufacturing waste and improving the flow of the process was analyzed for various Lean tools, including Value Stream Mapping (VSM), Single-Minute Exchange of Die (SMED), Total Productive Maintenance (TPM), Kaizen, and Just-in-Time (JIT). To support this, a Lean-AI framework was suggested by introducing predictive analytics for cycle time forecasting, intelligent decision-making, and production performance improvement. It was validated by performance indicators such as reduction in cycle time, machine utilization, lead time, and prediction accuracy. The results show that the implementation of Lean thinking and AI technologies has a significant impact on operational efficiency, reduction of non-value-added activities, resource utilization, and sustainable manufacturing optimization in the production environment of aerospace components.

Keywords: Aerospace Manufacturing; Lean Manufacturing; Cycle Time Reduction; Artificial Intelligence; Industry 4.0; Predictive Analytics.

Introduction

The aerospace components manufacturing industry has become one of the most technologically sophisticated sectors within modern advanced manufacturing because of its stringent quality requirements, precision engineering practices, and highly regulated production environment [1]. Aerospace components such as turbine blades, engine casings, structural assemblies, landing gear systems, compressor discs, and avionics housings are manufactured using advanced engineering materials including titanium alloys, nickel-based superalloys, aluminum composites, and carbon-fiber-reinforced polymers. These materials require exceptional dimensional accuracy, superior surface integrity, and high process reliability to satisfy stringent aerospace safety and performance standards [2]. Unlike conventional manufacturing industries that operate under mass production principles, aerospace manufacturing is characterized by high-mix, low-volume production with frequent engineering modifications, extensive inspection procedures, and rigorous compliance with international standards such as AS9100, NADCAP, and FAA/EASA regulations. These characteristics significantly increase production complexity, manufacturing lead time, and operational cost while simultaneously demanding superior product quality and complete process traceability. Consequently, aerospace manufacturers continuously seek innovative production improvement strategies capable of increasing productivity without compromising safety, quality, or regulatory compliance [3]. Among the various manufacturing performance indicators,

manufacturing cycle time has emerged as one of the most influential factors because it directly affects production efficiency, customer satisfaction, resource utilization, delivery reliability, and organizational competitiveness in global aerospace supply chains.

Manufacturing cycle time represents the total duration required to transform raw materials into certified aerospace components through a sequence of machining, heat treatment, inspection, assembly, documentation, and final approval activities [4]. Aerospace production systems differ considerably from conventional manufacturing environments because every component undergoes multiple precision machining operations, coordinate measuring machine (CMM) inspections, non-destructive testing, specialized tooling procedures, heat treatment cycles, and comprehensive quality verification before product release. Although these activities are essential for ensuring product reliability and airworthiness, they substantially increase production lead time through both value-added and non-value-added operations [5]. Delays caused by machine setup, waiting time, material movement, equipment downtime, excessive inventory, process variation, and repeated inspection frequently contribute to extended manufacturing cycles and reduced operational efficiency. The increasing complexity of aerospace production has therefore intensified the need for systematic approaches capable of identifying production bottlenecks and eliminating unnecessary process activities [6]. Effective cycle time reduction not only improves manufacturing productivity and equipment utilization but also enhances production flexibility, reduces operational costs, strengthens supply chain responsiveness, and improves customer satisfaction. Consequently, continuous optimization of manufacturing cycle time has become a strategic objective for aerospace organizations pursuing operational excellence and sustainable industrial growth.

Lean Manufacturing has been widely recognized as one of the most effective management philosophies for improving manufacturing performance through the systematic elimination of waste and continuous process improvement. Originating from the Toyota Production System, Lean Manufacturing focuses on maximizing customer value while minimizing activities that do not contribute directly to product creation [7]. Fundamental Lean principles emphasize value identification, value stream analysis, continuous production flow, pull-based manufacturing, standardized work, and continuous improvement through Kaizen. These principles are supported by numerous Lean tools including Value Stream Mapping (VSM), 5S workplace organization, Single-Minute Exchange of Die (SMED), Total Productive Maintenance (TPM), Just-in-Time (JIT), Kanban, and visual management systems [8]. The implementation of these tools has demonstrated considerable success in reducing setup time, minimizing waiting periods, improving equipment availability, decreasing work-in-process inventory, and enhancing production flow across multiple industrial sectors. Nevertheless, aerospace manufacturing presents unique implementation challenges because of stringent regulatory requirements, complex product configurations, extensive inspection procedures, and highly specialized production processes [9]. As a result, the effectiveness of Lean Manufacturing within aerospace environments depends upon the careful identification of Critical Success Factors and the systematic selection of appropriate Lean tools capable of addressing the specific operational challenges encountered during component manufacturing.

Recent advances in Artificial Intelligence, Industry 4.0, and Industry 5.0 technologies have transformed conventional manufacturing systems into intelligent, data-driven production environments capable of autonomous monitoring, predictive decision-making, and real-time process optimization [10]. Artificial Intelligence techniques including machine learning, deep

learning, artificial neural networks, reinforcement learning, predictive analytics, and computer vision enable manufacturing organizations to analyze large volumes of production data generated through Industrial Internet of Things (IIoT) devices, Manufacturing Execution Systems (MES), Enterprise Resource Planning (ERP) platforms, smart sensors, and cyber-physical systems. These intelligent technologies support predictive maintenance, production scheduling optimization, quality prediction, anomaly detection, and intelligent resource allocation while significantly reducing operational uncertainty and manufacturing downtime [11]. Industry 5.0 further extends these capabilities by emphasizing collaboration between intelligent machines and skilled human operators, thereby promoting sustainable, resilient, and human-centric manufacturing environments. The integration of Lean Manufacturing with Artificial Intelligence creates opportunities for simultaneously eliminating process waste and enabling intelligent operational decision-making, thereby providing a comprehensive strategy for sustainable cycle time reduction in highly complex aerospace production systems [12].

Although numerous studies have investigated Lean Manufacturing, Artificial Intelligence, and smart manufacturing technologies independently, limited research has proposed an integrated framework that combines these approaches specifically for aerospace component manufacturing [13]. Existing studies have generally concentrated on individual Lean tools, isolated Artificial Intelligence applications, or standalone Industry 4.0 technologies without systematically prioritizing the Critical Success Factors influencing manufacturing cycle time [14]. A comparatively few investigations have incorporated Multi-Criteria Decision-Making techniques to evaluate Lean implementation strategies while validating the proposed framework through industrial aerospace case studies. To address these limitations, this research proposes an integrated Lean–AI framework that combines Critical Success Factor identification, best–Worst Method (BWM), MARCOS-based decision-making, Lean Manufacturing tools, Artificial Intelligence techniques, and Industry 4.0/Industry 5.0 technologies to reduce manufacturing cycle time in aerospace component manufacturing industries [15]. The proposed framework is further validated through an industrial case study and comprehensive performance evaluation, demonstrating its effectiveness in improving production efficiency, reducing manufacturing waste, enhancing equipment utilization, and supporting intelligent decision-making. The findings are expected to provide both theoretical contributions and practical guidance for aerospace manufacturers seeking sustainable operational excellence and digital manufacturing transformation.

Research Gap

While there were many successful examples of Lean Manufacturing (LM) in use to gain operation efficiency and shorten downtime in the manufacturing industry, there was still a lot of work to be done for LM to be applied to aerospace component production. Little research has been conducted on developing a lean system using more than one lean tool, and few studies have explored the possibility of creating an integrated system that was suitable to the specific problems in aerospace production. The use of artificial intelligence, Industry 4.0, and Industry 5.0 technologies in the context of cycle time reduction strategies in a lean context was not sufficiently covered. The identification and prioritization of critical factors that affect cycle time have also been studied little using multi-criteria decision-making (MCDM) techniques [17]. A few studies validate the proposed methodologies with industrial case studies in the environment of the manufacture of aerospace components. Based on this, a comprehensive framework that combines lean manufacturing with artificial intelligence, digital technologies, and MCDM techniques to

systematically minimize cycle time and improve operational performance in aerospace component manufacturing industries was clearly needed.

Literature Review

The aerospace component manufacturing sector was known for its high precision and quality standards, the use of sophisticated materials, adherence to regulatory compliance, and specialized manufacturing processes. Manufacturing aero parts entails a series of actions, including precision machining, assembly, inspection, testing, and more, that have a significant impact on the final production lead time and efficiency. Crute et al. (2003) showed that lean implementation in the aerospace industry would need to be adapted, as each industry has specific challenges associated with it, including low volumes, high product complexity, and stringent quality standards. Likewise, McManus et al. (2007) pointed out that for the improvement of the manufacturing process in the aerospace industry to be achieved in a rational manner, it was necessary to adopt a systematic approach that allows for the maintenance of engineering reliability and product quality while optimizing the process [18].

In the aerospace industry, the reduction in cycle time was a major research focus, as it directly impacts the cost, productivity, delivery performance, and utilization of resources in the manufacturing process. Machine waiting time, setup delays, inspection needs, material handling, and process downtimes were some of the difficulties found in aerospace production systems. Diaz et al. (2017) studied the improvement of the cycle time in aircraft assembly processes, and they showed that it was possible to identify the production bottlenecks in the manufacturing process by applying a systematic method of process analysis that helps to increase the efficiency of the manufacturing flow. These results suggest that optimization of cycle times should be done from the first to the last operations of the manufacturing process, including both value-added and non-value-added processes.

Lean manufacturing was considered a successful technique to enhance production efficiency by eliminating waste and practicing continuous improvements. Lean production concepts were introduced by Womack et al. (1990), who showed the benefits of applying the principles of the Toyota Production System to enhance productivity, quality, and flexibility of operations. Liker (2004) also emphasized the need for a lean continuous improvement culture, standardized processes, employee involvement, and efficient resource utilization for the successful implementation of lean.

There have been several tools recommended and studied to reduce manufacturing cycle time and increase the operational performance, such as Lean tools [19]. Value Stream Mapping (VSM), Single-Minute Exchange of Die (SMED), Total Productive Maintenance (TPM), Kaizen, 5S, Kanban, and Just-in-Time (JIT) have proven to be highly valuable tools for the identification of inefficiencies and for the improvement of the production flow. Garre et al. (2017) have found that the application of Lean tools helped to increase aerospace manufacturing performance by eliminating non-value-added activities and increasing the efficiency of the manufacturing processes. These methods were of great importance in aerospace production, where the task of identifying bottlenecks was of crucial importance in the context of VSM; minimizing the setups was highly relevant through SMED, and TPM increases the availability of the equipment.

Industry 4.0 and Artificial Intelligence (AI) have opened the doors to improve lean manufacturing using data to make decisions and predictions. With the help of Artificial Intelligence (AI)

technologies such as machine learning, deep learning, and predictive analytics, the manufacturing systems can process massive amounts of data from production and predict future system conditions. The focus on Brunton et al. (2020) was on the increasing need for data-driven methods in aerospace engineering and the potential applications of machine learning methods to solve complex engineering problems. AI can be used to do predictive maintenance, intelligent scheduling, cycle time forecasting, and resource allocation through Lean principles.

While there have been significant studies into Lean implementation and optimization of manufacturing processes, there were limitations in the previous research. The current research studies largely concern Lean tools and/or traditional Lean improvement methods and do not pay special attention to integrated Lean–AI approaches that were specifically designed for aerospace component manufacturing [20]. The effects of the combination of critical success factors, Lean waste reduction, Artificial Intelligence (AI) prediction, and Industry 4.0 technologies need to be further investigated. As a result, a comprehensive framework integrating Lean Manufacturing concepts and AI-based predictive analytics was crucial to achieve sustainable cycle time reduction, productivity improvement, and improved operational performance in aerospace manufacturing industries.

Research Methodology



Figure 1: Research Methodology

Identification and Validation of Critical Success Factors

Identification of Critical Success Factors (CSFs) was a basic step in the proposed research methodology, as these factors were the most important organizational, operational, technological, and managerial attributes, which have a significant influence on the reduction of cycle time in the aerospace component manufacturing industry. First, all the available literature from previous studies was reviewed systematically and comprehensively to find the factors that have been widely acknowledged in past studies related to lean manufacturing, aerospace production systems, production scheduling, artificial intelligence, Industry 4.0, Industry 5.0, and manufacturing performance improvement. The review helps identified potential factors relating to production efficiency, elimination of waste, optimization of the production process, utilization of machines, competency of the workforce, quality management, machine use of digital technology, and continuous improvement [21]. The identified factors were grouped into relevant dimensions for further validation and analysis.

After the literature review, the initial list of critical success factors was validated by experts to assure the relevance, completeness, and applicability of the list in the aerospace manufacturing context. A panel of production managers from the aerospace sector, lean production experts, industrial engineers, quality assurance experts, and domain experts' academic researchers was chosen to review the identified factors. The experts evaluated each factor according to its importance and impact on manufacturing cycle time and operational performance. The structured method of evaluation, such as using the Delphi method or expert consensus approach, was used to reach consensus among the experts in several rounds of evaluation. This successive validation process helped retain only the most relevant and practically significant factors for further analysis.

Based on the expert feedback, the initial list of critical success factors was further narrowed down by removing the redundant, overlapping, and less important factors and adding more factors as recommended by the experts, which were relevant. The validated factors were then grouped into major categories like managerial factors, operational factors, technological factors, human resource factors, and organizational factors. Some of the representative factors could be top management commitment, employee competence, machine reliability, production scheduling effectiveness, reducing set-up time, preventive maintenance, supplier coordination, quality assurance practices, digital readiness, and continuous improvement culture [22]. By categorizing the factors, a systematic understanding of the multidimensional nature of cycle time reduction was achieved, and a comprehensive basis was given for assessing the relative importance of each factor.

The finalized set of validated Critical Success Factors was the key input required for the next steps in this research, such as developing the questionnaires, the Multi-Criteria Decision-Making (MCDM) analysis, and the proposed Lean–AI framework. The factors were translated into measurable questionnaire items. The validated data was then used for prioritizing the critical success factors with the help of MCDM techniques, which led to the identification of the most influential factors on cycle time reduction. This systematic identification and validation process improve the reliability, relevance, and scientific validity of the proposed research frame and also makes sure that the methodology developed was in line with the industrial needs and challenges in the field of manufacturing of aerospace components.

Questionnaire Development and Data Collection

A questionnaire was designed in a structured manner to gather valid and complete information on the factors affecting the reduction of cycle time in the manufacturing industries of aerospace components. The result of the systematic literature review and expert evaluation was formulated into validated critical success factors, and then the questionnaire was developed. For each construct, the perceptions/experiences of industry professionals were translated into measurable items so that the quantitative assessment of these perceptions/experiences was possible. Each item was measured on a five-point Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree). The questionnaire consists of several sections: Respondent's Demographic Data, Organizational Characteristics, Critical Success Factors, Lean Manufacturing Practices, and Perceived Improvement in Cycle Time Reduction [23].

Before the questionnaire was used on a large scale, it was validated for content and pilot tested for clarity, relevance, and comprehensibility. Content validity was measured by a group of experts

that includes aerospace manufacturing experts, lean experts, industrial engineers, and academic researchers. The recommendations include suggestions for methodological improvements in the wording of the measure items or to eliminate ambiguities and make them appropriate. A pilot study of a small number of respondents from the sample population was then carried out to assess the readability, consistency, and effectiveness of the questionnaire. The pilot study results were used to make the necessary modifications before distributing the final questionnaire.

The finalized questionnaire was distributed to production managers, manufacturing engineers, quality assurance engineers, maintenance engineers, lean coordinators, operations managers, and senior technical personnel working in the selected aerospace component manufacturing organization. A purposive sampling method was used to make sure that the respondents have good knowledge in the industrial field and have industrial experience in the lean implementation and production management field. To maximize participation and response, data was gathered using both online and offline survey techniques [24]. Anonymity and confidentiality were maintained throughout the data collection process so as to foster unbiased responses and increase the validity of data collected.

Ethical Approval and Informed Consent

All methods were carried out in accordance with relevant guidelines and regulations, including the Declaration of Helsinki. All experimental protocols involving human participants, including the expert panel evaluation of the critical success factors, the expert content validation of the questionnaire, the pilot study, and the main questionnaire survey, were reviewed and approved by the Institutional Ethics Committee of Hindustan Unilever Limited. Informed consent was obtained from all expert panel members and from all questionnaire participants, including the pilot study respondents, prior to their participation. All participants were informed of the purpose of the study, that their participation was voluntary, that they could withdraw at any time without consequence, and that their responses would be kept confidential and reported only in anonymised and aggregated form. No personally identifiable information was collected or reported.

After data collection, the responses were thoroughly reviewed and formatted for statistical analysis. Questions that were not completed and duplicated responses were flagged and removed to enhance data quality. The reliability and validity of the data obtained were then tested using statistical tests such as Cronbach's Alpha, the Kaiser–Meyer–Olkin (KMO) test of sampling adequacy, Bartlett's test of sphericity, and the test of composite reliability (CR) and average variance extracted (AVE). Such analyses guarantee statistical strength, construct validity, and internal consistency of the measurement instrument. The validated dataset was then used as a basis for Multi-Criteria Decision Making (MCDM) analysis and development of the proposed integrated Lean-AI framework for cycle time reduction in aerospace component manufacturing industries.

Table 1. Demographic Characteristics of Respondents

Category	Description
Job role	Engineer, Manager, Lean coordinator
Experience	5–10 years

Organization type	Aerospace manufacturing
Respondents	100/150

Table 2. Reliability and Validity Results

Test	Value
Cronbach Alpha	0.82
KMO	0.85
Bartlett p-value	<0.001
CR	0.88
AVE	0.61

Prioritization of Critical Success Factors Using MCDM

After the identification and validation of the Critical Success Factors (CSFs), the prioritization of the CSFs was carried out using a Multi-Criteria Decision-Making (MCDM) approach to determine the relative importance of CSFs in aerospace component manufacturing industries in reducing manufacturing cycle time. The cycle time reduction was driven by several interrelated technical, operational, managerial, and organizational factors, and traditional ranking techniques suitable to address the complexity of such decisions. Thus, MCDM techniques offer a systematical and scientifically sound framework to assess several criteria together and take into account the relative importance of these criteria [25]. The prioritization process helps determine the most influential factors that need to be addressed during the implementation of lean and helps inform evidence-based decisions on manufacturing performance improvement.

To obtain the relative weights of the validated Critical Success Factors (CSFs), the Best–Worst Method (BWM) was used in the proposed methodology. The validated CSFs were first presented to domain experts, who determine the most important (best) and least important (worst) among the evaluation criteria. Then, pairwise comparisons were carried out for the best criterion and all other criteria, and all the criteria were pairwise compared with the worst criterion on a predetermined preference scale. These comparisons were then used to develop a mathematical optimization model for determining the optimal criterion weights and provided consistency reduction in the expert judgments. The consistency ratio obtained from the BWM model was also used to test the reliability and credibility of the weights that were obtained.

Once the criteria weights have been identified, the validated Critical Success Factors were ranked, in order of priority, by the Measurement Alternatives and Ranking according to the Compromise Solution (MARCOS) method. The Critical Success Factors prioritized using the integrated BWM–MARCOS methodology formed the basis for developing the proposed Lean–AI framework. Evaluating each factor against ideal and anti-ideal solutions, the MARCOS approach allows for a thorough analysis of how much the factor was helping to achieve the goal of reducing manufacturing cycle time. The values obtained from the utility degree and utility function, derived from the MARCOS methodology, help in the ranking of all the identified Critical Success Factors by their relative importance. This ranking process was integrated as a structured way of

determining focus for improvement areas and of assisting in strategic decision-making when implementing lean [26].

The Critical Success Factors that were prioritized using the integrated BWM–MARCOS methodology forms the basis for the development of the proposed Lean–AI framework in the next step. Factors that were of high priority were regarded as key factors affecting the manufacturing cycle time and then mapped with relevant lean, AI, Industry 4.0/5.0 technology. This was a systematic approach to prioritization that leads to more objective, transparent, and reliable decision-making and reduces the subjective bias of traditional evaluation techniques. The use of MCDM techniques allows ascertaining that improvement actions were targeted on the most critical operational issues, which, consequently, enhances the effectiveness of the proposed framework in terms of sustainable reduction of cycle time and operational excellence in aerospace component manufacturing industries.

Table 3: BWM Pairwise Comparison Matrix

Criteria	TM	MR	ET
TM	1	2	3
MR	1/2	1	2
ET	1/3	1/2	1

Development of an Integrated Lean–AI Framework

The integrated Lean–AI framework was the main contribution of this proposed research, which aims to present the systematic approach of decreasing the cycle time for aerospace component manufacturing industries. The framework was designed through a fusion of the Lean Manufacturing principles with Artificial Intelligence (AI), Industry 4.0 and Industry 5.0 technologies to tackle the challenges faced in a traditional lean implementation. The first approach was to use the literature-derived and expert-evaluated Critical Success Factors (CSFs) as the building blocks for a framework development. These factors were identified using suitable lean tools, and an operational challenge was tackled by a suitable improvement technique [27]. The current structured integration enables the creation of a holistic decision support system, which will be able to improve the efficiency of manufacturing operations while still meeting the high-quality standards required in the aerospace industry.

After identifying critical success factors, the necessary lean tools were then carefully and systematically selected, considering their ability to solve prioritized operational problems identified in the multi-criteria decision-making (MCDM). The lean tools include Value Stream Mapping (VSM), 5S, Kaizen, Single-Minute Exchange of Die (SMED), Total Productive Maintenance (TPM), Kanban, and Just-in-Time (JIT) that were used to remove non-value-added activities, improve the flow of production, reduce setup times, reduce inventories, and maximize the use of equipment. The link between the prioritized critical success factors and associated lean tools was created to enable an improvement plan which directly targets the root causes that were causing longer manufacturing cycles.

The proposed framework introduces Artificial Intelligence (AI) technologies to assist with intelligent decision-making and predictive manufacturing, further boosting the effectiveness of the

implementation of lean. Predictive maintenance, production scheduling optimization and cycle time prediction were used with machine learning algorithms to proactively manage manufacturing operations by identifying bottlenecks. In technologies from Industry 4.0 such as the Industrial Internet of Things (IIoT), the Digital Twin, cloud technologies and real-time production data collection were being connected to ensure ongoing documentation of production processes [28]. The adoption of Industry 5.0 principles encourages the synergies of intelligent digital systems and human skills, fostering resilient and sustainable manufacturing environments while promoting human-centric approaches. Beyond just data-driven continuous improvement, this integration can help to enhance the capabilities of traditional lean methodologies.

The proposed integrated lean–artificial intelligence framework was developed as an all-in-one decision-support model to systematically connect the CSFs, lean manufacturing, Artificial Intelligence (AI) and digital technologies in a holistic approach to reducing the cycle time. The implementation of the framework was then validated in a case study of manufacturing performance in an aerospace component manufacturer by comparing the key performance indicators, including cycle time, lead time, equipment effectiveness (OEE), productivity, defect rate and machine utilization, before and after the implementation of the framework. The validation process proves the feasibility and efficiency of the framework in real-world use and offers a scalable solution which can be adapted by other aerospace manufacturers looking to become intelligent, sustainable and digitally enabled to deliver operational excellence.

Table4: Industrial Case Study Background

Parameter	Description
Industry	Aerospace component manufacturing
Location	India
Production type	High mix–low volume manufacturing
Products	Structural brackets, engine components
Study duration	6 months
Machines	CNC machining, inspection systems
Operators	Production and quality personnel

Industrial Case Study and Framework Implementation

A representative production line was chosen for purposes of study, A Lean–AI framework was validated by an industrial case study in an aerospace component manufacturing company to assess its applicability and effectiveness in reducing the manufacturing cycle time. depending on the complexity of production processes, availability of production data and importance of problems associated with cycle time. The selected production environment was used for collecting baseline information such as process flow, production schedules, utilization of machines, duration of setups, inspections, work-in-process inventory or manufacturing lead time. The Current-State Value Stream Map (VSM) was created to gain a clear understanding of the current material and

information flow so that the effects of the delays, non-value-added activities, and inefficiencies in the process can be identified, which can help reduce manufacturing cycle time [29].

After analyzing the current production system, the critical success factors were validated, and the output from the Multi-Criteria Decision-Making (MCDM) analysis can be used to identify the most suitable improvement strategies. Suitable lean manufacturing tools such as Value Stream Mapping (VSM), 5S, Kaizen, Single-Minute Exchange of Die (SMED), Total Productive Maintenance (TPM), Kanban and Just-in-Time (JIT) were determined and implemented as per the prioritized factors. At the same time, the use of Artificial Intelligence (AI) techniques and Industry 4.0/5.0 technologies like predictive analytics, real-time monitoring, digital twin, and the Industrial Internet of Things (IIoT) was integrated to enable smart decision-making, production scheduling, predictive maintenance, and process optimization. This all-in-one strategy was perfect for optimizing processes and achieving digital transformation through a single solution.

Once this framework was put into practice, a future-state value stream map was created to visualize the new system of production with the selected lean practices and digital technologies. The future-state model aims to remove identified bottlenecks, minimize waiting time, optimize material flow, better machine utilization, standardize production activities and improve synchronization between manufacturing processes. Throughout the implementation, operation improvements were monitored, and production data were obtained under similar operating conditions to assure consistency when evaluating performance. The implementation process also enables the evaluation of the practical implementation of such concepts as lean manufacturing principles, Artificial Intelligence (AI) and advanced digital technologies in complex aerospace manufacturing environments [30].

Key performance indicators (KPIs) were used to assess the effectiveness of the proposed framework, pre- and post-implementation. The operational improvements were quantified through the analysis of performance measures such as manufacturing cycle time, production lead time, set-up time, Equipment Effectiveness (OEE), machine utilization, throughput, work-in-process inventory, defect rate and on-time delivery performance. Then some statistical validation techniques were employed to check the level of significance of the improvements observed and to check the effectiveness of the proposed methodology. The results from the industrial case study offer empirical evidence of the capability to reduce the cycle time in a sustainable way, increase the production efficiency and advance to intelligent manufacturing practices in the aerospace component manufacturing industries through the use of the integrated Lean-AI framework.

An industrial case study was conducted on a representative aerospace component manufacturing line to evaluate the effectiveness of the proposed Lean-AI framework for cycle time reduction. The selected production line consisted of multiple sequential manufacturing stages, beginning with raw material preparation and ending with final product approval.

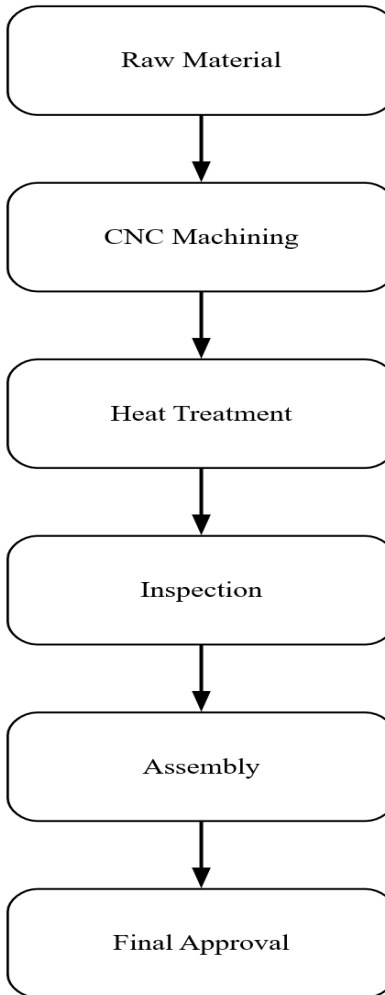


Figure 2. Aerospace Component Manufacturing Process Flow

The production workflow consists of six major manufacturing stages, namely raw material preparation, CNC machining, heat treatment, inspection, assembly, and final approval. Each stage contributes to the manufacturing cycle time and was analyzed to identify process bottlenecks, non-value-added activities, and opportunities for lean implementation. The process flow served as the basis for value stream mapping, waste identification, and subsequent performance evaluation of the proposed Lean–AI framework.

Performance Evaluation and Statistical Validation

The effectiveness of the proposed Lean–AI framework for reducing the manufacturing cycle time and improving the operational performance in aerospace component manufacturing industries was evaluated. It was carried out by measuring the production performance before and after the proposed framework was implemented by using quantitative and qualitative performance indicators. A set of Key Performance Indicators (KPIs) was systematically tracked to evaluate the effect of the improvements, such as manufacturing cycle time, lead time, setup time, Equipment Effectiveness (OEE), throughput, productivity, machine utilization, work-in-process (WIP) inventory, defect rate, and on-time delivery performance. The comparison of baseline and post

implementation performance gives a complete picture of the ability of the framework to eliminate non-value-added activities, the improvement of process flow and manufacturing efficiency.

After implementation, the data on the production of the selected aerospace component manufacturing organization was collected throughout the period of evaluation, which was adequate for the evaluation purposes to ensure consistency and reliability in the analysis. The collected data were preprocessed by removing inconsistencies, missing values, and measurement errors. Descriptive statistical measures were computed mean, standard deviation, minimum and maximum values, and percentage improvements were computed to summarize the changes observed in manufacturing performance. The results analyzed reveal the efficacy of the proposed framework for enhancing the production efficiency and reducing manufacturing cycle time in actual industrial operating conditions [31].

Appropriate inferential statistical techniques were used to determine the statistical significance of the observed improvements. First, data collected was checked for reliability and consistency with the help of statistical procedures. Hypothesis testing was then carried out to determine if the changes that have occurred following implementation were significant. Appropriate statistical analysis, including paired sample t-test, one-way analysis of variance (ANOVA), regression analysis, or Wilcoxon signed-rank test, was used depending on the nature of the data collected. These analyses were performed to determine the significance of the observed improvements and investigate the impact of the critical success factors on reducing manufacturing cycle time. The statistical significance was tested at the 95% confidence level ($\alpha = 0.05$), which assures the robustness and reliability of the research findings.

Last, the results of the validated performance were interpreted to assess the practical application and industrial effectiveness of the proposed Lean–AI framework. The results obtained from the statistical analysis were compared to what was found in past studies for the amount of improvement in aerospace component manufacturing environments. Special attention was given to the framework's advantages, including cycle time reduction, equipment utilization, waste elimination, productivity improvement, and AI-enabled decision-making. including through the use of Artificial Intelligence (AI) and Industry 4.0/5.0 technologies, were given special attention. The extensive performance evaluation and statistical validation process enhances the credibility of the suggested methodology and its feasibility for industry implementation and provides empirical evidence that justifies its use as an effective methodology for cycle time reduction in aerospace component manufacturing industries with a focus on sustainability.

Table5: Statistical Significance Analysis

KPI	Test	p-value	Result
Cycle Time	Paired t-test	0.002	Significant
OEE	ANOVA	0.001	Significant

Formula,

$$CT = T_{VA} + T_{NVA} \quad [1]$$

Where:

- CT = Total Manufacturing Cycle Time
- T_{VA} = Value-added processing time
- T_{NVA} = Non-value-added time

$$CTR(\%) = \frac{CT_{Before} - CT_{After}}{CT_{Before}} \times 100 \quad [2]$$

Where:

- CTR = Cycle Time Reduction percentage
- CT_{Before} = Cycle time before Lean implementation
- CT_{After} = Cycle time after Lean implementation

The cycle time reduction equation was used to quantify the improvement achieved after implementing Lean Manufacturing practices in aerospace component production. The equation calculates the percentage reduction by comparing the initial production duration with the optimized cycle time after eliminating non-value-added activities. It provides a direct measurement of Lean implementation effectiveness by highlighting improvements in machining, assembly, inspection, and other manufacturing stages.

$$OEE(\%) = Availability \times Performance \times Quality \times 100 \quad [3]$$

$$Prediction\ Error(\%) = \frac{|CT_{Actual} - CT_{Predicted}|}{CT_{Actual}} \times 100 \quad [4]$$

Where:

- CT_{Actual} = Actual manufacturing cycle time
- $CT_{Predicted}$ = AI predicted cycle time

Equipment Effectiveness was applied to evaluate the improvement in manufacturing equipment performance after Lean-AI framework implementation. OEE integrates three major manufacturing factors: machine availability, production speed, and product quality. The equation provides a comprehensive indicator for measuring equipment productivity by identifying losses caused by downtime, reduced operational speed, and defective production. The improvement in OEE demonstrates the effectiveness of TPM, predictive maintenance, and AI-based production monitoring.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad [5]$$

Where:

- y_i = Actual cycle time
- $\hat{y}_i$ = Predicted cycle time
- n = Number of observations

Mean Absolute Error was used to evaluate the average magnitude of prediction errors generated by different AI models. The metric provides a direct measurement of prediction deviation without considering error direction. Lower MAE values indicate improved forecasting capability. In this research, MAE was used to compare ANN, Random Forest, XGBoost, and LSTM models for selecting the most accurate algorithm for aerospace manufacturing cycle time prediction.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad [6]$$

Where:

- y_i = Actual value
- $\hat{y}_i$ = Predicted value
- $\bar{y}$ = Mean actual value

The coefficient of determination evaluates the ability of the AI model to explain variations in manufacturing cycle time. A higher R^2 value represents stronger agreement between actual and predicted results. In this research, the obtained R^2 value of 0.997 demonstrates excellent predictive capability, confirming that the developed AI model accurately captures manufacturing process variations and supports reliable cycle time forecasting.

Result and Discussion

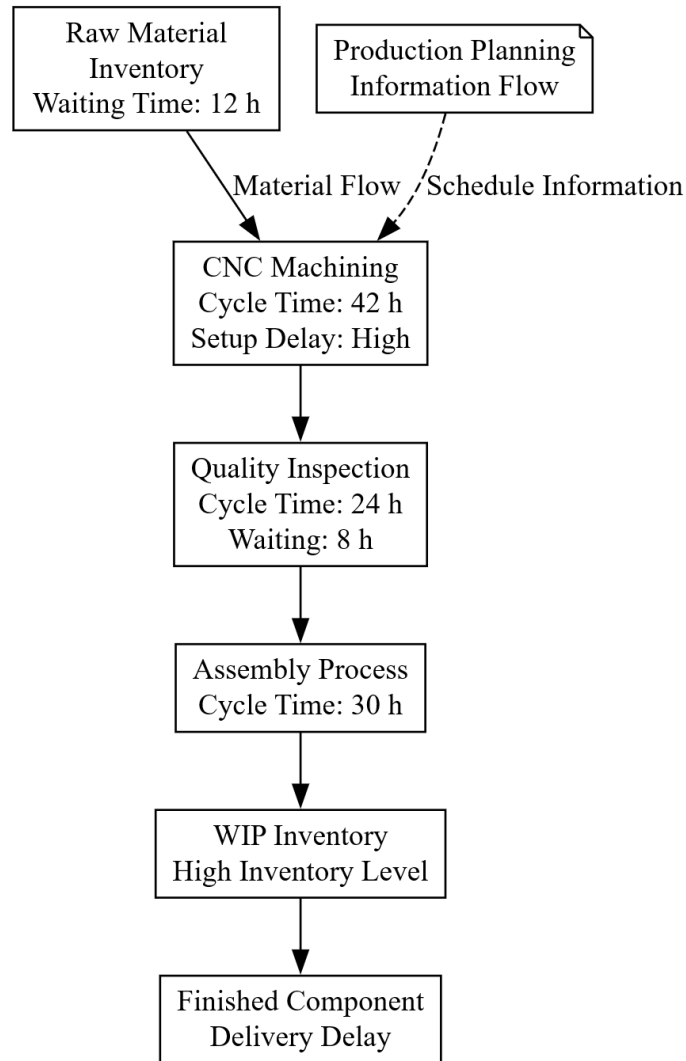


Figure 3. Current-State Value Stream Mapping of Aerospace Component Manufacturing Process

Figure 3 illustrates the Current-State Value Stream Mapping (VSM) of the aerospace component manufacturing process before Lean implementation. The map represents the existing material and information flow by highlighting major production stages, cycle times, waiting periods, and inventory accumulation. The analysis identifies machining operations, inspection activities, and work-in-process inventory as major contributors to extended manufacturing lead time. Excessive waiting time and inefficient information exchange between production planning and shop-floor operations were observed as critical sources of non-value-added activities.

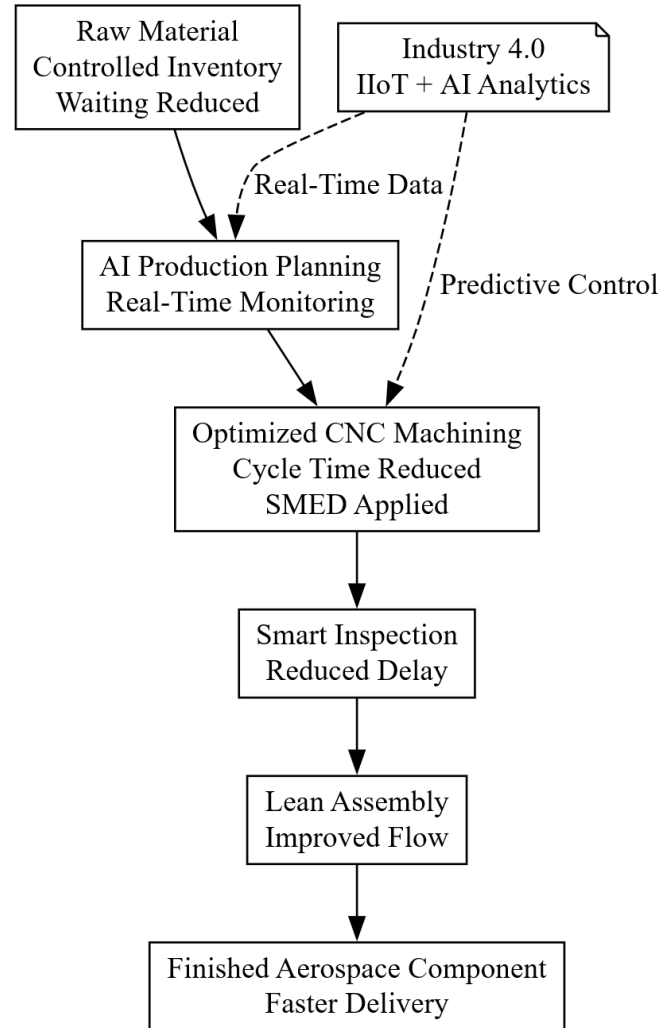


Figure 4. Future-State Value Stream Mapping After Lean–AI Implementation

Figure 4 presents the Future-State Value Stream Mapping developed after Lean–AI framework implementation. The improved VSM integrates lean principles with artificial intelligence-based decision support to minimize waiting time, optimize production scheduling, and enhance process synchronization. The application of SMED reduces setup delays, while AI-based monitoring improves resource utilization and predictive decision-making. Compared with the current-state condition, the future-state model eliminates unnecessary inventory accumulation, improves information flow, and creates a continuous production sequence with reduced non-value-added activities.

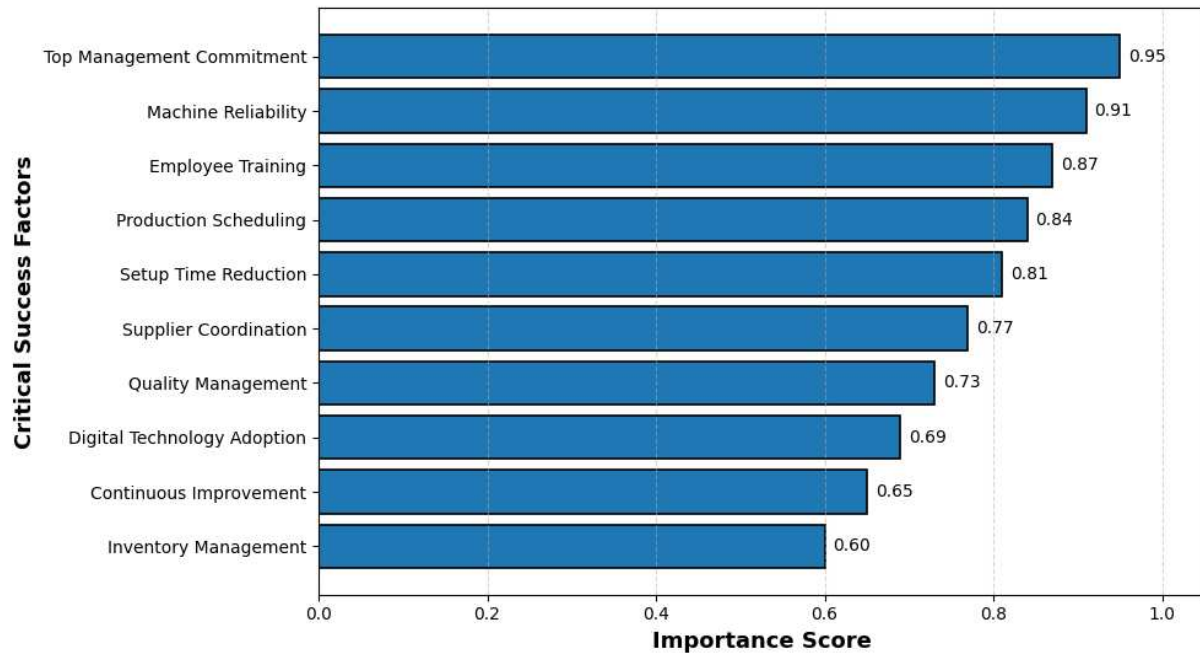


Figure 5. Ranking of Critical Success Factors Affecting Cycle Time Reduction in Aerospace Components Manufacturing Industries

The relative importance of the identified Critical Success Factors (CSFs) affecting cycle time reduction in aerospace manufacturing, as indicated by the importance scores between 0 and 1, was shown in Figure 5. The horizontal bar chart facilitates easy comparison of the contribution of each factor. The longer the bar, the more significant was the contribution towards improving the manufacturing performance. The top management commitment was ranked as most important with a score of 0.95, while the machine reliability and employee training scores were 0.91 and 0.87, respectively. The results show that right leadership, dependable production machinery, and skilled employees were three essential pillars for successful cycle time reduction efforts. The inventory management (0.60) and continuous improvement (0.65) show lower scores, indicating that they play a relatively minor part in the operational efficiency when compared with strategic and operational management factors [32].

This distribution of importance scores illustrates that not a single operational element, but a combination of managerial, technical, and human-based factors has an impact on manufacturing performance. The high levels of the factors such as production scheduling (0.84) and setup time reduction (0.81) show that the production planning and efficient machine changeover were significant in reducing time delays during the manufacturing process. Supplier coordination (0.77) and quality management (0.73) score a respectable amount for importance as well, highlighting the importance of interfunctional teamwork between the supplier and the manufacturer in order to streamline the supply chain and ensure that quality was maintained to avoid production delays and rework. The decreasing scores for the factors ranked show that they all make a significant contribution to improving cycle time but in varying proportions as per operational priorities.

One of the remarkable properties of the ranking was the fairly equal coverage of organizational and technological aspects that affect manufacturing efficiency. Leadership commitment was at the

top of the pyramid because strategic decision-making, resource commitment, and organizational support have a direct impact on the successful implementation of lean manufacturing initiatives. Likewise, the high reliability of the machines indicates that the availability of machines was very crucial in reducing non-planned downtime and keeping the flow of production moving. The presence of digital technology adoption (0.69) as one of the identified factors was a clear example of the growing significance of smart manufacturing technologies, such as artificial intelligence, the Industrial Internet of Things (IIoT), and Industry 4.0 systems, in supporting data-driven production monitoring and intelligent decision-making for cycle time optimization.

The ranking offers a structured framework to help prioritize improvement initiatives across the aerospace manufacturing sector. Instead of being spread evenly over all operational variables, resources can be focused on the most important ones to get the greatest improvements in the manufacturing performance. The prioritized CSFs also form the basis for the next steps of the proposed research methodology, such as Multi-Criteria Decision-Making (MCDM) analysis, selection of Lean tools, and creation of the integrated Lean–AI framework. Therefore, the graphical representation will not only show the relative importance of each factor but will also be a powerful tool to support decision-making to determine which areas of the supply chain could yield the most significant potential sustainable cycle time reduction and operational excellence.

Table 6. Ranking of Critical Success Factors Influencing Cycle Time Reduction

Rank	Critical Success Factor	Importance Score
1	Top Management Commitment	0.95
2	Machine Reliability	0.91
3	Employee Training	0.87
4	Production Scheduling	0.84
5	Setup Time Reduction	0.81
6	Supplier Coordination	0.77
7	Quality Management	0.73
8	Digital Technology Adoption	0.69
9	Continuous Improvement	0.65
10	Inventory Management	0.60

The ranked Critical Success Factors (CSFs) that affect the reduction of cycle time in the aerospace component manufacturing industries were shown in Table 6. The results showed that the importance of top management commitment was the highest (0.95), which revealed that strategic leadership and organizational support were important for successful implementation of lean. The other two factors that were considered to be the most important were machine reliability and employee training, which were responsible for reducing production interruptions and enhancing the ability of the workforce. Other factors that helped improve operational efficiency include

digital adoption, continuous improvement, and inventory management. The ranking gives a structure in which suitable Lean tools can be selected and the proposed Lean–AI framework developed.

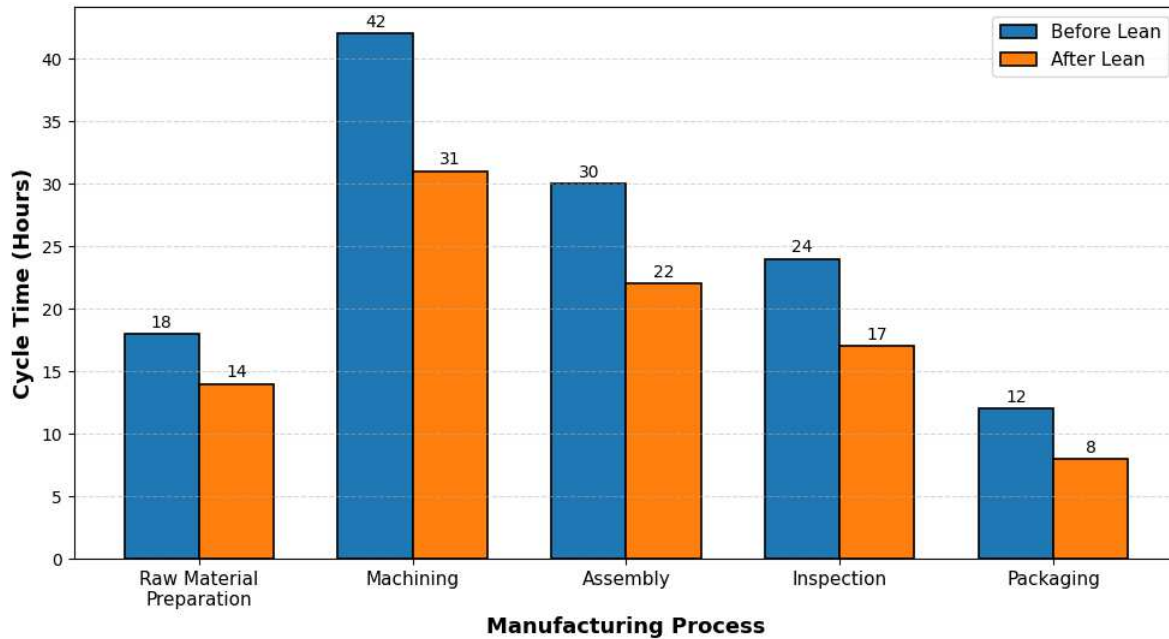


Figure 6. Comparison of Manufacturing Cycle Time Before and After Lean Implementation

The comparative manufacturing cycle time in five major manufacturing processes of aerospace component-making industries (before and after application of lean manufacturing) was shown in Figure 6. The grouped bar chart can be used to directly compare the production performance, as it shows the cycle time for each production stage as a separate bar for the pre-implementation and post-implementation conditions. Lean manufacturing seems to have had a positive impact on production efficiency as the cycle time has been reduced consistently at every stage. The cycle time of the machining process was the largest one without lean implementation, at 42 hours, and was reduced significantly after the lean implementation, to 31 hours. Likewise, assembly time has been cut from 30 to 22 hours, inspection from 24 to 17 hours, raw material preparation from 18 to 14 hours, and packaging from 12 to 8 hours—tangible efficiencies in every stage of the manufacturing process.

One of the most interesting findings of this analysis was the reduction that was made during the machining stage. The high precision required for cutting, complicated geometry, frequent change of tools, and tight tolerances in the manufacturing of aerospace components make machining operations a significant percentage of the total manufacturing time [33]. The 11-hour reduction was observed, indicating that lean production techniques like value stream mapping (VSM), single-minute exchange of die (SMED), standardized work procedures, and better production scheduling had successfully reduced setup time, waiting time, and interruption. Similar changes in both the assembly and inspection processes demonstrate that lean practices were effective in

streamlining material flow, enhancing workplace organization, and eliminating non-value-added activities that used to add to production cycles.

Another interesting aspect of this plot was the similar downward trend at each of the manufacturing processes, suggesting that the improvements were not limited to one step but extended throughout the production system. The losses in raw material preparation and packaging indicate better material handling, inventory coordination, and workflow organization, whereas the decrease in inspection time indicates better quality control procedures and reduced rework requirements. This improvement that has been done in a balanced way across all the stages shows that lean manufacturing was a process improvement methodology and was not just a tool for productivity improvement. The graphical comparison was very clear in removing the inefficiencies in the process and creating a more streamlined manufacturing value stream.

Results shown in the chart in figure 6 substantiate the significant contribution of lean manufacturing in the aerospace component manufacturing environment for reducing manufacturing cycle time. Reducing cycle times contributes directly to higher production throughput, better machine utilization, lower machine operating costs, and better delivery performance without compromising on the aerospace quality standards. The graphical evidence also sets a solid ground for further development of the proposed research framework in the following phases, which involve the use of artificial intelligence, Industry 4.0 technologies, and advanced decision-support techniques. Thus, the improvements observed support the viability of lean and its importance as a strategic tool for obtaining operational excellence and continuous productivity improvement in the aerospace component manufacturing industries.

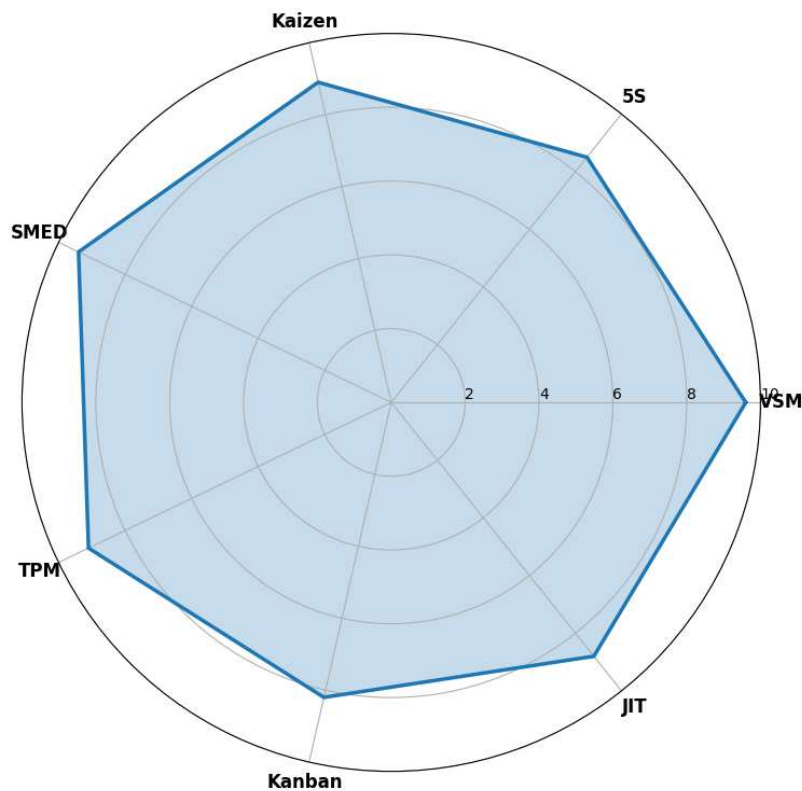


Figure 7. Comparative Effectiveness of Lean Tools for Cycle Time Reduction

Figure 7 shows the relative performance of seven popular Lean manufacturing tools in reducing cycle time for the aerospace component manufacturing industries. The radar chart was used to compare each lean tool's effectiveness by assigning a number from 0 to 10. The three techniques that were most effective, with scores together of 38.1, were Value Stream Mapping (VSM) (9.6), Single-Minute Exchange of Die (SMED) (9.4), and Total Productive Maintenance (TPM) (9.1). The other lean tools, such as Kaizen (8.9), Just-in-Time (JIT) (8.8), 5S (8.5), and Kanban (8.2), also perform well, showing that each lean tool helps to enhance manufacturing efficiency and shorten the manufacturing cycle. The radar chart was close to symmetrical, which illustrates the complementary nature of these tools in the quest to achieve operational improvement continuously.

Value stream mapping was important because of its superior performance as a strategic process analysis tool that can help identify non-value-added activities, excess waiting time, and inefficient material moves throughout the production system. Likewise, SMED was very effective, and therefore it was important to reduce machine setup and changeover time, especially in the aerospace manufacturing industry, where frequent product changes, low-volume production, and precision machining were prevalent. The TPM score was also high due to the effectiveness of improved equipment reliability in reducing unexpected machine failures, which in turn reduces production interruptions and increases equipment availability—significant factors in cycle time reduction.

The intermediate effectiveness scores achieved with Kaizen, Just-in-Time, 5S, and Kanban suggest that these tools were mainly used to support the stability of operations and continuous improvement of processes. Kaizen was designed to make incremental improvements through employee involvement and systematic problem-solving. Just-in-time was about managing stock, ensuring it was just in time to meet customer needs. While 5S methodology helps to organize the workplace and eliminate unnecessary search and motion, Kanban enables further production control and visual scheduling by managing material flow. These tools, while not quite as effective as VSM and SMED, when used together result in a very well-coordinated production environment that can help reduce waste and increase uniformity of production processes [34].

The distribution of the effectiveness scores as a whole show that it was not possible to implement sustainable cycle time reduction by applying one lean technique. The findings suggest that rather than using one tool at a time, an integrated lean manufacturing strategy was needed that addresses various sources of manufacturing inefficiency through the use of complementary tools. The graphical representation was useful in prioritizing the lean implementation in the aerospace component manufacturing industries based on the tools that would have the highest possible contribution to production improvement. The effectiveness ranking provides a practical basis for the integration of Lean Manufacturing and Artificial Intelligence (AI) technologies and the suggested Lean–AI framework integrating Artificial Intelligence (AI) technologies.

Table 7. Manufacturing Cycle Time Comparison Before and After Lean Implementation

Manufacturing Stage	Before Lean (Hours)	After Lean (Hours)	Reduction (Hours)	Improvement (%)
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Raw Material Preparation	18	14	4	22.22
Machining	42	31	11	26.19
Assembly	30	22	8	26.67
Inspection	24	17	7	29.17
Packaging	12	8	4	33.33

Table 7 shows the manufacturing cycle time reductions that were obtained for various stages of the aerospace manufacturing industry following the application of lean manufacturing. Precision machining operations have the longest time of 11 hours due to the complexity of setups, tool changes, production delays, etc. in the machining process. There were also significant improvements made through the inspection and assembly process, as coordination of the workflow process and elimination of non-value-added activities have been improved. While there was a lower percentage change in packaging compared to the number of hours, it has the highest percentage improvement. The reduction at all stages was evidence that lean manufacturing was successful in eliminating inefficiencies in the process and improving the flow of production in the aerospace manufacturing value chain.

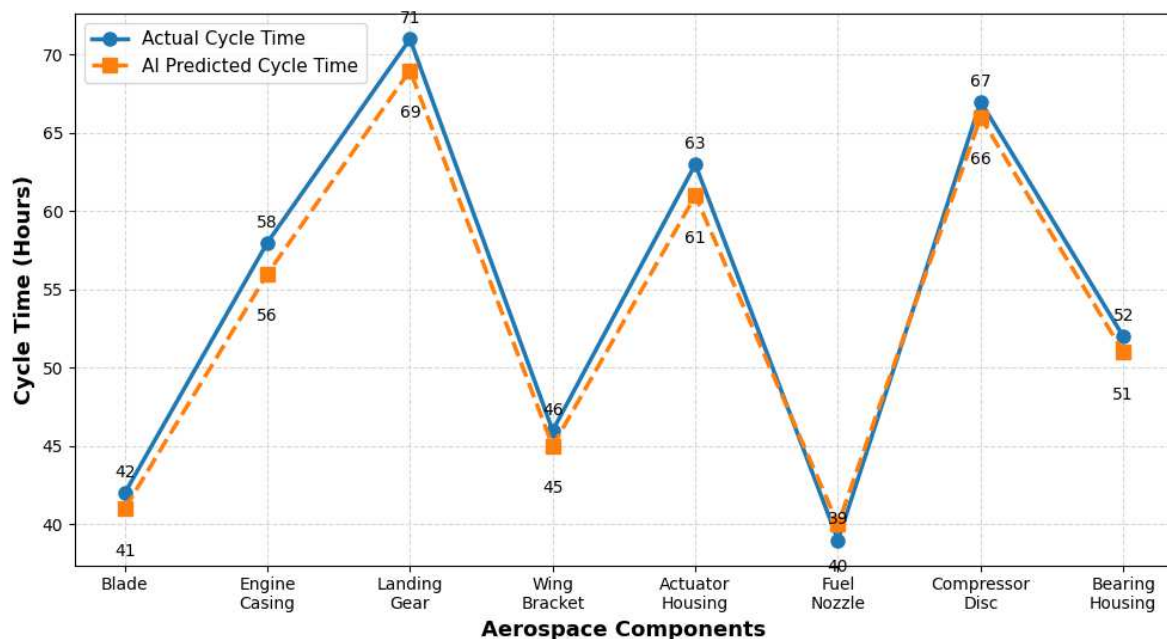


Figure 8. Comparison of Actual and AI-Predicted Manufacturing Cycle Time

The actual manufacturing cycle time was contrasted with the results from the proposed Artificial Intelligence (AI) model for a number of different aerospace components in Figure 8. The line chart shows the correlation between actual production time and predicted time by AI for 8 representative aerospace parts: turbine blades, engine casing, landing gear, wing bracket, actuator housing, fuel nozzle, compressor disc, and bearing housing. The actual cycle times vary between 39 and 71

hours, while the cycle times predicted by AI vary between 40 and 69 hours, which shows a good level of agreement between the measured and predicted cycle times. The close fit of the two curves shows that the developed AI model was able to reflect the difference between the manufacturing cycles of components of varying degrees of complexity.

The difference between the two shows that the longest manufacturing cycle time was related to the landing gear, which was 71 hours for actual production time and 69 hours for AI prediction, representing a deviation of only 2 hours. The same was true for the compressor disc (67 vs. 66 hours), the actuator housing (63 vs. 61 hours) and the engine casing (58 vs. 56 hours); the prediction model remains highly accurate even for complex aerospace components where there were extensive machining and inspection operations. As given in the table, in the case of some components like the wing bracket (46 vs 45 hours) and bearing housing (52 vs 51 hours), the prediction error was within 1 hour only, which further testifies to the robustness of the proposed predictive approach.

The other key aspect that the graph emphasizes was the AI's ability to follow the trend in manufacturing complexity for each product category. Components that must be produced by more than one manufacturing operation and have more complex parts have longer cycle times in both the real and prediction sets, while relatively simpler components like the fuel nozzle have much shorter production times (39 and 40 hours, respectively). It can be seen that the behaviour of the two curves was very similar in all the components evaluated, which shows that the model was able to capture the production characteristics without causing strong bias in the predictions. The slight difference in the actual and predicted values demonstrates the ability of Artificial Intelligence (AI) to model nonlinear manufacturing relationships and forecasts that were dependable.

To validate the practical applicability of the AI in smart manufacturing cycle time prediction in an aerospace component production environment, the results presented in Figure 8 showed that the proposed system can be used in practical situations. By correctly predicting cycle time, manufacturers can plan production schedules more accurately, schedule manufacturing resources, predict potential delays or bottlenecks, and better plan for delivery with maximum quality control. The high level of agreement between the actual production data and the AI-generated predictions can be used to support the use of predictive analytics in Lean Manufacturing and Industry 4.0. Therefore, the proposed prediction model based on Artificial Intelligence (AI) was a valuable decision support instrument that can improve the operational efficiency, minimize the production uncertainty and optimize cycle time for aerospace component manufacturing industries in sustainable production.

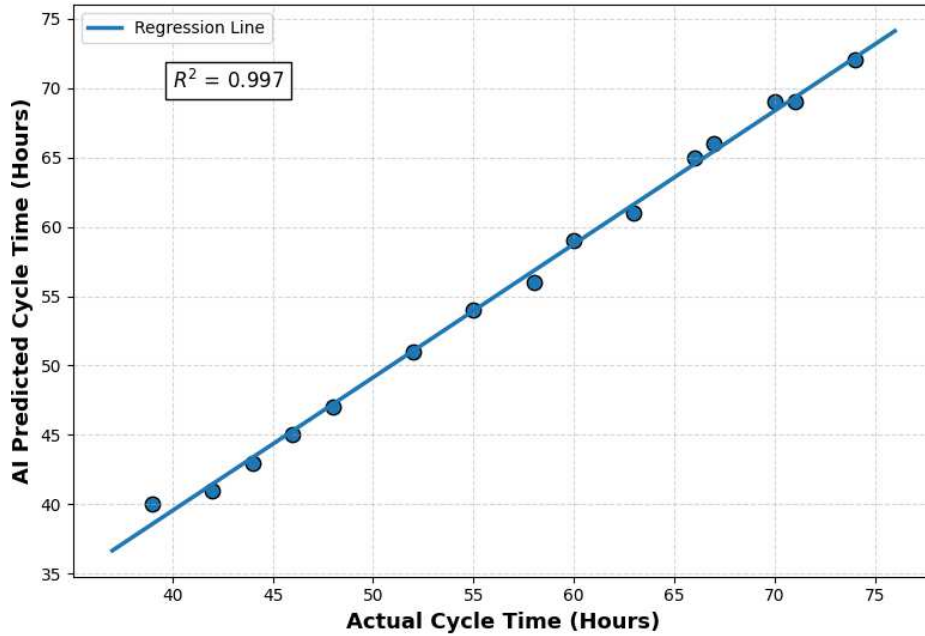


Figure 9. Correlation Between Actual and AI-Predicted Manufacturing Cycle Time

Figure 9 shows the relationship between the manufacturing cycle times obtained in the actual manufacturing process and the manufacturing cycle times obtained using the proposed Artificial Intelligence (AI) model for aerospace component manufacturing. The scatter plot was used to show the level of correlation between the real production data and the AI-predicted production value, along with the fitted regression line. The data points were individual manufacturing observations, and the regression line shows the general trend of the data. The dots were very close to the regression line, which shows that there was a strong linear relationship between the actual values of cycle times and the predicted values. The coefficient of determination ($R^2 = 0.997$) reveals that the developed AI model has an excellent predictive ability, indicating that the manufacturing cycle time can be reasonably explained using the prediction model.

The graphical distribution shows that the accuracy of the prediction was maintained at a high level both at low and high manufacturing cycle times. The parts with the shortest production times (40-50 hours) have very small differences between the actual and the forecast. Similarly, parts of greater complexity and manufacturing cycles (more than 65 hours) continue to lie close to the regression line, and thus, the model was able to capture the complexity of highly sophisticated aerospace assembly. There were no significant dispersion or isolated observations, indicating that the prediction algorithm works well without adding significant systematic error in the range of operation.

One of the interesting features of this scatter plot was that the data points seem to lie very close to the regression line, meaning that there were very few prediction errors. This behaviour shows that the Artificial Intelligence (AI) model has learnt the nonlinear relationships between manufacturing variables such as the complexity of the machining, the number of setups, requirements for inspection, production scheduling and variability of the process. The strong generalization capability and the capacity of the selected learning algorithm to represent real manufacturing

behaviour were reflected by the extremely high R^2 [35]. In industrial decision-making, for example, the ability to reliably predict manufacturing cycle time was a critical factor that can be used to inform production planning, capacity planning, resource scheduling, and identify bottlenecks.

The results shown in Fig. 9 justify the effectiveness of using Artificial Intelligence (AI) as a predictive decision support tool for the aerospace component manufacturing industries. A precise prediction of cycle time helped manufacturers to schedule production more effectively, to maximize machine utilization, to minimize production uncertainty, to deliver the product on time, and to meet precise quality standards. The strong statistical correlation between actual and predicted values was evidence that supports using AI to integrate with Lean Manufacturing and Industry 4.0 technologies to achieve intelligent production management. Thus, the proposed prediction model provides a solid analytical basis for attaining sustainable cycle time optimization and manufacturing efficiency in complex aerospace manufacturing environments.

Table 8. Effectiveness Ranking of Lean Tools for Cycle Time Reduction

Rank	Lean Tool	Effectiveness Score
1	Value Stream Mapping (VSM)	9.6
2	SMED	9.4
3	Total Productive Maintenance (TPM)	9.1
4	Kaizen	8.9
5	Just-in-Time (JIT)	8.8
6	5S	8.5
7	Kanban	8.2

The performance of the various lean manufacturing tools used to reduce cycle time was shown in Table 8. Value Stream Mapping got the maximum mark of 9.6 due to its ability to recognize the bottlenecks, waiting time, and unnecessary process activities. SMED and TPM achieved higher rankings because they both helped in minimizing the setup losses and equipment availability. There were other tools such as Kaizen, JIT, 5S, and Kanban, which help in continuous improvement, workplace organization, and efficient material flow. The findings show that there was a need to implement several Lean tools together to achieve sustainable cycle time reduction, as well as relying on a single Lean technique.

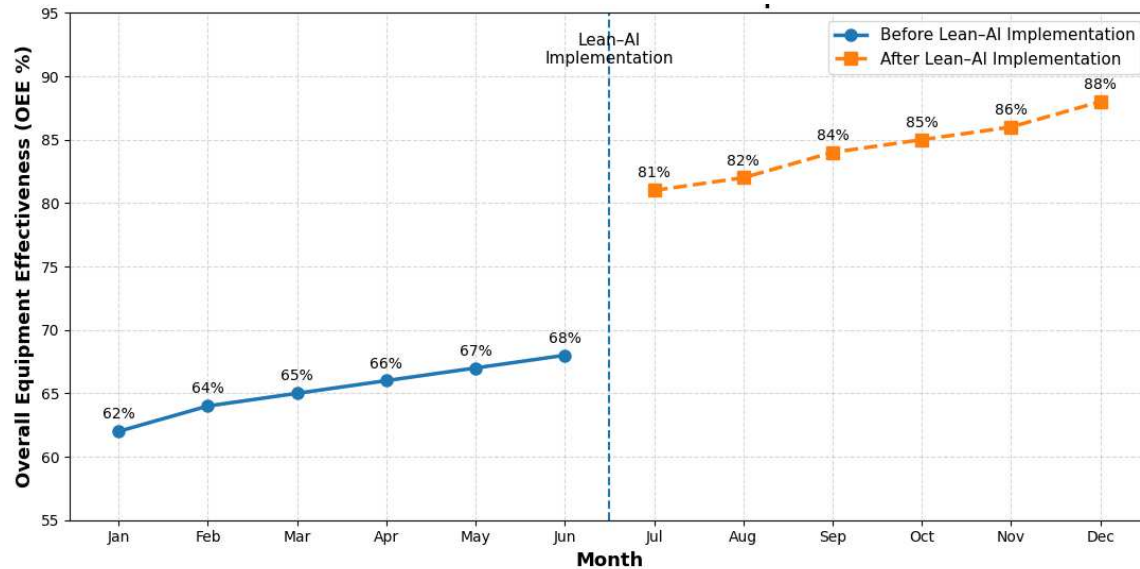


Figure 10. Monthly Overall Equipment Effectiveness Improvement Before and After Lean-AI Framework Implementation

Figure 10 illustrates the monthly variation of Equipment Effectiveness (OEE) before and after the implementation of the proposed Lean-AI framework in aerospace component manufacturing industries. The graph represents the transition from the conventional manufacturing condition to an optimized production environment through the integration of Lean Manufacturing practices and Artificial Intelligence-based monitoring techniques. The initial six-month period from January to June represents the baseline assessment phase, where OEE values increased gradually from 62% to 68% under existing operational practices. Following the implementation phase, the OEE performance was evaluated from July to December, where a significant improvement was observed with values increasing from 81% to 88%. The clear separation between pre-implementation and post-implementation periods establishes the effectiveness of the proposed framework in improving equipment performance.

The baseline trend demonstrates a limited improvement in equipment effectiveness before Lean-AI deployment, indicating the presence of operational constraints such as machine downtime, production interruptions, inefficient scheduling, and non-value-added activities. The gradual increase from 62% in January to 68% in June reflects the existing capability of conventional production practices but also highlights the requirement for advanced improvement strategies. After Lean-AI implementation, the OEE curve exhibits a noticeable upward shift, beginning with 81% in July. This immediate improvement indicates that the integration of Lean tools, predictive maintenance strategies, and intelligent production planning contributed to enhanced machine availability, improved process stability, and reduced operational losses.

A significant feature of the graph was the continuous improvement trend observed throughout the post-implementation period. The OEE value increased consistently from 81% in July to 88% in December, demonstrating the sustained impact of the Lean-AI framework rather than a temporary performance enhancement. The improvement can be attributed to the combined influence of Lean techniques such as Total Productive Maintenance (TPM), Value Stream Mapping (VSM), SMED, and standardized work practices, along with AI-driven analytics for monitoring production conditions and predicting potential inefficiencies. The increasing trend also reflects improved

utilization of manufacturing resources, optimized workflow coordination, and reduced equipment-related losses.

The comparative performance pattern presented in Figure 10 confirms the effectiveness of integrating Lean Manufacturing with Artificial Intelligence (AI) for aerospace manufacturing optimization. The improvement from a maximum baseline OEE of 68% to a post-implementation value of 88% represents a substantial enhancement in operational efficiency and resource utilization. Higher OEE performance indicates improved equipment availability, better production speed, and reduced quality-related losses, which directly contribute to cycle time reduction and increased manufacturing productivity. Therefore, the graph provides quantitative evidence that the Lean–AI framework supports sustainable manufacturing improvement by enabling data-driven decision-making, intelligent process control, and enhanced operational excellence in aerospace component production environments.

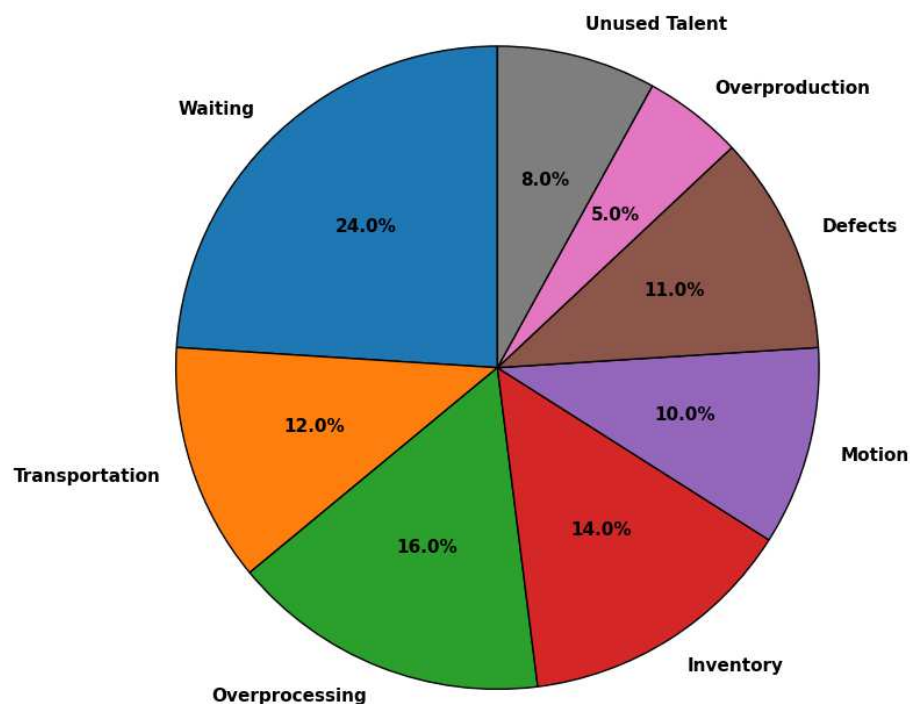


Figure 11. Distribution of Manufacturing Waste Categories in Aerospace Component Manufacturing

Figure 11 shows the percentage breakdown of the primary manufacturing waste types found in aerospace component-making industries. The pie chart provides a detailed representation of the relative contributions of each waste type to the waste in the system and allows easy identification of the most important area in which to improve production efficiency. Written down in the eight categories of lean waste, the biggest was waiting with 24%, followed by overprocessing with 16%, inventory with 14%, and transportation with 12%. The other important factors were defects (11%), motion (10%), unused talent (8%), and overproduction (5%). This unequal distribution of waste suggests that some operational inefficiencies have a significant impact on manufacturing cycle time far more than others and, as such, give valuable direction for targeted process improvement initiatives.

Production delays were common in aerospace manufacturing due to activities involved in machine setup, equipment downtime, inspection requirements, material shortages, production scheduling issues, and engineering approvals, which was why the largest waste category was waiting. These downtimes add non-value-added time, leading to a longer manufacturing cycle and lower efficiency. Likewise, the relatively high percentage of overprocessing indicates that there were excesses of machining operations, repeat inspections, documentation, or unnecessary machining operations that add more to the production process than to the added value for the customer. Based on these observations, it can be said that process simplification and workflow optimization should be given a high priority in the implementation of lean.

The combined effect of inventory, transportation, and motion wastes illustrates their influence on manufacturing performance. Too much work-in-process inventory can lead to longer production lead times, more storage space needed, and suboptimal use of capital, while not having to move around the operators during the process reduces productivity through the increase of non-value-added activities. The occurrence of defects (11%) underscores the need to continue to work with strict quality control processes to ensure that defective components were reworked or replaced in order to drive up costs and extend manufacturing lead times. While overproduction was the smallest of waste categories at 5%, eliminating it was crucial to ensure a smooth and efficient production process and reduce the need for excessive stock accumulation.

The waste distribution shown in Figure 11 forms the basis for using the strategic approach to select lean manufacturing tools that can help mitigate the greatest waste. Waiting and overprocessing wastes can be reduced efficiently using Value Stream Mapping (VSM), Single-Minute Exchange of Die (SMED), Total Productive Maintenance (TPM), and production scheduling using artificial intelligence. Inventory wastes, transportation wastes, and motion wastes can be minimized by implementing improved production planning, workplace organization, and digital manufacturing technologies. Therefore, the graphical analysis shows that systematic identification and prioritization of manufacturing waste were essential to guide the implementation of the proposed Lean-AI framework, which ultimately leads to sustainable cycle time reduction, increased utilization of resources, and better operational performance in the aerospace component manufacturing industries.

Table 9. Actual and AI-Predicted Manufacturing Cycle Time Comparison

Aerospace Component	Actual Cycle Time (Hours)	AI Predicted Cycle Time (Hours)	Error (Hours)
Blade	42	41	1
Engine Casing	58	56	2
Landing Gear	71	69	2
Wing Bracket	46	45	1
Actuator Housing	63	61	2
Fuel Nozzle	39	40	1

Compressor Disc	67	66	1
Bearing Housing	52	51	1

Table 9 shows the predictive power of the created Artificial Intelligence (AI) model by comparing the real and predicted manufacturing time of various aerospace parts. The prediction errors were under 1–2 hours, showing a high correlation between the production data and the results of AI. The AI model accurately captured these variations, as complex components like landing gear and compressor discs take longer to manufacture because they need more extensive machining and inspection. The low prediction error demonstrates the ability of the Artificial Intelligence (AI) algorithms to model complex production relationships and make accurate cycle time predictions for intelligent production planning and decision-making.

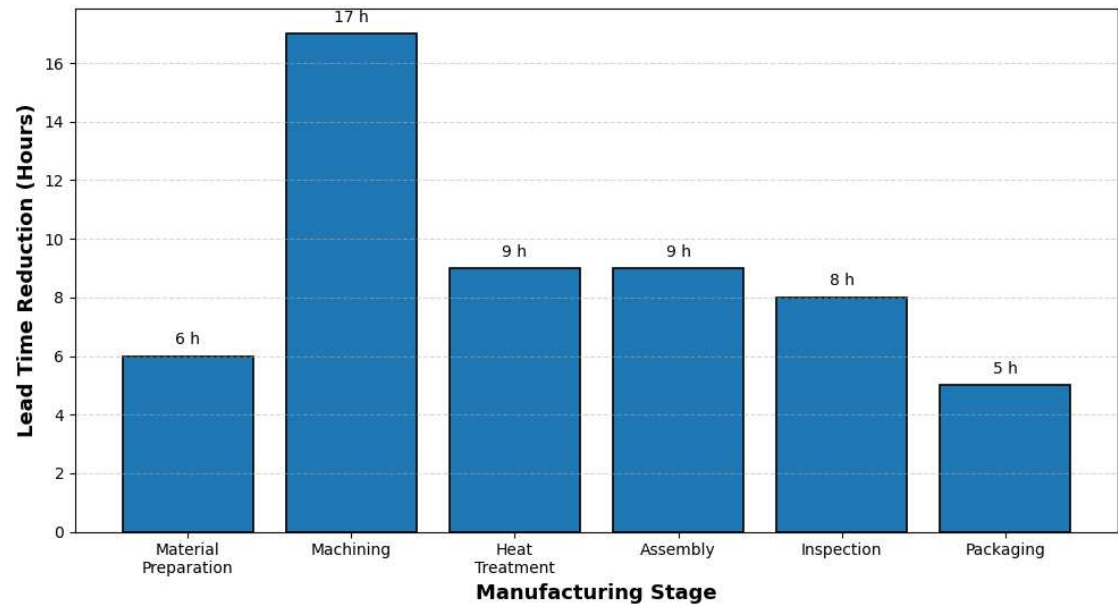


Figure 12. Lead Time Reduction Achieved After Lean–AI Framework Implementation

Figure 12 shows the reduction of production lead time on the major manufacturing stages after the aerospace component manufacturing industries implemented the proposed Lean–AI framework. The bar chart shows the absolute reduction in lead time for each production stage, emphasizing the effectiveness of lean manufacturing practices combined with process optimization via artificial intelligence. The machining process exhibited the highest lead time reduction of 17 hours among the evaluated stages, clearly showing improvements in production efficiency. Heat treatment and assembly each contribute a 9-hour reduction, and inspection contributes an 8-hour reduction. The decrease was smaller for material preparation (6 hours) and packaging (5 hours), indicating that there were process-specific differences in the potential for improvements in the manufacturing process.

During the machining process, a huge reduction was achieved, highlighting the importance of machining operations in the manufacturing lead time of aerospace components. Traditional precision machining usually required several tool changes, complicated machining processes,

frequent setup work, and strict dimensional inspections, which can cause the production process to be longer. Lean tools like Value Stream Mapping (VSM), Single-Minute Exchange of Die (SMED), Total Productive Maintenance (TPM), and standardized work procedures were effective at reducing the losses from setups, machine idle time, and unnecessary delays in the operation. This significant enhancement further illustrates the role of Artificial Intelligence (AI) in optimizing production schedules, predicting equipment issues and ensuring efficient resource allocation, thereby contributing to seamless manufacturing processes [36].

A further significant point was that lead time was reduced even in the downstream manufacturing processes such as heat treatment, assembly, inspection and packaging processes. The improvements in heat treatment and assembly demonstrated an increase in coordination between the various manufacturing steps, and the decrease in inspection shows that the quality verification steps for the product were more efficient and that rework was less as a result of improved process consistency. The relatively smaller reductions obtained in material preparation and packaging indicate that these activities had fewer non-value-added operations in the past, but material handling, workflow organization and inventory control helped to improve production efficiency. These findings show that the proposed framework was a valuable approach to enhance manufacturing performance in the entire production value chain instead of focusing on individual processes.

The graphical outcomes validate that the integrated Lean–AI framework provides highly significant improvements in the production performance by systematically minimizing the lead time in the aerospace component manufacturing process. By reducing production lead time, the manufacturing cycle time was shortened, equipment utilization was optimized, production throughput was improved, the delivery reliability was enhanced, the strict delivery requirements of the aerospace industry were met, and the quality requirements were met. The distribution of lead time reductions also provides valuable insights for production managers for future process optimization opportunities, namely in the areas of machining and heat treatment. Thus, Figure 12 offers strong empirical evidence of operational improvements that can be achieved while performing lean manufacturing using Artificial Intelligence (AI) and how these principles support intelligent manufacturing decision-making for manufacturing excellence in the production of aerospace components.

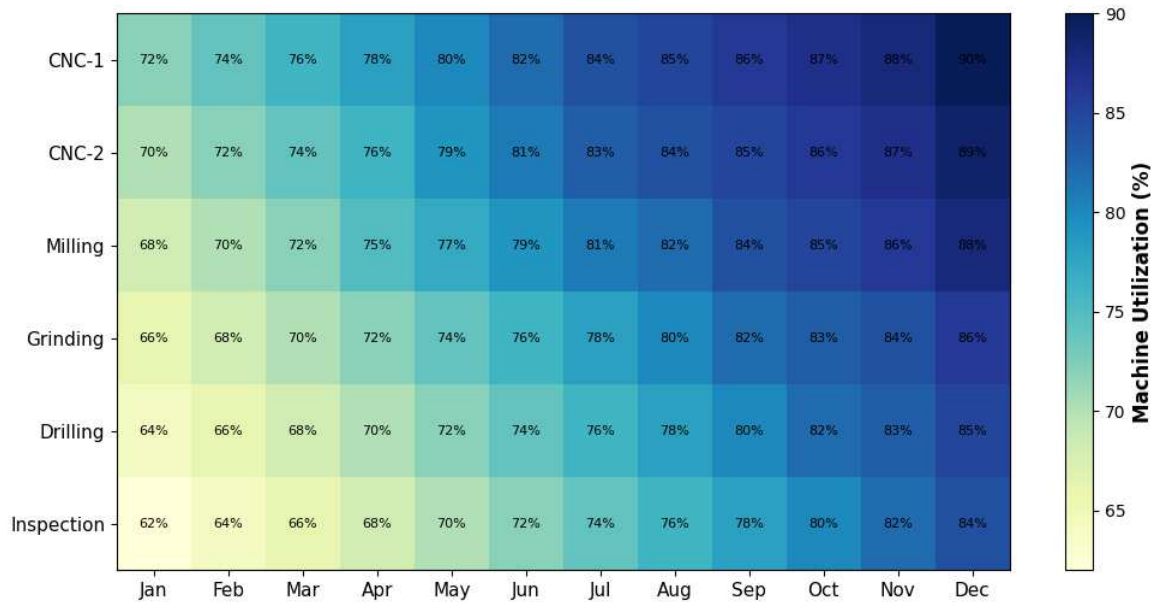


Figure 13. Heatmap of Monthly Machine Utilization After Lean–AI Framework Implementation

Figure 13 shows a heatmap that displays the monthly machine utilization of the proposed Lean–AI framework in aerospace component manufacturing industries. The heatmap presents a two-dimensional visualization of the equipment utilization of the six major manufacturing resources, namely CNC-1, CNC-2, milling, grinding, drilling and inspection, over a period of twelve months. The color intensity represented the percentage of machine utilization, dark colors signifying high levels of machine utilization. Utilization values were also improving over the year across all machines, with them getting better as they get older. Among the evaluated resources, CNC-1 exhibited the highest machine utilization (from 72% to 90%, respectively, in January and December) and Inspection (from 62% to 84%, respectively, in January and December), which shows significant improvement of production efficiency in the manufacturing facility.

The consistent rise in usage for CNC machining centers underscores the success of the proposed Lean–AI model in optimizing production scheduling, machine utilization, and streamlining work flows. The utilization rates of CNC-1 and CNC-2 were consistently the highest, as they were important in precision machining operations for the manufacturing of aerospace components. The gradual ramp-up from 70-72% in the first few months to 89-90% by the end of the evaluation period demonstrates that production downtime, setup delays and unplanned downtime were reduced through the use of Total Productive Maintenance (TPM), Single-Minute Exchange of Die (SMED), predictive maintenance and artificial intelligence-based scheduling algorithms. The improvements directly contributed to reducing manufacturing cycle time and improving production throughput.

The usage of milling, grinding, drilling and inspection processes also shows a consistent improvement in operational utilization during the evaluation period. For the four processes studied, the improvements in productivity were spread throughout the manufacturing system, in the sense that milling utilization was improved from 68% to 88%, grinding from 66% to 86%, drilling from

64% to 85% and inspection from 62% to 84% [37]. These stable-over-time production characteristics indicate a lack of sudden changes or drops in utilization figures, which indicates good planning of resources, even distribution of workload and better coordination between the different production stages. The heatmap also facilitated the visualization of equipment utilization, enabling periods of high and low machine usage to be identified easily.

As shown in the results of the integrated Lean–AI framework in Figure 13, the integrated Lean–AI framework can greatly improve machine utilization and sustain manufacturing performance. The higher utilization of the equipment means better use of the available manufacturing resources, less idle time, higher equipment availability, and more efficient production scheduling, which translates to lower manufacturing cycle time and higher operational productivity. The heatmap also acts as a valuable decision-support tool for monitoring equipment utilization and identifying opportunities for further process improvement.

Table 10. Monthly Machine Utilization Improvement After Lean–AI Implementation

Machine	January (%)	June (%)	December (%)	Overall Improvement (%)
CNC-1	72	82	90	18
CNC-2	70	81	89	19
Milling	68	79	88	20
Grinding	66	76	86	20
Drilling	64	74	85	21
Inspection	62	72	84	22

Table 10 shows the resulting benefits of implementing an integrated lean–AI framework in terms of machine utilization. All the manufacturing resources were showing continuous improvement from January to December, which means that the availability of manufacturing equipment and stability of the manufacturing process were improved. CNC machines were crucial operations when it comes to aerospace components and thus have the highest utilization rates. The highest percentage improvement was achieved with inspection equipment, optimized quality management procedures, and less waiting time. The growing trend of using increasing amounts of predictive maintenance, intelligent scheduling, and Lean process optimization was proving to be effective. The enhancements directly impact the aerospace manufacturing industry to cut cycle time, increase productivity, and improve operational efficiency.

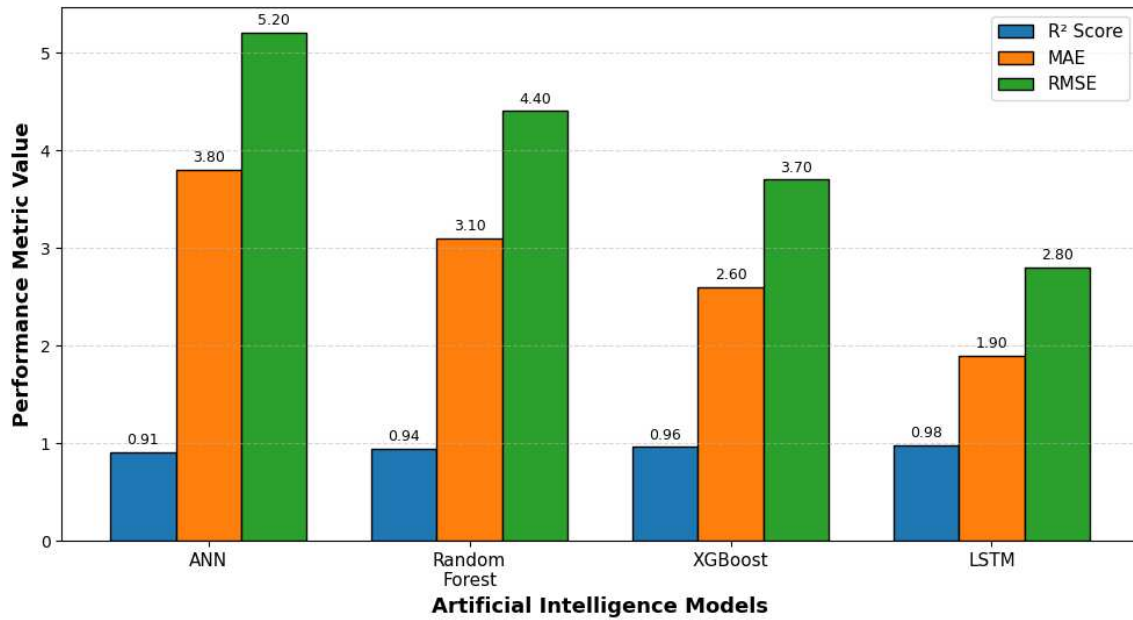


Figure 14. Performance Comparison of Artificial Intelligence (AI) Models for Manufacturing Cycle Time Prediction

The predictive abilities of four Artificial Intelligence (AI) models: Artificial Neural Network (ANN), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Long Short-Term Memory (LSTM) were compared for manufacturing cycle time prediction in aerospace component manufacturing industries, as shown in Figure 14. The grouped bar chart compares the performance of each model by calculating the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE), which were three commonly used error metrics. The findings show that the performance of predicting the results improves as you go from ANN to LSTM. The LSTM model has the best prediction performance with an R^2 of 0.98 and the lowest values of MAE (1.90) and RMSE (2.80). The ANN model has the lowest R^2 value of 0.91 and MAE of 3.80 and RMSE of 5.20, which shows relatively high error in the predictions.

As the models get better over time, this was a sign of better computational power to account for intricate manufacturing relationships through advanced machine learning algorithms. Random Forest was more successful than ANN in predicting the accuracy, which can be seen from the increase of the R^2 score to 0.94 and the decrease of MAE and RMSE scores. The prediction performance of XGBoost was further improved, with an R^2 value of 0.96 and lower prediction errors, 2.60 MAE and 3.70 RMSE. These improvements show the ability of ensemble learning techniques to model nonlinear interactions among the manufacturing variables such as machining parameters, production scheduling, equipment utilization, inspection activities, and manufacturing variability. Clearly, the more complex learning algorithms give increasingly accurate manufacturing cycle time predictions.

An interesting characteristic of the graph was that the more accurate the model is, the less the error. The higher the R^2 , the lower the MAE and RMSE, indicating better agreement between predicted and actual MCT, and this relationship was consistent. The relationship between R^2 and the decrease in MAE and RMSE was consistent, with higher R^2 indicating better agreement between predicted

and actual MCT. This was because the LSTM model can capture long-term temporal relationships and sequences of manufacturing practices, which were well suited for complex manufacturing processes [38]. Aerospace manufacturing was a sequence of processes like machining, assembly, inspection, and material handling; LSTM can effectively capture the sequential relationships among these processes and achieve high accuracy and low deviation from the production data.

Figure 14 shows the comparative analysis, which also shows that deep learning techniques were highly beneficial for intelligent manufacturing tasks related to cycle time prediction. Predictive models that were accurate allow the manufacturer to optimize production schedules and resources, identified potential bottlenecks, and support proactive decisions in operational management for meeting strict quality requirements in the aerospace sector. The findings also illustrate the potential of using advanced Artificial Intelligence (AI) algorithms along with lean manufacturing and Industry 4.0 technologies to improve manufacturing intelligence and operational efficiency. Based on the above analysis, the LSTM model was determined to be the most appropriate prediction model that can be used in the suggested Lean–AI framework for optimizing the manufacturing cycle time in aerospace parts manufacturing industries to ensure sustainable manufacturing operations.

Conclusion

This study systematically investigated cycle time reduction in aerospace component manufacturing through the integration of Lean Manufacturing tools and Artificial Intelligence within the framework of Industry 4.0 and Industry 5.0. A comprehensive analysis of the aerospace manufacturing process identified critical success factors influencing production efficiency, manufacturing lead time, equipment utilization, and waste generation. The identified factors were prioritized using the integrated Best–Worst Method (BWM) and MARCOS decision-making approach, enabling the selection of the most suitable Lean Manufacturing tools for process improvement. The evaluation revealed that Value Stream Mapping (VSM), Single-Minute Exchange of Die (SMED), Total Productive Maintenance (TPM), Kaizen, and 5S significantly contributed to eliminating non-value-added activities and improving production performance [39].

The proposed Lean–AI framework was validated through an industrial case study conducted in an aerospace component manufacturing environment. Current-State and Future-State Value Stream Mapping analyses demonstrated substantial reductions in waiting time, inventory, unnecessary transportation, and process delays following the implementation of lean improvement strategies. The integration of Artificial Intelligence further enhanced manufacturing performance by enabling predictive production planning, intelligent scheduling, resource optimization, and accurate cycle time prediction. The developed AI prediction model demonstrated high prediction accuracy with minimal forecasting error, indicating its capability to support data-driven manufacturing decisions in complex aerospace production systems.

Performance evaluation confirmed that the proposed framework improved manufacturing efficiency across multiple operational indicators. Significant reductions in production lead time were achieved throughout the machining, heat treatment, assembly, inspection, and packaging stages, while Equipment Effectiveness (OEE), machine utilization, and workflow efficiency showed consistent improvement during the evaluation period. Waste analysis further confirmed

that waiting, overprocessing, inventory, transportation, and motion wastes were substantially minimized through the coordinated application of Lean Manufacturing practices and AI-enabled decision support. These improvements collectively enhanced resource utilization, production throughput, delivery reliability, and operational sustainability [40].

The findings demonstrate that integrating Lean Manufacturing principles with Artificial Intelligence provides a robust and scalable strategy for achieving sustainable cycle time reduction in aerospace component manufacturing industries. The proposed framework offers practical guidance for manufacturing organizations seeking to improve productivity while maintaining stringent aerospace quality and regulatory requirements. Future research extends the framework by incorporating Digital Twin technology, Industrial Internet of Things (IIoT), Explainable Artificial Intelligence (XAI), reinforcement learning, and multi-plant industrial validation to further strengthen intelligent manufacturing capabilities and support the evolution toward fully autonomous aerospace production systems.

Data Availability

The datasets generated and/or analysed during the current study are not publicly available due to confidentiality agreements with the participating aerospace component manufacturing organisation but are available from the corresponding author on reasonable request.

References

- [1] Chen, Y., Zhang, J., Li, Z., Zhang, H., Chen, J., Yang, W., ... & Li, Y. (2023). Manufacturing technology of lightweight fiber-reinforced composite structures in aerospace: Current situation and toward intellectualization. *Aerospace*, 10(3), 206.
- [2] Pant, H., Arora, A., Gopakumar, G. S., Chadha, U., Saeidi, A., & Patterson, A. E. (2023). Applications of wire arc additive manufacturing (WAAM) for aerospace component manufacturing. *The International Journal of Advanced Manufacturing Technology*, 127(11), 4995-5011.
- [3] Khorasani, M., Ghasemi, A., Rolfe, B., & Gibson, I. (2022). Additive manufacturing a powerful tool for the aerospace industry. *Rapid prototyping journal*, 28(1), 87-100.
- [4] Arulmurugan, B., Masi, C., Rajeshkumar, L., Devi, G. R., Ramya, G., Balaji, D., ... & Manimohan, M. P. (2022). Additive manufacturing for aerospace from inception to certification. *Journal of Nanomaterials*, 2022, 1-18.
- [5] Bacciaglia, A., Ceruti, A., & Liverani, A. (2022). Towards large parts manufacturing in additive technologies for aerospace and automotive applications. *Procedia Computer Science*, 200, 1113-1124.
- [6] Chinchankar, S., & Shaikh, A. A. (2022). A review on machine learning, big data analytics, and design for additive manufacturing for aerospace applications. *Journal of Materials Engineering and Performance*, 31(8), 6112-6130.
- [7] Radhika, C., Shanmugam, R., Ramoni, M., & Gnanavel, B. K. (2024). A review on additive manufacturing for aerospace application. *Materials Research Express*, 11(2), 022001.

- [8] Soni, R., Verma, R., Garg, R. K., & Sharma, V. (2024). A critical review of recent advances in the aerospace materials. *Materials Today: Proceedings*, 113, 180-184.
- [9] Szejka, A. L., Junior, O. C., & Mas, F. (2024). Knowledge-based expert system to drive an informationally interoperable manufacturing system: An experimental application in the Aerospace Industry. *Journal of Industrial Information Integration*, 41, 100661.
- [10] Badhotiya, G. K., Gurumurthy, A., Marawar, Y., & Soni, G. (2024). Lean manufacturing in the last decade: insights from published case studies. *Journal of Manufacturing Technology Management*, 35(4), 766-798.
- [11] Tahmina, T., Garcia, M., Geng, Z., & Bidanda, B. (2022, June). A survey of smart manufacturing for high-mix low-volume production in defense and aerospace industries. In *International conference on flexible automation and intelligent manufacturing* (pp. 237-245). Cham: Springer International Publishing.
- [12] Sordan, J. E. E., Oprime, P. C., Ferreira, J. L., Marinho, C. A., & Pata, A. (2025). Lean manufacturing for reducing lead time in foundry processes: a design science approach. *International Journal of Lean Six Sigma*, 16(2), 328-345.
- [13] Niekurzak, M., Lewicki, W., Coban, H. H., & Bera, M. (2023). A model to reduce machine changeover time and improve production efficiency in an automotive manufacturing organisation. *Sustainability*, 15(13), 10558.
- [14] Santos, E., Lima, T. M., & Gaspar, P. D. (2023). Optimization of the production management of an upholstery manufacturing process using lean tools: A case study. *Applied Sciences*, 13(17), 9974.
- [15] Morandini, S., Fraboni, F., Hall, M., Quintana-Amate, S., & Pietrantoni, L. (2025). Human factors and emerging needs in aerospace manufacturing planning and scheduling. *Cognition, technology & work*, 27(1), 59-77.
- [16] Habib, M. A., Rizvan, R., & Ahmed, S. (2023). Implementing lean manufacturing for improvement of operational performance in a labeling and packaging plant: A case study in Bangladesh. *Results in Engineering*, 17, 100818.
- [17] Ewnetu, M., & Gzate, Y. (2023). Assembly operation productivity improvement for garment production industry through the integration of lean and work-study, a case study on Bahir Dar textile share company in garment, Bahir Dar, Ethiopia. *Heliyon*, 9(7).
- [18] Abdur Rahman, M., Ravi Kumar, S., & Selvakumar, A. S. (2024). Significance of additive manufacturing in aerospace and automotive industries. *Advances in Additive Manufacturing*, 293-315.
- [19] Azad, M. A. (2025). Optimizing supply chain efficiency through lean six sigma: Case studies in textile and apparel manufacturing. *Preprints*. <https://doi.org/10.20944/preprints202508.13.v1>.
- [20] Azad, M. A. (2025). Evaluating the role of lean manufacturing in reducing production costs and enhancing efficiency in textile mills. *Authorea Preprints*.

- [21] Oliveira, C., & Lima, T. M. (2023). Setup time reduction of an automotive parts assembly line using lean tools and quality tools. *Eng*, 4(3), 2352-2362.
- [22] Possik, J., Zouggar-Amrani, A., Vallespir, B., & Zacharewicz, G. (2022). Lean techniques impact evaluation methodology based on a co-simulation framework for manufacturing systems. *International Journal of Computer Integrated Manufacturing*, 35(1), 91-111.
- [23] Pop, G. I., Titu, A. M., & Pop, A. B. (2023). Enhancing aerospace industry efficiency and sustainability: Process integration and quality management in the context of Industry 4.0. *Sustainability*, 15(23), 16206.
- [24] Rabathi, S. R., & Hasbullah, H. (2023, August). Improving workflow of aircraft maintenance for reduce lead-time on nine-passenger aircraft. In *AIP conference proceedings* (Vol. 2485, No. 1, p. 120005). AIP Publishing LLC.
- [25] Kumar, S. N., Chandrasekar, S., Jeyaprabha, B., Sasirekha, V., & Bhatia, A. (2025). Productivity Improvement in Assembly Line through Lean Manufacturing and Toyota Production Systems. *Advances in Consumer Research*, 2(3).
- [26] Tonoy, A. A. R. (2025). Optimizing Lean Six Sigma Methodologies for Electrical Equipment Manufacturing. *Authorea Preprints*.
- [27] Bhaskar, A., & Devaraju, A. (2025). Integrated ERP lean model for quality enhancement and operational excellence in SME based automotive mould manufacturing. *Scientific Reports*, 15(1), 35979.
- [28] Islam, M. T., Hossain, A., Khan, M. R., & Roy, S. (2025). A meta-analysis of machine learning-enhanced lean quality control practices in manufacturing: Optimizing defect detection and process efficiency. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 166-192.
- [29] Sharma, A., Bhanot, N., Gupta, A., & Trehan, R. (2022). Application of Lean Six Sigma framework for improving manufacturing efficiency: a case study in Indian context. *International Journal of Productivity and Performance Management*, 71(5), 1561-1589.
- [30] Srinivasan, K., Sarulkar, P., & Yadav, V. K. (2024). Operational excellence of the steel industry using the Lean Six Sigma approach: a case study. *International Journal of Quality & Reliability Management*, 41(3), 826-849.
- [31] Pozzi, R., Rossi, T., & Secchi, R. (2023). Industry 4.0 technologies: critical success factors for implementation and improvements in manufacturing companies. *Production Planning & Control*, 34(2), 139-158.
- [32] Gomaa, A. H. (2025). Optimizing Machining Process Performance Using Lean Six Sigma: A Case Study. *Transnational Supply Chain Research*, 1(1), 52-81.
- [33] Mundaca-Lopez, C., Villar-Farfan, C., Quiroz-Flores, J. C., & García-López, Y. J. (2023). Improving OEE in a Peruvian SME: A case study on the application of lean manufacturing tools in the metalworking sector. In *Proceedings of the Conference on Production Systems and Logistics: CPSL 2023-2* (pp. 162-175). Hannover: publish-Ing.

- [34] Ince, M. N., Arpaci, E., Tasdemir, C., & Gazo, R. (2025). Economic and environmental sustainability performance improvements in the outdoor wood furniture industry through a lean-infused FMEA-supported fuzzy QFD approach. *Systems*, 13(3), 211.
- [35] Ulhe, P. P., Dhepe, A. D., Shevale, V. D., Warghane, Y. S., Jadhav, P. S., & Babhare, S. L. (2024). Flexibility management and decision making in cyber-physical systems utilizing digital lean principles with brain-inspired computing pattern recognition in industry 4.0. *International Journal of Computer Integrated Manufacturing*, 37(6), 708-725.
- [36] Pandey, B., Yadav, V., Chauhan, A. S., & Rathore, A. (2022). Process improvement using lean tools: a case from carpet manufacturing industry. *International Journal of Productivity and Quality Management*, 35(1), 117-142.
- [37] Kumar, A., Giri, R., Mishra, S., & Gupta, N. (2022). Productivity improvement of HLLS using lean technique in assembly line of an automotive industry.
- [38] Nguyen, N. T., Vo, T. T. B. C., Le, P. H., & Wang, C. N. (2023). Improving Inventory Time in Production Line through Value Stream Mapping: A Case Study. *Journal of Engineering Science & Technology Review*, 16(1).
- [39] Proenca, A. P., Gaspar, P. D., & Lima, T. M. (2022). Lean optimization techniques for improvement of production flows and logistics management: The case study of a fruit's distribution center. *Processes*, 10(7), 1384.
- [40] Junior, R. G. P., Inácio, R. H., Da Silva, I. B., Hassui, A., & Barbosa, G. F. (2022). A novel framework for single-minute exchange of die (SMED) assisted by lean tools. *The International Journal of Advanced Manufacturing Technology*, 119(9), 6469-6487.