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ORIGINAL

# Application of the Lean Six Sigma Methodology Enhanced by Fuzzy Logic Optimizing Mold Changeover Times in the Automotive Injection Industry

## Aplicación de la Metodología Lean Six Sigma Mejorada con Lógica Difusa para Optimizar los Tiempos de Cambio de Molde en la Industria de Inyección de Automoción

Yasmine El Belghiti[1,2], Abdelfattah Mouloud[1,2], Mehdi El Bouchti[1], Samir Tetouani[1], Aziz Soulhi[1,2]

[1]Higher School of Textile and Clothing Industries, Casablanca Morocco.
[2]National Higher School of Mines of Rabat. Morocco.

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**Corresponding Author:** Yasmine El Belghiti

## ABSTRACT

Minimizing mold changeover time is a critical challenge in the plastic injection molding industry, as it directly impacts productivity, operational efficiency, and competitiveness. This study introduces an integrated approach that combines Lean Manufacturing tools, the DMAIC methodology (Define, Measure, Analyze, Improve,Control), and Single Minute Exchange of Dies (SMED) techniques, enhanced by fuzzy logic and artificial intelligence (AI). The methodology focuses on improving mold changeover processes for the NEGRI BOSSI 650 machine by identifying bottlenecks, transforming internal tasks into external ones, and optimizing workflows to reduce downtime and improve overall efficiency.
Key phases of the study included identifying the root causes of inefficiencies through data collection and analysis, streamlining task sequences using real-time process data, and balancing the production line by redistributing workloads and reducing bottlenecks. Fuzzy logic and AI technologies were employed to support decision-making and enhance optimization, ensuring a robust and adaptable framework for continuous improvement. The results obtained were of high impact a 65 % reduction in mold changeover time and a 46,8 % improvement in Process Cycle Efficiency (PCE) with significant
improvements in terms of the global line balancing. These findings validate the effectiveness of combining Lean principles with advanced technologies such as fuzzy logic in solving Industry challenges, improving resource utilization, and ensuring long-term operational performance.
This study just goes to prove that a structured Lean Manufacturing approach combined with innovative tools and automation can drive significant improvement in the plastic injection molding industry, establishing a scalable and competitive strategy for operational excellence.

**Keywords**: Fuzzy Logic; Line Balancing; LSS Approach; Operational Efficiency (PCE); Mold Injection.

## RESUMEN

Minimizar el tiempo de cambio de moldes es un reto crítico en la industria del moldeo por inyección de plástico, ya que afecta directamente a la productividad, la eficiencia operativa y la competitividad. Este estudio presenta un enfoque integrado que combina herramientas de fabricación ajustada, la metodología DMAIC (Definir, Medir, Analizar, Mejorar, Controlar) y técnicas de cambio de moldes en un solo minuto (SMED), mejoradas mediante lógica difusa e inteligencia artificial (IA). La metodología se centra en la mejora de los procesos de cambio de moldes de la máquina NEGRI BOSSI 650 mediante la identificación de cuellos de

botella, la transformación de tareas internas en externas y la optimización de los flujos de trabajo para reducir los tiempos de inactividad y mejorar la eficiencia general.
Las fases clave del estudio incluyeron la identificación de las causas raíz de las ineficiencias mediante la recopilación y el análisis de datos, la racionalización de las secuencias de tareas utilizando datos de proceso en tiempo real y el equilibrio de la línea de producción mediante la redistribución de las cargas de trabajo y la reducción de los cuellos de botella. Se emplearon tecnologías de lógica difusa e IA para apoyar la toma de decisiones y mejorar la optimización, garantizando un marco sólido y adaptable para la mejora continua. Los resultados obtenidos fueron de gran impacto una reducción del 65 % en el tiempo de cambio de moldes y una mejora del 46,8 % en la Eficiencia del Ciclo de Proceso (PCE) con importantes
mejoras en términos de equilibrio global de la línea. Estos resultados validan la eficacia de combinar los principios Lean con tecnologías avanzadas como la lógica difusa para resolver los retos de la Industria, mejorar la utilización de los recursos y garantizar el rendimiento operativo a largo plazo.
Este estudio no hace sino demostrar que un enfoque estructurado de Lean Manufacturing combinado con herramientas innovadoras y automatización puede impulsar mejoras significativas en la industria del moldeo por inyección de plásticos, estableciendo una estrategia escalable y competitiva para la excelencia operativa.

**Palabras clave**: Lógica Difusa; Equilibrado de Líneas; Enfoque LSS; Eficiencia Operativa (PCE); Inyección de Molde.

## INTRODUCTION

In today's competitive manufacturing environment, operational efficiency and productivity are pivotal to sustaining profitability and maintaining a competitive edge.[1] The plastic injection molding sector, essential to the automotive industry, encounters recurring challenges in optimizing mold changeover times (MCT). High MCT leads to increased downtime, disrupted production flow, and diminished overall efficiency, highlighting the critical need for innovative approaches to streamline this process.[2]

This article presents a comprehensive case study on reducing MCT in plastic injection molding operations by integrating the Single Minute Exchange of Dies (SMED) methodology within the Lean Manufacturing framework. The study adopts the DMAIC (Define, Measure, Analyze, Improve, Control) approach to identify inefficiencies, minimize non-value-added activities, and achieve significant operational improvements.[3,4] To further enhance decision-making and adaptability, the integration of fuzzy logic introduces an advanced layer of predictive analytics. By modeling uncertainties inherent in real-world manufacturing scenarios, fuzzy logic provides actionable insights and facilitates real-time optimization of critical processes.[5]

The methodology leverages tools such as Value Stream Mapping (VSM), time-motion studies, and statistical analysis to identify bottlenecks and implement targeted solutions.[6] By converting internal tasks into external ones and standardizing operations, the proposed approach significantly reduces changeover times and improves Process Cycle Efficiency (PCE).[7] The inclusion of fuzzy logic supports dynamic adjustments to task scheduling and equipment utilization, ensuring a robust and flexible production system.

The results of this study demonstrate the synergistic benefits of combining Lean tools with fuzzy logic, achieving substantial reductions in MCT, enhanced production line balance, and sustainable process improvements. This innovative integration underscores the potential of intelligent systems in modern manufacturing, paving the way for smarter, more resilient production processes.[8]

### Production process

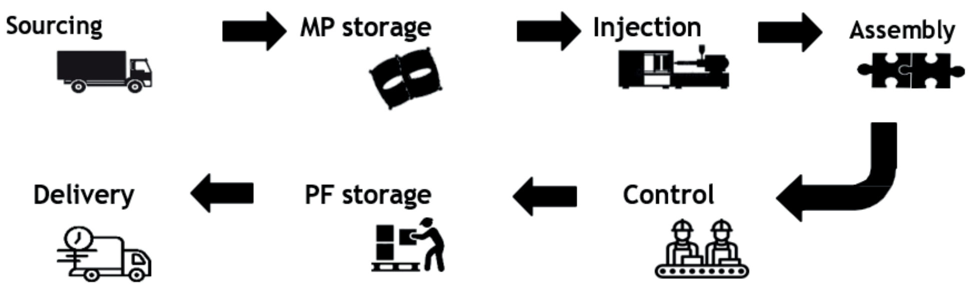


**Figure 1.** Flow diagram

Fuzzy logic is emerging as an effective tool for the solution of complex problems on which conventional decision-making systems are strained to their limit.[9,10] Applied to six sigma, it enables us to better characterize the uncertainty and imprecision that are present in operating data. Furthermore, in the predictive case, fuzzy logic offers the unique ability to predict performance and required changes from linguistic variables and non-linear interactions difficult to represent with standard mathematical approaches.[11] This opens up the potential for more robust and versatile solutions, highly applicable in uncertain industrial settings.

**Literature Review**

The integration of Artificial Intelligence (AI) into production line balancing has garnered significant attention in recent years due to its potential to revolutionize manufacturing processes. This section reviews the traditional approaches to line balancing, the emergence of AI-driven methodologies, and their applications in enhancing production efficiency.

*Traditional approaches to process optimization*

For decades, manufacturers have used Lean Manufacturing and Six Sigma methodologies to improve efficiency by eliminating wastes and defects. Lean Manufacturing, derived from the Toyota Production System (TPS), is focused on the elimination of non-value-added activities, streamlining of process flows, and minimization of inventory.[12] Conversely, Six Sigma is more data-driven and dependent on statistics for variances reduction and quality control.[13]

A number of classical Lean tools are widely used to improve efficiencies in manufacturing, including Value Stream Mapping (VSM), Kanban, and Kaizen among others. However, these methods, at times, appear to be outdone—notably by the high variability and unpredictability inherent in a modern-day production environment. Similarly, although DMAIC (Define, Measure, Analyze, Improve, Control), the Six Sigma methodology, has proven effective for structured problem-solving, it can be deficient in flexibility in terms of real-time in-production adjustments and complex disruptions in processes.[14]

*Evolution of SMED for Manufacturing Efficiency*

To improve manufacturing processes, presented Single Minute Exchange of Dies (SMED), a specific methodology designed to reduce setup and changeover times. By separating internal and external setup tasks, SMED allows manufacturers to continue production while preparing for the next cycle, thus keeping down the amount of time spent in an idle condition.[15] SMED has seen significant success in industries such as automotive plastic injection molding by achieving a reduced cycle time of 20-30 % while no longer allowing for these non-value-added activities.[16] Nevertheless, traditional SMED implementations are often dependent on manual adjustment and standardized work instructions, hence making them less applicable in the high-mix low-volume production setting. For example, in automotive component manufacturing, SMED has improved lead time but requires further tuning to address process uncertainties.[17]

*The Role of AI and Fuzzy Logic in Process Optimization*

With the growing complexities in manufacturing environments, Artificial Intelligence (AI) and Fuzzy Logic are making waves propagating themselves as game-changers to bolster Lean and Six Sigma methodologies. These technologies are engineered to facilitate real-time decision-making, enabling dynamic adjustments in processes as well as probability-based forecasting.[18]

- Adaptive Process Control- AI-driven models rely on real-time sensor data to make immediate adjustments to setup and changeover processes, leading to the most effective use of resources and minimum downtime.[19]
- Fuzzy Logic for Process Optimization- Traditional optimization models may not be capable of withstanding uncertainties and process variations. Fuzzy logic presents an adaptable, more astute way of continuously adjusting changeover times for molds, machine conditions, and workforce efficiency modifications. [9,20]
- Predictive Maintenance & Smart Scheduling – AI-powered predictive models can anticipate potential failures and inefficiencies, allowing for proactive maintenance and optimized scheduling.[20]

Recent studies have noted how applications of Fuzzy Logic in the SMED processes enabled manufacturers to predict optimized changeover conditions leading to a decrease of up to 30 % of cycle time. Furthermore, AI-supported decision support systems in plastic injection molding have been reported to analyze past performances and dynamically update process sequencing, thereby minimizing inconsistencies and increasing lead time predictability.[21]

*Comparing Traditional vs. AI-Enhanced Approaches*

On comparison with traditional Lean-Six Sigma approaches, an evaluation of AI-driven optimization manifests

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clear superiority regarding its ability to cope with real-time perturbation, operations with high variability, and predictive maintenance.

- In plastic injection molding, supplementing SMED with AI achieves a 65 % reduction in mold changeover times.
- In automotive manufacturing, AI scheduling improved process efficiency by 30-35 %, outperforming traditional Lean methods, particularly in managing dynamic production demands.

## METHOD

This study uses the DMAIC methodology to optimize the MCT in plastic injection molding under the Lean Six Sigma environment. The DMAIC methodology is well-known to give a framework to increase the operational efficiency by eliminating the bottlenecks and non-value-added activities.(19)

The Define phase outlines the goals of the project, keeping a focus on reducing the MCT to improve productivity and flexibility in the injection molding process. Critical parameters, such as setup time and equipment readiness, are identified. During the Measure phase, the baseline data is gathered on mold change times and machine downtime, using methods such as time-motion studies to identify inefficiencies.(22,23)

The Analyze phase uses root cause analysis tools, such as the Ishikawa or Fishbone diagrams and value stream mapping, to ascertain primary causes of lengthy changeover times. Studies have demonstrated that such tools are efficient in identifying the inefficiencies in tooling preparation and scheduling that are most often delayed during changeovers. It is vital to address the root causes since they affect throughput and production capacity.(24)

In the Improve stage, solutions towards chain-reaction root cause mitigation are applied. The study already reviewed has pointed out that integration of Lean tools with DMAIC does not only enhance the flow of work but also allows line balancing, minimizes interruptions, and enhances productive time.(17) The final phase is Control, which shall ensure that improvements remain standardized and monitored for durability with artificial intelligence and fuzzy logic.(8)

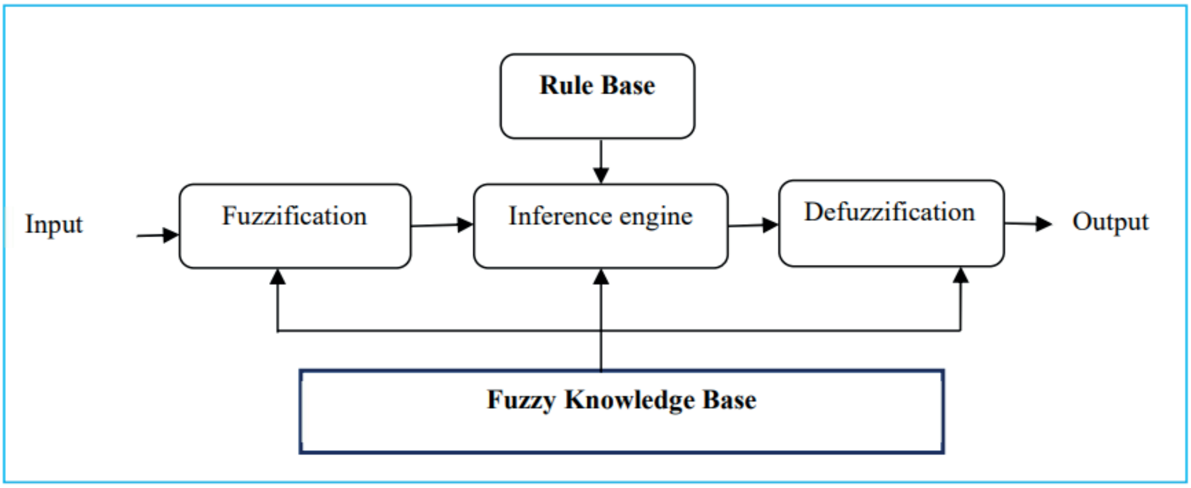


**Figure 2.** Fuzzy Inference Process(25)

### Case study

Mould changing has been recognized as an important source of inefficiency within the plastic injection process at the company's plant. While a standard of minutes is defined as the time taken for mold changeover, very rarely is this benchmark achieved due to various operational and organizational challenges.(26) This phase aims to define and analyze the problem with the aim of achieving its objectives: reducing the MCT times, minimizing waste, and optimizing the assembly process.(6) The NEGRI BOSSI 650 machine is recognized as the most critical point of delay, therefore specifying the focus of any implementing changes.

*Define Phase*

A Value Stream Mapping (VSM) methodology was used to give the complete overview of the mold change process, where both value-added and non-value-added activities were identified as the figure 6 shows. This analysis forms the basis for spotting the bottlenecks and ascertaining the requisite resources to enable performance benchmarks to be quickly identified.(27)

In addition to developing prediction-based methods using fuzzy logic, reliability and availability of this equipment are to be made better. Identifying the root causes of the problem and closing the gap between LSS tools will streamline the mould changeover process and lead to performance improvement.(8)

*The mould change process*

The process of changing series can be divided into 3 phases: Dismantling, Assembly and Adjustment of parameters plus quality control:

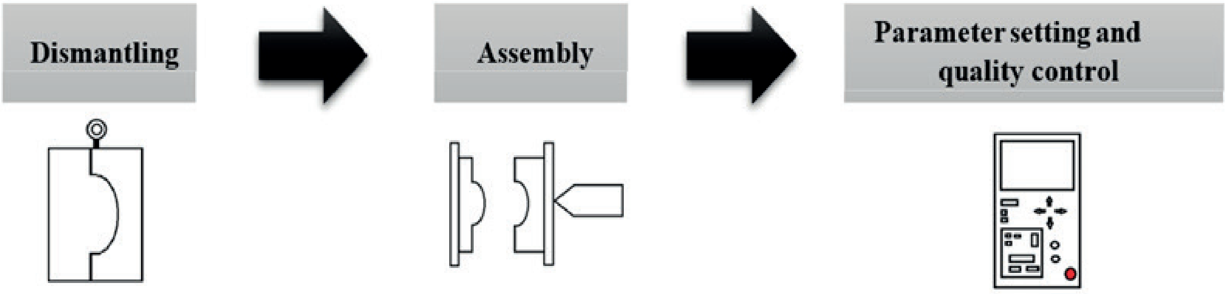


**Figure 3.** The mould change process

**Table 1.** Assembly mold changing operations

| Stage | Operation | Estimated Time (min) |
|---|---|---|
| Preparation | Cleaning of mold | 15 |
| | Identification of required mold tools | 10 |
| | Preparation of materials and equipment | 10 |
| Dismantling | Removal of the current mold | 20 |
| | Disconnection of water and electrical lines | 10 |
| | Cleaning of machine surfaces | 15 |
| Assembly | Installation of new mold | 25 |
| | Connection of water and electrical lines | 10 |
| | Adjustment of alignment and parameters | 20 |
| Final Adjustments | Testing the mold setup | 15 |
| | Quality control of the first batch | 15 |
| Other Operations | Additional cleaning and maintenance tasks | 10 |
| Total | | **175** |

The data needed to construct the Value Stream Mapping (VSM) of plastic injection molding operations have been summarized in table 1 and table 2. The VSM of mold change activities illustrates the activities that characterize the various stages of the operation. Such data include operator numbers (O) and automated machines (R). The tables provide a summary of the mold change activities and times taken to carry out specific activities, from which information can be ascertained to analyze information, work and material flows, and value-adding and non-value-adding times. This information is key in determining Process Cycle Efficiency (PCE). Present VSM analysis (figure 6) demonstrates the necessity for specific improvements, assesses the number of operators needed for each workstation, value-adding and non-value-adding times needed to accomplish specific activities, and improvement measures for the enhancement of PCE by minimizing the total time for changeover.[7,28]

Present Lead Time = Value Added Time + Non-Value-Added Time
Process Cycle Efficiency = (ValueAddedTime ÷ LeadTime) ×100 %

*Measure phase*

At this phase, primary data were personally collected to estimate lead time and cycle time for an important activity such as mold preparation, cleaning, disassembly, installation, and equipment adjustments. Several video recordings were taken from more than a dozen operations on the NEGRI BOSSI 650 machine, with observed times taken of between 125 and 172 minutes (figure 3), revealing large variability in the process.

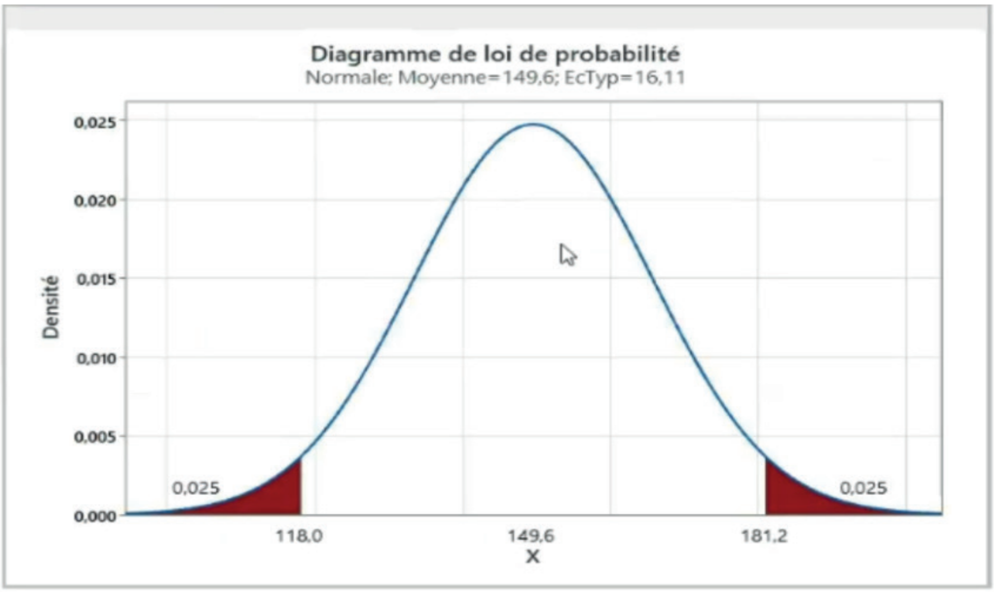


**Figure 4.** Diagram Gauss

Descriptive statistical analysis was performed to obtain the mean, deviations, and variations in lead times. The Value Stream Mapping (VSM) technique was also used to distinguish value-adding activities from non-value-adding, thereby finding bottlenecks and wastes in the flow.[3,29] The result showed very low PCE-value-generation efficiency, with an average value beneath 30 % far short of the acceptable mark of 65 % as an industry benchmark.

A Pareto analysis (figure 4) revealed that PCE must be improved by 70-75 % to meet the minimum benchmark, thus making process optimization inevitable. This was the basic premise to categorize tasks into disassembly, setup, and reducible/eliminable activities to prioritize improvements during the next phases.[3]

*Analysis phase*

This phase involved the assessment of the mold change process to determine the root causes for low process cycle efficiency (PCE) and variations in lead time, which was done through collaborative meetings and brainstorming sessions with operators, technicians, and production managers.The causes of low efficiency and delay were represented in a fishbone diagram (figure 5), wherein five broad causes of issues were categorized: work organization, machinery, method, mechanical means, and manpower. The root causes were further elaborated upon using the five whys technique to find the ultimate issues causing deviations from the benchmark.[30,31]

**Table 2.** The value added and non-value-added time of the assembly operation

| /N | Activities | No of operators | No of robots | Value-added time (min) | Non-value-added time (min) | Total lead time (min) | Up time (min) | Down time (min) | Total cycle time (min) | Process cycle efficiency (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| A | Mold preparation and tool setup | 2 | - | 25 | 20 | 45 | 25 | 20 | 45 | 55,56 |
| B | Mold removal and hoist operation | 2 | 1 | 15 | 20 | 35 | 15 | 20 | 35 | 42,86 |
| C | Mold cleaning and inspection | 1 | - | 5 | 15 | 20 | 5 | 15 | 20 | 25,00 |
| D | New mold installation | 2 | 1 | 10 | 25 | 35 | 10 | 25 | 35 | 28,57 |
| E | Adjustment and alignment | 1 | - | 10 | 20 | 30 | 10 | 20 | 30 | 33,33 |
| F | Testing and quality control | 1 | - | 5 | 30 | 35 | 5 | 30 | 35 | 14,29 |
| G | Total | 9 | 2 | 55 | 145 | 200 | 55 | 145 | 200 | 27,50 |

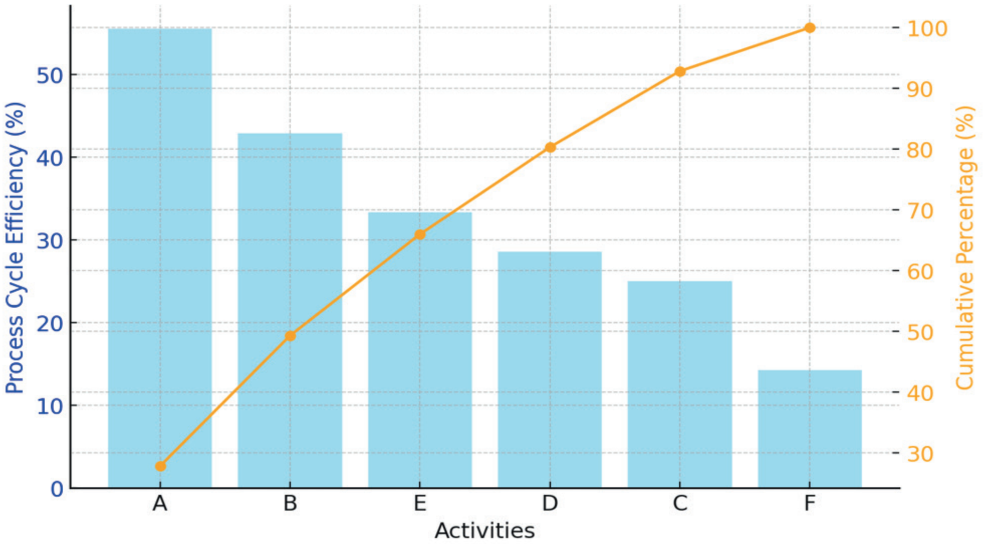


**Figure 5.** Pareto Analysis of the present PCE for mold change operations

It was found as shows the figure 5 that inefficient work organization significantly contributed to wasted time, particularly due to poorly coordinated tool placement and an unstructured sequence of tasks. Frequent equipment breakdowns and low levels of automation were also major obstacles. Additionally, inconsistent procedures and the absence of standardized methods extended lead times, while material shortages and quality issues disrupted workflow. Operator training gaps and resistance to new processes further compounded these challenges.

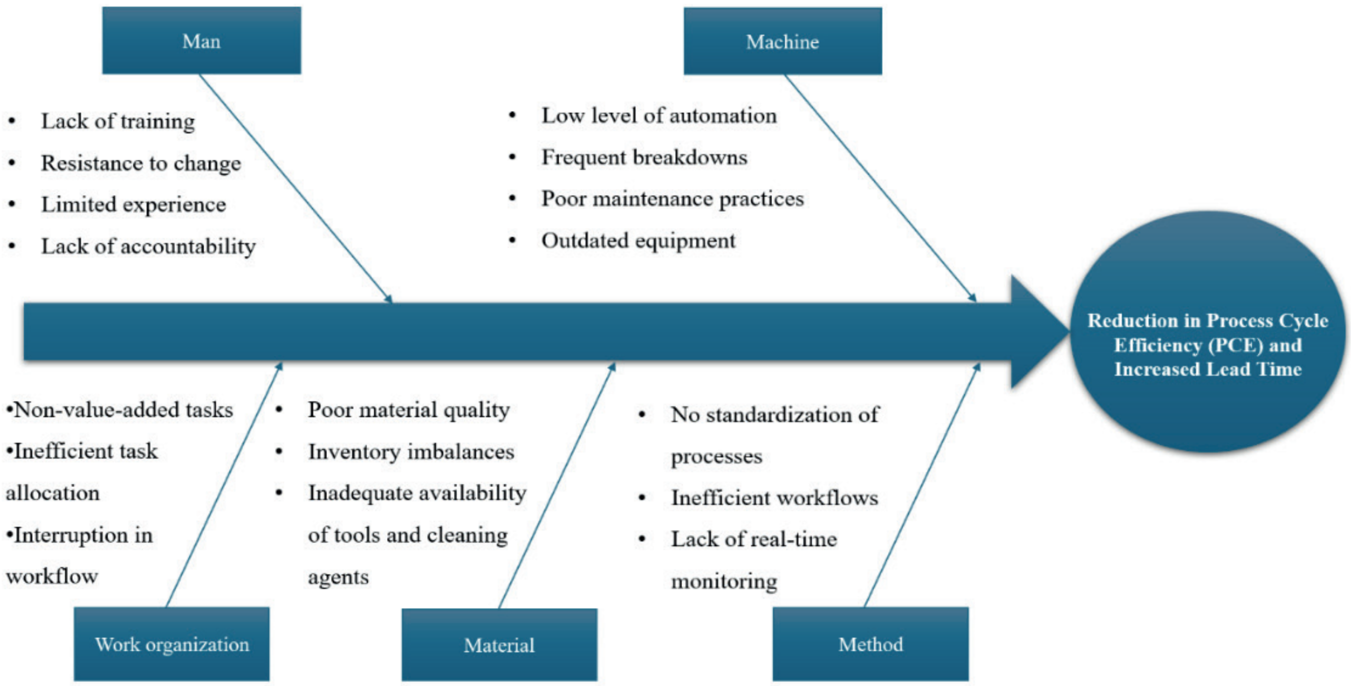


**Figure 6.** Ishikawa diagram for reducing PCF and increased lead time

The workspace layout also played a crucial role, as poorly positioned equipment led to inefficiencies in mold handling, cleaning, and installation. To address this, optimizing the plant layout was proposed to ensure a logical and sequential arrangement of equipment, enabling a smoother and more efficient workflow. This approach aligns with Lean manufacturing principles, which focus on minimizing waste and improving process efficiency.[32,33]

Further analysis revealed that supply chain disruptions caused inventory imbalances, highlighting the need for Lean manufacturing techniques and a Just-in-Time (JIT) approach. These strategies were suggested to simplify processes, minimize waste, and improve inventory management. Another key recommendation was to introduce modularity into the mold change process, breaking it down into independent sub-processes to enhance flexibility and streamline operations.[34,35]

Additionally, low levels of automation were identified as a significant constraint, with only limited robotic assistance available. To improve process control and reduce errors, increasing automation and implementing real-time monitoring systems were recommended. These improvements would enhance productivity, shorten lead times, and create a more efficient mold change process.(17)

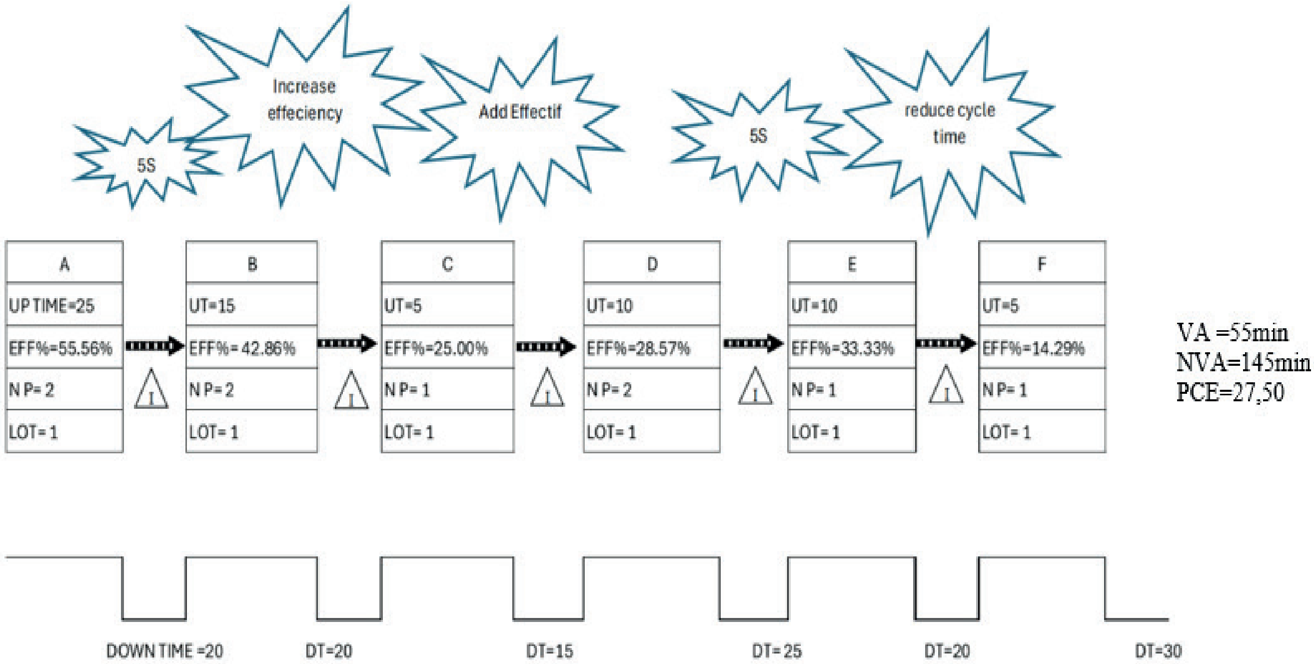


**Figure 7.** Present value stream of the assembly operation

*Improve phase*

In our instance of the improvement phase of the systematic implementation of the Kaizen approach, the changeover process of the mold was set out to be executed in a simple, gradual, and continuous way. Not only is this approach expected to result in major reductions in mold changeover time, but it is also expected to reduce much downtime and product deficiency in the gap interval between production cycles. The aims of this phase include making the mold change scheduling as efficient as possible so that resources will be used efficiently, minimizing downtime, and facilitating the production of high-quality products on time.(36)

*Implementation of Lean Tools in the Mold Change Process*

The improvement phase focuses on implementing Lean tools to optimize the mold change process and reduce inefficiencies. Key tools like SMED (Single Minute Exchange of Dies) and the 5S methodology were employed to achieve significant reductions in mold changeover times and enhance overall efficiency.(3,37)

*Implementation of SMED*

The SMED method was applied after observing the mold changeover activities through time studies and flow analysis. The aim was to categorize all tasks into value-added and non-value-added activities. The detrimental non-value-added tasks identified focused mostly on eliminating unnecessary delays and wastage of resources. The value-added tasks were, however, separated as internal (done while the machinery is down) or external (done before the machinery stops). As many internal activities as possible were to be eliminated and converted to external activities so that machine downtime was minimized, and waste was eliminated.(28)

Training sessions were conducted for operators to impart skills on how to effect mold changeovers and efficiently hold operational tasks. Standard work procedures for every task were also introduced so that there would be uniformity in operation and reduced variability. Enhanced people learning included Total Productive Maintenance (TPM), which empowered operators to learn preventive and corrective maintenance techniques for reducing machine downtime, thus enabling smooth operations.

*Implementation of the 5S Methodology*

The 5S methodology was implemented in our case study to minimise the frequent downtime caused by machine breakdowns and inefficient workspaces.(38)

The five steps of the 5S method are as follows:

- Sort: inspect and remove unnecessary tools, parts and instructions to eliminate clutter.

- Putting things in order: arranging tools and materials in a systematic way to facilitate access and reduce search time.
- Shine: clean and maintain the workspace to eliminate hazards and ensure smooth operations.
- Standardise: establish standardised procedures for mould change tasks to ensure consistency.
- Maintain: continuously review and maintain established standards to avoid falling back into inefficiency.

*Improved VSM for Mold Change Operations*

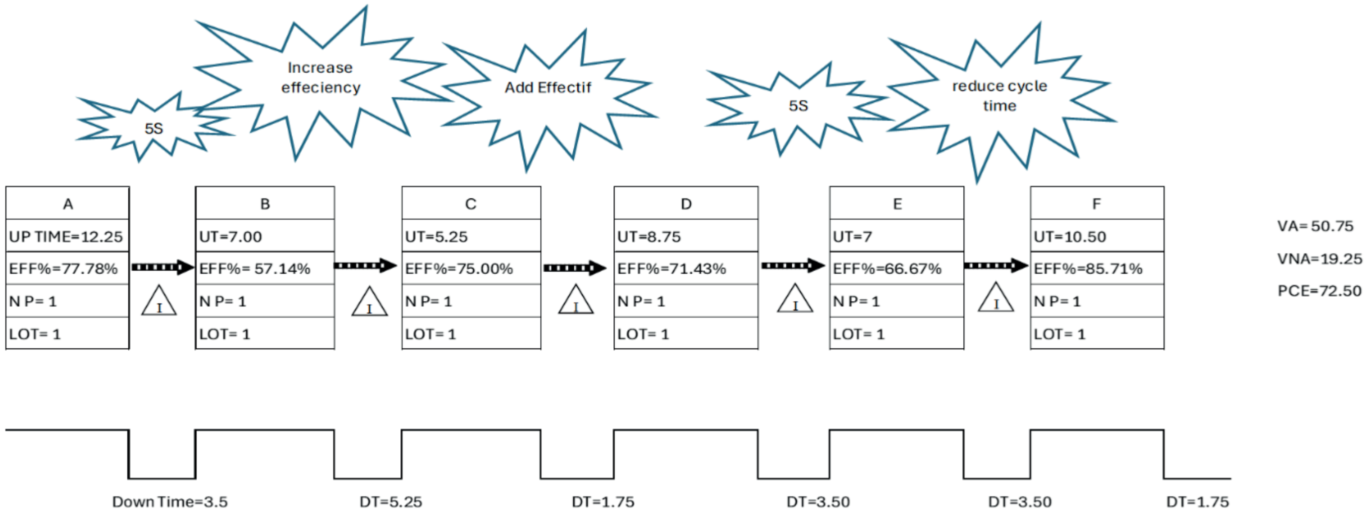


**Figure 8.** Improved value stream of the assembly operation

The application of Lean tools resulted in a significant improvement in the Value Stream Mapping (VSM) of the mold change process. These improvements included an increase in value-added time and a reduction in non-value-added time. For example, non-value-added time decreased by 86,72 %. These results are presented in the updated VSM (figure 7).

The reduction in non-value-added time directly contributed to a more productive and efficient mold change process. Additionally, the number of human operators was reduced by almost 40 % and replaced with robotic systems to improve speed, accuracy, and consistency, thereby reducing cycle time and defects.

*Future PCE of the Mold Change Process*

**Table 3.** The value added and non-value-added time of the assembly operation after improvement

| /N | Activities | No of operators | No of robots | Value-added time (min) | Non-value-added time (min) | Total lead time (min) | Up time (min) | Down time (min) | Total cycle time (min) | Process cycle efficiency (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| A | Mold preparation and tool setup | 1 | 1 | 12,25 | 3,50 | 15,75 | 12,25 | 3,50 | 15,75 | 77,78 |
| B | Mold removal and hoist operation | 1 | 1 | 7,00 | 5,25 | 12,24 | 7,00 | 5,25 | 12,25 | 57,14 |
| C | Mold cleaning and inspection | 1 | - | 5,25 | 1,75 | 7,00 | 5,25 | 1,75 | 7,00 | 75,00 |
| D | New mold installation | 1 | 1 | 8,75 | 3,50 | 12,25 | 8,75 | 3,50 | 12,25 | 71,43 |
| E | Adjustment and alignment | 1 | - | 7,00 | 3,50 | 10,50 | 7,00 | 3,50 | 10,50 | 66,67 |
| F | Testing and quality control | 1 | - | 10,50 | 1,75 | 12,25 | 10,50 | 1,75 | 12,25 | 85,71 |
| G | Total | 6 | 3 | 50,75 | 19,25 | 70,00 | 50,75 | 19,25 | 70,00 | 72,50 |

Following the implementation of Lean tools, the Process Cycle Efficiency (PCE) of the mold change process increased significantly from an initial value of 27,50 % to 72,50 %, surpassing the industry minimum benchmark

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of 25 %.[39] This improvement represents a 46,8 % increase in PCE and was achieved through the systematic elimination of non-value-added activities and improved resource utilization.

The reduction in lead time was also notable, with the total lead time decreasing by 27,9 % from its initial value. This reduction highlights the impact of Lean tools in optimizing workflow and achieving more efficient operations.[40]

*Validation of Improvements*

The improvements were validated using statistical analysis and a Kolmogorov-Smirnov (K-S) test to compare current and improved lead times. The results showed a significant reduction in lead time variability and an overall improvement in process performance, confirming the effectiveness of the Lean tools applied in this study.

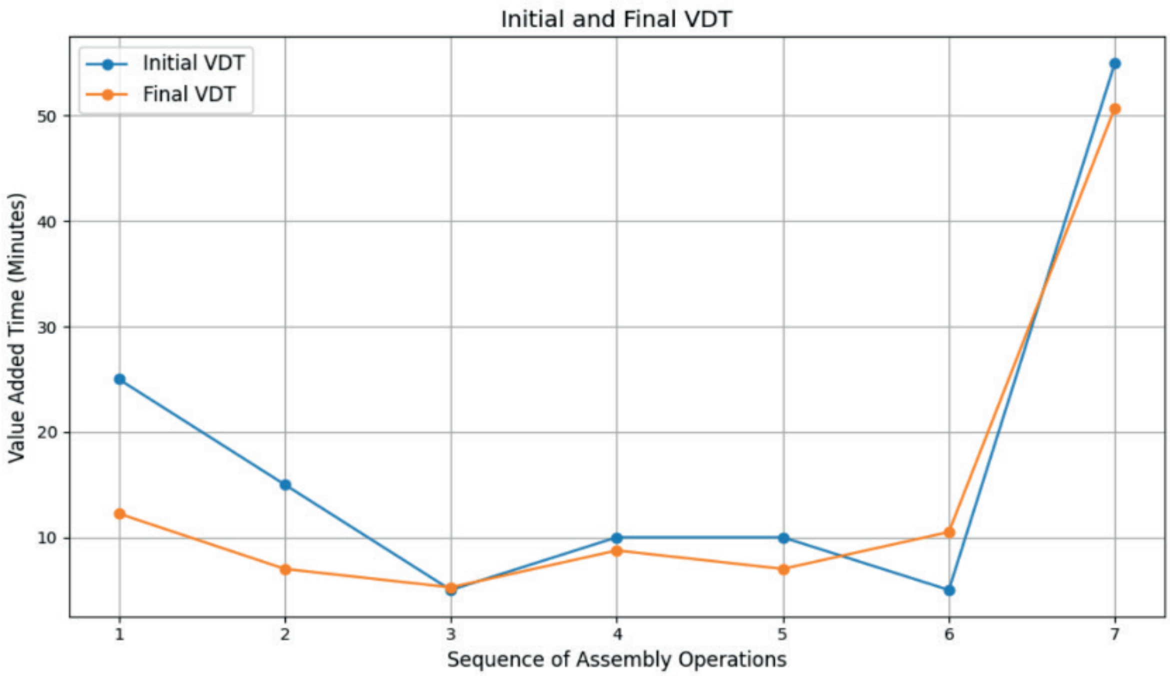


**Figure 9.** The initial and final Value-Added Time

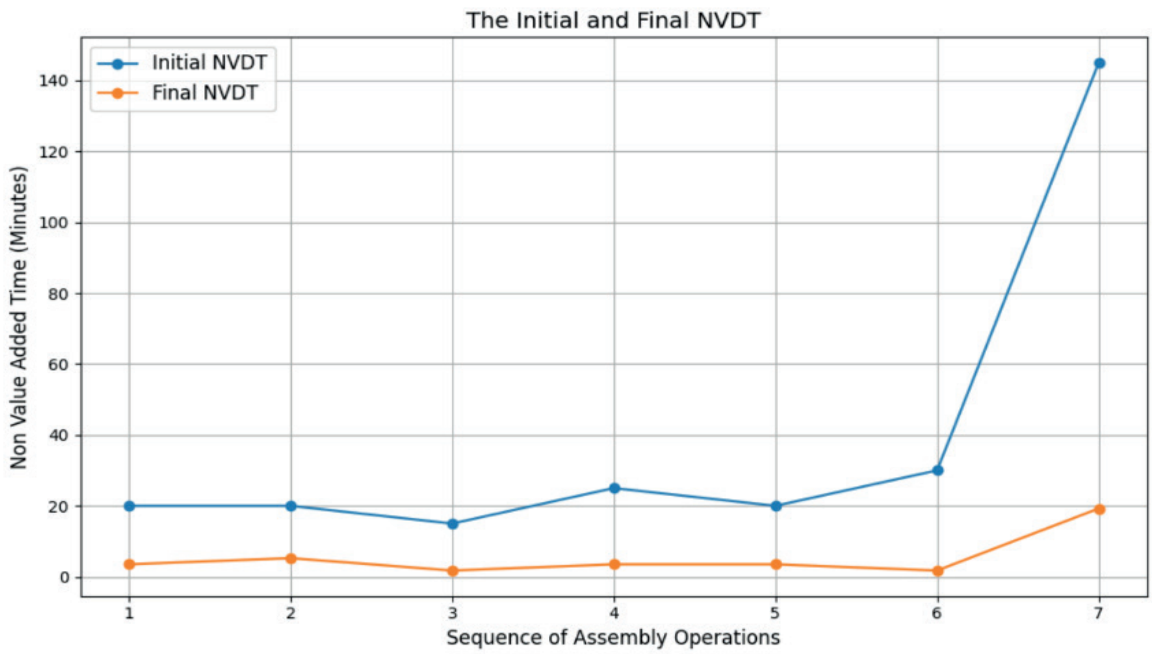


**Figure 10.** The initial and final Non Value Added Time

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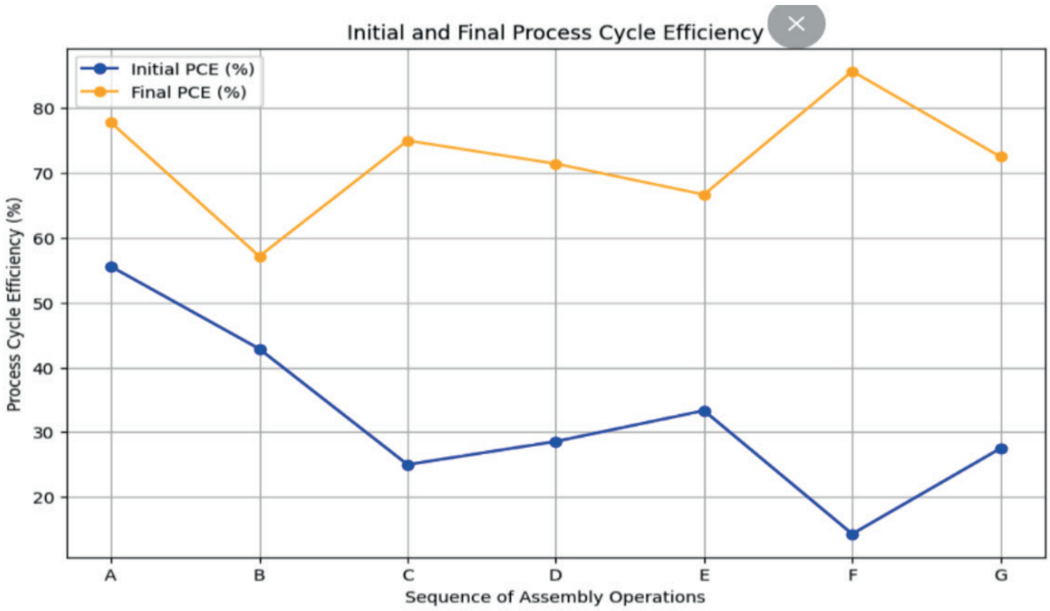


**Figure 11.** The initial and final PCE

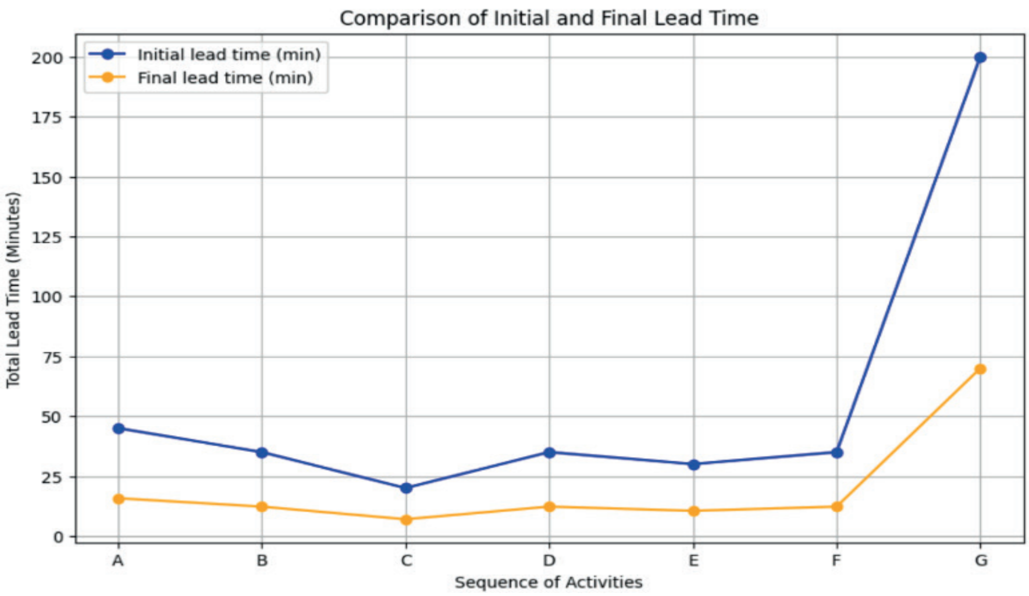


**Figure 12.** The initial and final Lead Time

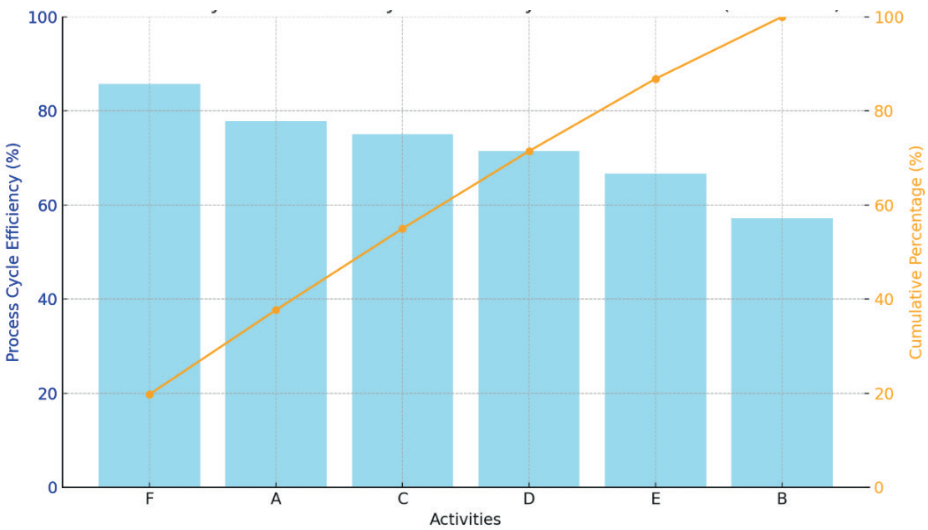


**Figure 13.** The initial and final PCE

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*Control phase*

The control phase ensures that the long-term improvement objectives are not compromised by measuring system performance and comparing it to established benchmarks. This stage involved the implementation of rigorous monitoring tools to track the process and quickly identify any deviations from the standards. To sustain the achieved improvements, control measures were introduced, including the standardization of procedures through a Standardized Work Plan (SWP), particularly for mold assembly and component integration operations. A systematic documentation review was established by the compliance team to ensure traceability and continuous improvement of practices. Additionally, regular training and retraining sessions for operators on continuous improvement tools such as 5S and SMED were scheduled to embed these changes permanently. To maintain process stability, control charts were developed to analyze the variability of mold changeover times, ensuring that fluctuations remain within permissible limitsThis result highlights the success of the improvements achieved through the application of Lean Six Sigma tools, ensuring a sustainable reduction in mold changeover time and greater process stability.[19,23,41]

*Standardization and Continuous Optimization with Fuzzy Logic*

The improvements implemented in the Improve phase need to be standardized and continuously monitored to sustain the efficiency gains. Traditional monitoring methods rely on fixed threshold values, which may not fully capture the variability inherent in mold changeovers. To address this, we integrate a fuzzy logic-based SMED model that allows for a more adaptive and intelligent decision-making process.[11]

*Implementation of the Fuzzy SMED Model*

The fuzzy logic system is designed to evaluate mold changeover time based on multiple variables that influence the process, namely:

- Mold size (Small, Medium, Large)
- Robot hand adaptation (Adapted, Partially Adapted)
- Mold complexity (Simple, Complex)

Each of these inputs is associated with membership functions, enabling a gradual transition between categories rather than abrupt classifications. The system then applies fuzzy rules to determine the expected changeover time category (Short, Medium, Long), guiding operators in optimizing setup times.

**Table 4.** The prediction method based on fuzzy logic

| Mold Size | Robot Hand Adaptation | Mold Complexity | Changeover Time |
|---|---|---|---|
| Small | Adapted | Not Complicated | Short |
| Small | Adapted | Complicated | Medium |
| Small | Slightly Adapted | Complicated | Medium |
| Small | Slightly Adapted | Not Complicated | Medium |
| Medium | Adapted | Not Complicated | Medium |
| Medium | Adapted | Complicated | Medium |
| Medium | Slightly Adapted | Complicated | Medium |
| Medium | Slightly Adapted | Not Complicated | Medium |
| Large | Adapted | Not Complicated | Medium |
| Large | Adapted | Complicated | Medium |
| Large | Slightly Adapted | Not Complicated | Medium |
| Large | Slightly Adapted | Complicated | Long |

*Fuzzy-Based Decision Support for SMED*

A set of fuzzy inference rules is constructed based on expert knowledge and historical data. For instance :

- A small mold, well-adapted robot hand, and simple design results in a short changeover time.
- A large mold, poorly adapted robot hand, and complex design extends the changeover time.
- Intermediate cases allow for flexible adjustments, avoiding rigid classifications.

This adaptive approach ensures that the standardization phase accounts for real-world variability, improving prediction accuracy and enhancing responsiveness to process fluctuations.

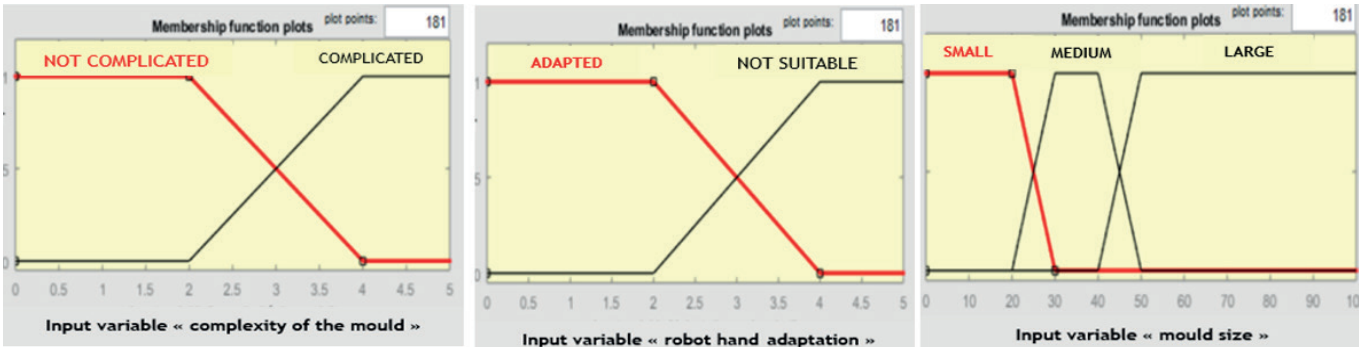


**Figure 14.** Input variable of fuzzy logic

*Control System Integration*

To implement the fuzzy control system, the following steps were taken:

- Real-time classification of mold changeover times using fuzzy logic, identifying deviations before they become bottlenecks.
- Integration with monitoring tools (such as Qi Macros in Excel) for real-time visualization of mold changeover efficiency.
- Decision-making guidance for operators, allowing proactive interventions rather than reactive problem-solving.

*Benefits of the Fuzzy SMED Model*

The integration of fuzzy logic in the Control phase brings several key advantages:

- Adaptive decision-making: Instead of fixed time targets, changeover performance is evaluated based on continuous input variations.
- Real-time monitoring: The system enables early detection of inefficiencies, ensuring that necessary corrections are made before disruptions occur.
- Sustainable improvements: By systematically categorizing changeover tasks, the root causes of inefficiencies are continuously refined and addressed.

By incorporating fuzzy logic into SMED, the Control phase ensures that improvements are not only sustained but also dynamically adjusted based on real-time data. This method enhances decision-making precision, minimizes process variability, and contributes to long-term operational efficiency in mold changeover processes.

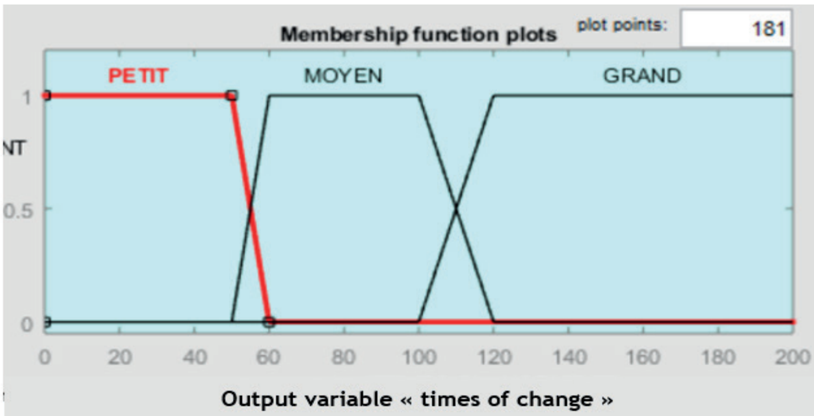


**Figure 15.** Output variable “time change”

*Interpretation of results*

Fuzzy logic curves shown in (figures 14) and (figure 15) give us a clear view of how the system interprets the input and output variables for decision-making. Figure 14 shows the breakdown of the input variables in mold size that is categorized as small, medium, and large; the robot hand adaptation is adapted or not suitable; and mold complexity is not complicated or complicated. Accordingly, these curves enable smooth transitions between categories instead of rigid classifications, which accounts for the natural uncertainties and variations in real-world manufacturing. Figure 15, on the other hand, presents the output variable of the changeover time, grouped into small, medium, and large. In this way, this system can make a flexible and adaptive decision by combining these inputs with fuzzy rules, predicting the changeover times with more accuracy and helping in streamlining the operations.

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Figures 16, 17, and 18 provide a clear visual representation of how key factors influence mold changeover time.

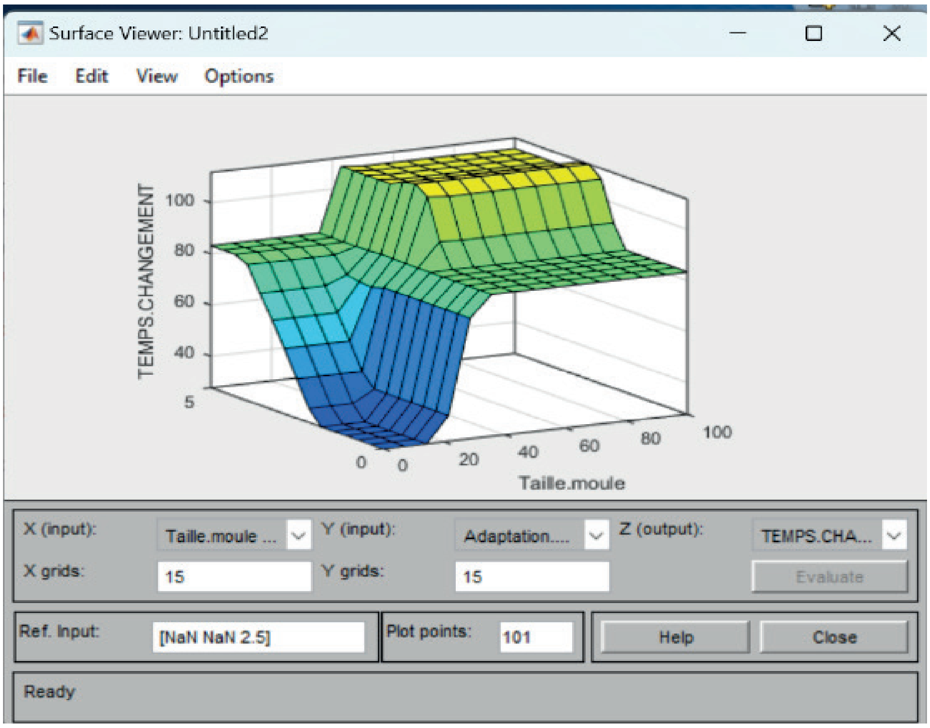


**Figure 16.** Surface Visualization of Mold Size, Adaptation, and Changeover Time

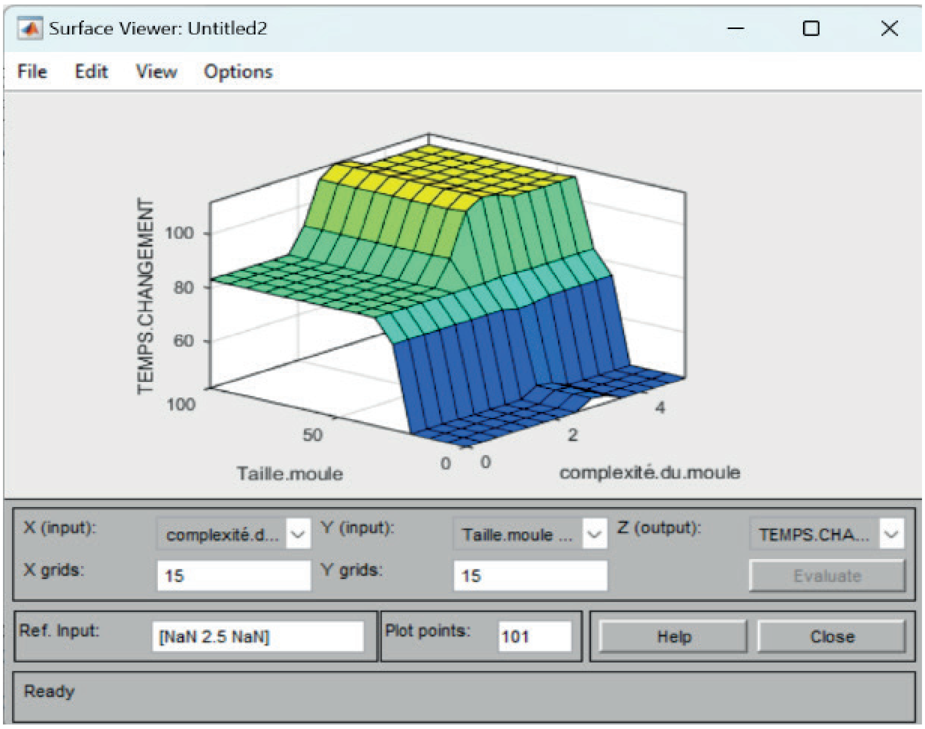


**Figure 17.** Surface Visualization of Mold Size, Complexity, and Changeover Time

In figure 16, we see how the size of the mold and the level of robot hand adaptation affect the process. Larger molds and less adapted robot hands tend to make the changeover take longer. Figure 17 adds another layer by showing how mold size and complexity work together, with higher complexity—especially for larger molds—leading to longer times. Finally, figure 18 highlights how improved robot adaptation can significantly cut down changeover times, even for bigger molds. These 3D visuals make it easier to understand how these variables interact and show how fuzzy logic can help tackle real-world challenges by capturing and analyzing these complexities.

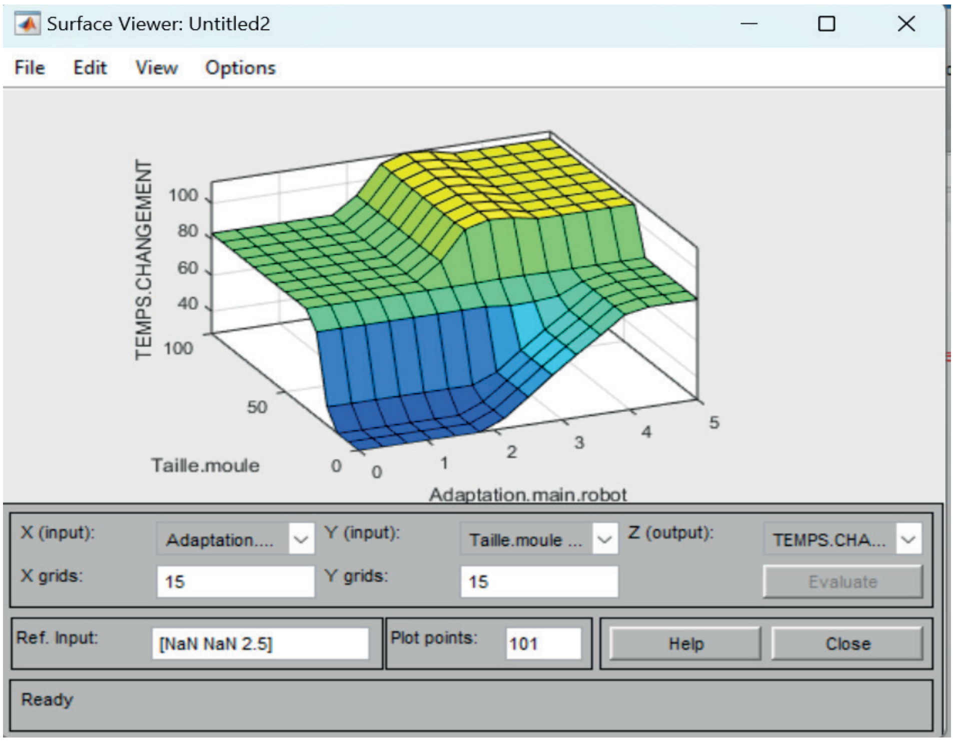


**Figure 18.** Surface Visualization of Mold Size, Robot Adaptation, and Changeover Time

*Lesson learnt and limitation of study*

This paper presents a case of optimizing the mold changeover time in the automotive injection molding using LSS, and it shows how combining DMAIC methodology with SMED techniques and enhancing them with fuzzy logic helped to show that when such traditional Lean tools are coupled with modern technologies, meaningful improvements could be achieved. The findings cemented about shifting the mind of academics and industry to work together; that was pointed out in previous studies as the most important thing that helps to implement LSS in companies.(8,23)

The achievement in the project was a direct reduction in mold changeover time of 65 % with a further increase in Process Cycle Efficiency of 46,8 %. This shows that elimination of wastes and improvements in processes are not one-time activities but a journey. Moreover, engaging workers and getting structured problem-solving done right was key to sustaining these improvements.(37)

That said, the study does have some limitations:

Thus, we must say the research has certain limitations which are as follows:

- Limited Scope: the study was limited to a particular machine (NEGRI BOSSI 650) within a particular organization; hence its results may not be entirely relevant for other setups.
- Data Issues: data was a considerable constraint; thus, we could not leverage advanced simulation tools that could have provided very sound validation of our results.
- Process Scope: the focus of the work was limited to the mold changeover. An examination of other associated operations in the production workflow would provide a more complete view of the efficiency gains right along the whole scope of production.

Further research could follow this up with the deployment of this approach in a broader spectrum, making use of predictive models for wider verification, as well as looking into how it could apply within the context of other steps in the production process. Incorporation of real-time monitoring alongside decision-support systems could render these methods highly effective in addressing a number of modern manufacturing issues.

## CONCLUSIONS

This study demonstrated the successful application of Lean Six Sigma (LSS), in conjunction with the SMED methodology and enhanced by fuzzy logic, for the purpose of optimizing mold changeover times in plastic injection molding. The main aim is to improve production equipment efficiency and reduce downtime, leading to improved Process Cycle Efficiency (PCE), and is reflected in the results.(42)

Extrapolated lesson learned are as follows:

- Significant Reduction in Changeover Time: mold changeover times were reduced by 65 %, which improved equipment availability and facilitated the smoothness of production workflows.

- Improved Process Cycle Efficiency (PCE): increased the PCE from 27,5 % to 72,5 %, which was better than industry benchmarks. This represents eliminating all waste activities and followed structured Lean toolkits like SMED and 5S.
- Increase in Value-Added Time: value-added time also rose by as high as 59,3 %, demonstrating a more efficient allocation of tasks and improved synergies between human operators and automated systems.
- Reduction in Non-Value-Added Time: non-value-added activities decreased by 71,9 %, reflecting the power of standardizing processes and optimizing workflows.

These results show that conventional Lean tols and advanced technologies go hand in glove and can present real value for manufacturing operations. Smoothed processes, reduced waste-all a sound platform to build upon for the success of operational excellence.

Besides this specific case, the approaches here can be applied to other manufacturing challenges like improving product quality, reduction of total turn-around time, or achieving zero defects. Other areas of further work might apply this framework by the inclusion of more advanced simulation tools or expanding the scope of the framework into other production stages. These will provide complete insight into how the framework can be used in holistic applications within a complex manufacturing environment.

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## AUTHORSHIP CONTRIBUTION
*Conceptualization:* Yasmine El Belghiti, Abdelfattah Mouloud, Mehdi Elbouchti.
*Data curation:* Yasmine El Belghiti.
*Formal analysis:* Yasmine El Belghiti, Abdelfattah Mouloud, Samir Tetouani.
*Research:* Yasmine El Belghiti.
*Methodology:* Yasmine El Belghiti, Abdelfattah Mouloud, Samir Tetouani.
*Supervision:* Mehdi Elbouchti, Aziz Soulhi.
*Validation:* Aziz Soulhi.
*Original drafting and editing:* Yasmine El Belghiti, Abdelfattah Mouloud.
*Writing - proofreading and editing:* Yasmine El Belghiti, Aziz Soulhi.