Increasing the overall efficiency of injection molding equipment in the plastics industry: A Lean and Industry 4.0 innovation

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Abstract*– Organizations seek to improve their operational efficiency by addressing a key challenge in the plastics industry: low equipment efficiency, particularly in injection molding processes. This research analyzes the causes of high mold setup and disassembly times, as well as increased machine downtime due to electrical failures in the injection molding process. It also examines the high rate of defective products due to the temperature instability of the injection molding machine and its performance, which currently operates at an efficiency of only 71.68%. To address this problem, an improvement project is proposed that integrates Lean Manufacturing methodologies such as SMED, Andon, and FMEA, as well as the use of digital twins and statistical process control (SPC). The objective is to optimize the effectiveness of the injection molding machine, measured by the Overall Equipment Effectiveness (OEE) indicator, and improve the company's competitiveness within the sector.

***Keywords*-- SMED, Digital Twins, Injection Molding, Lean Manufacturing Tools, Plastic Industry.**

I. Introduction

Plastic, a petroleum-derived polymer, has revolutionized the development of modern societies due to its versatility and ability to contribute to diverse industries. This exponential growth has been accompanied by a significant increase in its production and demand, reaching 390.7 million tons globally in 2021, with a projection that it will exceed 413.8 million tons in 2023, reflecting a 5.91% increase compared to previous years [1]. In Peru, the plastics industry has followed a growth trajectory, experiencing a 9.4% increase in 2024 compared to the previous year, driven by growing internal and external demand [2]. However, this rapid growth also brings with it substantial challenges, especially in terms of operational efficiency. Inefficiencies in production processes, particularly in injection molding, negatively impact the competitiveness of companies within the sector. This problem is clearly reflected in the Overall Equipment Effectiveness (OEE) indicator, which measures the availability, performance, and quality of production equipment. In the case of the Kero Eco bank production line, the average OEE has been below the global standard of 85%, registering an average of only 71.68%, reflecting a gap of 13.32% with respect to ideal performance. This disparity highlights the urgent need to optimize production processes.

The plastics industry in Peru is key to the country's manufacturing sector, representing 0.5% of the country's GDP in 2024 [3]. However, the sector faces a great economic disparity, where only a small percentage of companies report sales exceeding S/ 50 million annually, while more than 90% generate less than S/ 3 million [4]. This outlook underscores the need to adopt emerging technologies to improve the competitiveness and sustainability of companies in the sector.

In this context, digital transformation and the use of artificial intelligence (AI) are presented as key tools for increasing competitiveness and optimizing production processes. Tools such as Single-Minute Exchange of Dies (SMED), digital twins, and Statistical Process Control (SPC) are proven methodologies for improving OEE, reducing downtime, and minimizing defects. Furthermore, the use of AI and the Digital Twin not only improves operational efficiency but also facilitates innovation in business models, optimizing strategic decision-making through simulations and predictive analytics.

A successful example in the global manufacturing industry is the use of Digital Twin and Value Stream Mapping (VSM), which allowed a company to eliminate bottlenecks and improve its OEE by 15% [5]. This type of integration of digital technologies demonstrates how digital transformation can be a lever for business innovation.

This study aims to increase the OEE of the injection molding process at a Peruvian plastics company using advanced technologies such as SMED, FMEA, SPC, and Digital Twins. Improving OEE not only optimizes production times but also ensures better use of resources, reducing losses and improving equipment availability.

One of the study's objectives is to reduce mold assembly and disassembly times, minimizing unplanned downtime and improving production flow efficiency. SMED implementation will focus on transforming internal activities into external ones, to standardize and accelerate the mold changeover process. Another objective is to implement automated monitoring systems, optimizing component oversight and minimizing operational interruptions. The integration of advanced sensors and the use of FMEA will enable early detection of faults, ensuring optimal equipment performance. Finally, the company aims to reduce thermal instability in the injection process by using ANDON temperature sensors and statistical process control (SPC) to ensure more precise and efficient control of final product quality. This will reduce process variability and improve product consistency.

These technological interventions are expected to not only improve OEE but also contribute to cost reduction, greater market competitiveness, and improved sustainability of production operations. The successful implementation of these solutions could position the company as a leader in the sector, optimizing its processes and aligning itself with the best practices of Industry 4.0.

II. State of the Art

To develop the state-of-the-art, an exhaustive search for articles was conducted, applying specific selection and exclusion criteria to ensure adequate compilation. The analysis of these criteria focused on the application of engineering and Industry 4.0 methods, techniques, and tools with the goal of improving efficiency in the plastics industry. In this context, the following typologies were identified: OEE, most common root causes, injection temperature variability, increased electrical failures, and long mold assembly and disassembly times.

A. Overall Equipment Effectiveness (OEE)

Recent studies have shown that the strategies implemented to improve OEE in various industries, particularly in plastics manufacturing, vary in complexity and scope. [6] achieved a 12% increase in OEE through Artificial Intelligence and Human-in-the-Loop labeling, optimizing quality in real time and reducing defective products. On the other hand, other authors achieved a 26.32% improvement by applying Six Sigma and DMAIC to decrease changeover times and increase consistency [7]. On the other hand, another study obtained a 48% increase in OEE by integrating SMED with Fuzzy FMEA, focusing on avoiding failures that prolonged setup times [8]. A 13% improvement can also be achieved by combining SMED and Jidoka to detect errors and reduce machine or mold setup times or increase OEE by 18.35% by adding a VSM to eliminate bottlenecks [9][5].

Studies confirm that OEE improvement depends on methodologies adapted to the process. On the one hand, techniques such as SMED and DMAIC, which were developed [7][8], have proven to be effective in optimizing changeover times and preventing failures, achieving significant increases. Furthermore, Lean tools, such as VSM combined with SMED and 5S ensure sustainable improvements by eliminating waste and unproductive times [9][5]. These strategies allow to achieve significant operational efficiencies, adapted to the specific needs of each industry.

B. Most common root causes

The reviewed studies highlight various root causes affecting OEE in injection molding machines. On one hand, OEE losses are attributed to the lack of predictive maintenance systems integrated with advanced sensors, making it difficult to detect problems in real-time and prevent unplanned downtimes [10]. Furthermore, it is noted that variations in process parameters such as mold pressure and temperature directly affect product quality and operational availability [11]. On the other hand, authors such as [12] establish that critical failures in key components are due to the lack of predictions based on historical data, resulting in unplanned downtimes. Although, excessive energy consumption and inefficient parameter settings can be correlated with poor operational performance, such as identifying fluctuations in mold cavity pressure due to ambient temperature and product quality [13] [14].

The conclusion of the articles converges that technical and operational failures, together with poor parameter optimization, are the main causes of low OEE in injection machines. It is highlighted that predictive systems based on data and real-time monitoring are key to reducing downtime and hybrid machine learning models optimize quality and productivity [10] [15]. Furthermore, it is emphasized that conventional tools reduce unexpected failures, improving availability and the optimization of parameters such as pressure and speed improves quality and energy efficiency [12] [13]. On the other hand, it is concluded that control systems correct deviations in real time, reducing defects and improving product consistency [14].

C. Main root causes of the project

The Single-Minute Exchange of Die (SMED) approach significantly optimizes assembly and disassembly times by transforming internal activities into external ones and standardizing operations, thereby reducing setup times in complex industrial processes [16] [17].

On the other hand, [18] demonstrates that the FMEA tool, applied to injection molding, allows to identify and prioritize critical electrical faults such as malfunctions in thermal control systems. Through the systematic evaluation of severity, occurrence and detection, FMEA facilitates the implementation of effective corrective actions, thus improving the operational reliability of the injection molding machine and reducing downtime due to electrical failures.

This approach can be further enhanced with the implementation of digital twins, which allow injection molding operations to be simulated and analyzed in real time, anticipating electrical failures and optimizing assembly sequences, which reduces downtime and improves operational efficiency [19][20].

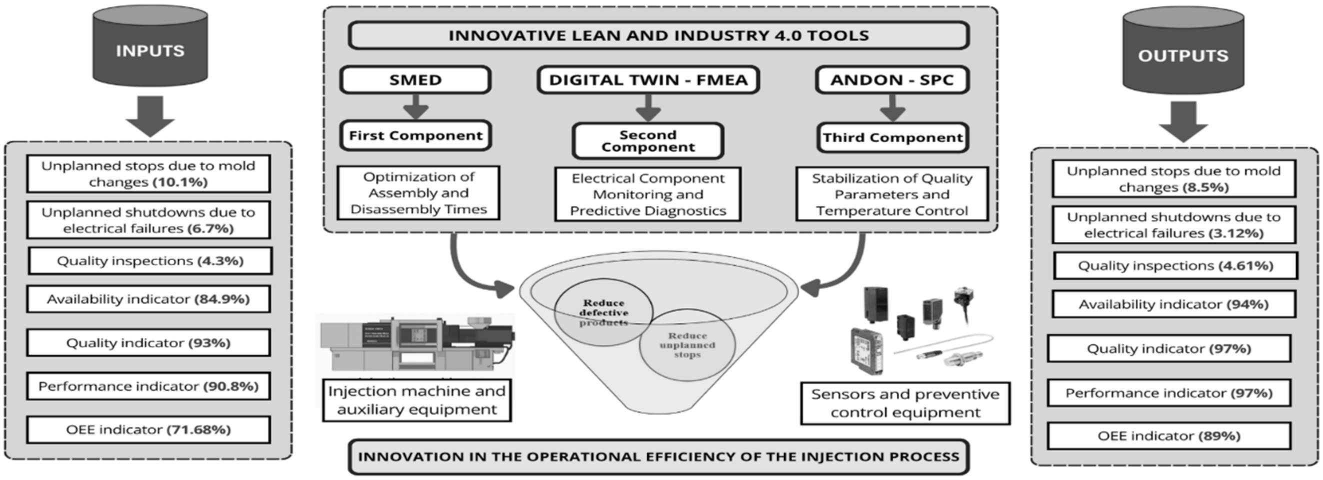

Fig. 1 Conceptual model

Injection temperature variability is a key cause of defects in injection molding. [21] demonstrates that real-time monitoring of variables such as viscosity index and peak pressure using sensors allows for the application of SPC principles to stabilize the process and reduce product variation. Additionally, the implementation of a digital ANDON system provides immediate alerts in the event of thermal deviations, facilitating a rapid operational response. Thus, SPC and ANDON act synergistically: one statistically controls the process, and the other allows for visual and timely intervention in the event of anomalies.

Various studies in Latin America have shown that the application of continuous improvement tools generates significant impacts on the operational efficiency of manufacturing companies. For example, [21] managed to increase machine availability from 69.74% to 90.17% through the implementation of TPM, SMED, and Lean tools. Similarly, [22] improved the OEE from 67.60% to 79.75% in a SME in the plastics sector by applying 5S, DMAIC, autonomous and planned maintenance. In addition, the application of SMED has allowed to reduce changeover times by 64.81% [23].

III. Contribution

A. *Foundation*

The proposed model shown in Figure 1 is divided into three components. It seeks to optimize the injection molding process in a plastics company, aligning with the principles of Industry 4.0. Its structure integrates tools such as Digital Twin and SPC, and classic methodologies such as SMED, FMEA, and ANDON. These technologies are used to improve efficiency and quality, addressing operational issues and reducing defective products and unplanned downtime.

B. *Proposed model*

The conceptual model is organized into three main components, each with its own specific inputs, including setup times, mold changeover procedures, monitoring equipment, preventive inspection frequency, quality records, and temperature sensors. These inputs, located at the top, represent the initial data and resources required for the implementation of each component.

The central arrows then reflect the flow of actions and tools applied: SMED to optimize setup times, the combination of Digital Twin and FMEA for electrical fault detection and prevention, and the integration of SPC and ANDON to control variability and ensure quality. These connections show the sequence and synergy between the components that transform inputs into operational results.

Finally, at the bottom, the output reflects the expected results: a reduction in unplanned downtime and a reduction in defective products, which together contribute to the primary objective of increasing the operational efficiency of the injection molding process. (See Fig. 1.)

C. *Details of the model with an innovative approach*

Component 1 focuses on reducing long setup times caused by non-optimized internal activities during mold changeovers on the injection molding machine. This component considers key variables such as setup times and procedures or standards associated with mold changeovers. The application of the SMED (Single-Minute Exchange of Dies) methodology will significantly reduce unplanned downtimes, thus optimizing the machine's operational availability.

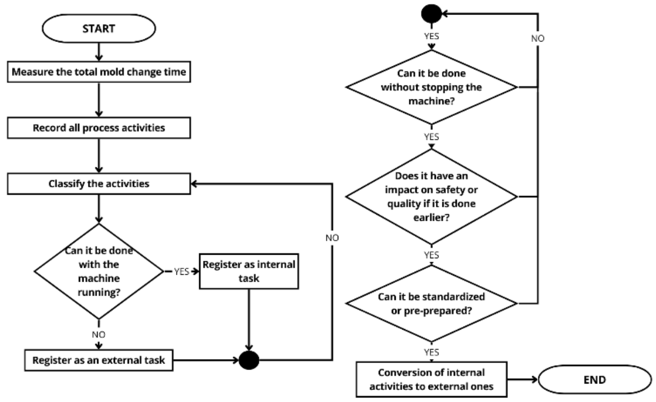

Fig. 2 Design of phase 1 of the model

Component 2 then integrates the FMEA (Failure Mode and Effects Analysis) methodology with the use of Digital Twins for the detection and prevention of electrical faults during the production process. This component relies on monitoring equipment and the frequency of preventive inspections to anticipate and mitigate potential failures that could affect the continuity and quality of the production process. The synergy between Digital Twin and FMEA will facilitate predictive control and greater system reliability.

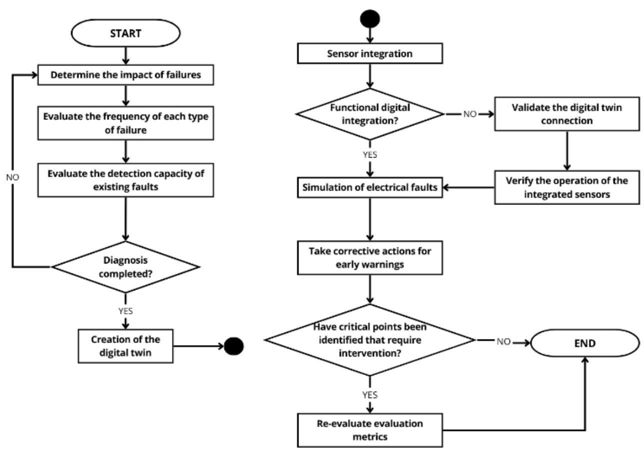

Fig. 3 Design of component 2 of the model

Finally, component 3 focuses on controlling injection temperature variability using ANDON technologies and SPC (Statistical Process Control) statistical tools. This component includes continuous monitoring using temperature sensors, displays, and indicator lights, as well as the analysis of quality records. The joint implementation of SPC and ANDON aims to reduce the number of defective products, ensuring process stability and consistency.

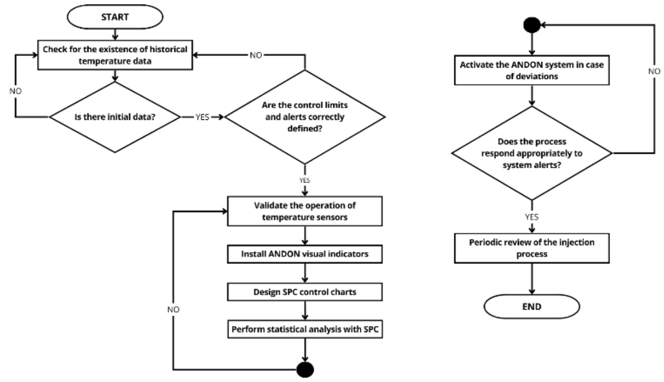

Fig. 4 Design of component 3 of the model

D. Model indicators

Upon completion of the proposed model's phases, the performance of each component is evaluated and analyzed by measuring the essential indicators for efficiency.

1) OEE

This indicator measures the overall efficiency of the injection molding machine by multiplying three key factors: availability, throughput, and quality. It is essential for evaluating the overall performance of the production system, as it provides a comprehensive view of the effective uptime and quality of the die banks.

$$\boldsymbol{Availability} \times \boldsymbol{Performance} \times \boldsymbol{Quality} \qquad (1)$$

IV. Validation

This solution model is based on the application of Lean and Industry 4.0 tools. To verify the effectiveness of the proposal to improve the efficiency of the Kero Eco bank injection process, it was decided to use computer simulation through Arena Simulation software, building the current production system (As-Is) and the proposed one (To-Be), where key variables such as availability, performance, quality and efficiency will be incorporated.

Based on the Murata model, the separation of internal and external tasks allows for effective standardization, reducing downtime [24]. Likewise, [16][21] highlight that digital twins optimize processes and detect bottlenecks before they affect the operation. It is also emphasized that tools such as Arena validate improvement proposals by modeling scenarios without interrupting production [5]. This integration of SMED with digital technologies increases OEE by maximizing availability and minimizing downtime.

A. *Starting Diagnostic*

First, the time recording of the injection process and the unplanned downtime response process were collected; the sample size was 100 records. Subsequently, we performed an analysis of each process in the Arena Input Analyzer, where we obtained the distributions and expressions corresponding to the actual behavior of the data in its current state. See TABLE I.

TABLE I
RESULTS OF VARIABLES BY INPUT ANALYZER

Activity	Average	Current Distribution
Intake of MP	2.00	NORM(1.8 , 0.8)
MP Formulation	0.13	TRIA(0.07, 0.13, 0.18)
Injection	0.58	NORM(0.584, 0.0315)
Quality Control	0.08	NORM(0.0827, 0.0134)
Setup Arrival	253.30	NORM(350, 1)
Mold Change Attention	16.00	TRIA(6, 8, 10)
C2 Attention Arrival	117.40	NORM(200 , 3)
Electrical Failure Attention	11.85	NORM(5.2, 3.5)

B. *Validation Design*

For the simulation, the work time is considered to be two shifts of 8 hours each per day, including a 30-minute break, with a 95% probability of failure and a 5% margin of error. The injection molding process begins with the entry of the raw material and ends with the visual quality control performed by the operator, which determines the number of defective products due to temperature variability and insufficient injected volume. Furthermore, tail formation is observed during the injection molding process, which occurs because the machine has unplanned stops for mold changes and electrical failures. See Fig. *5*.

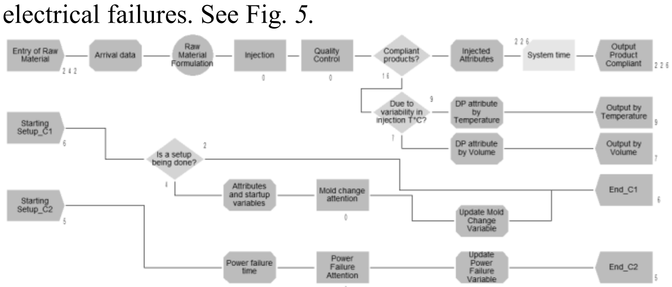

Fig. 5 Simulation of the current situation

Using SMED, FMEA, and Andon, we simulated the proposed scenario, considering improvements in mold changeover times, electrical fault response times, and the percentage of defective products.

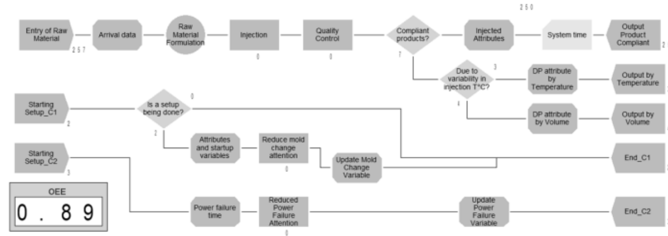

Fig. 6 Simulation of the proposed model

After simulating the proposed model, it was observed that reducing the 22 internal and external activities grouped together for mold changeover to 17 external activities achieved a positive reduction in downtime. Furthermore, through the proposed FMEA, downtime was reduced from 36.35 minutes to just 9.64 minutes. (See Fig. *6***¡Error! No se encuentra el origen de la referencia.**)

C. *Results Obtained*

The results obtained from the simulation of the proposal surpassed current indicators such as availability, quality and performance, achieving an increase in the current OEE by 17.32%, surpassing the 85% proposed by [25], going from 71.68% to 89%. (See TABLE II)

TABLE II
COMPLEMENTARY INDICATORS

Indicator	As Is	To Be
Availability	85.00%	94%
Quality	93%	97%
Performance	91%	97%
OEE	70%	89%
Banks produced	241	257
Defective products	15	7

In addition, electrical failure times were reduced by 73.48% (from 36.35 to 14.80 minutes). We also achieved significant improvements by reducing mold changeover time by 48.90% (from 32.37 to 16.54 minutes) and temperature variability by 20%. (See TABLE III)

TABLE III
PROPOSAL MEASUREMENT INDICATORS

Indicator	As Is	To Be	Actual result
OEE	71.68%	85%	89%
Long mold changeover times	32.37 min	15 min	16.54 min
Long electrical failure durations	36.35 min	14.80 min	9.64 min
Temperature variability	185°C - 215 ° C	190 °C - 210°C	188 °C - 212 °C

Based on the results obtained, it is concluded that the implementation of SMED, along with Digital Twin, FMEA, and Andon technology, makes it possible to prevent unplanned downtimes before they occur and reduce response times for each downtime when it occurs.

V. DISCUSSION

A. *Interpretation of results*

The simulation results show a substantial improvement in OEE, reaching 89%, representing a 17.32% increase compared to the baseline value (71.68%). This exceeds the industry benchmark of 85% and validates the proposed approach, which integrates Lean tools (SMED, FMEA and ANDON) with Industry 4.0 technologies (SPC and Digital Twin). The synergy among these tools effectively addressed the three critical OEE dimensions: availability, performance, and quality. Nevertheless, it is important to highlight that achieving these values in real industrial environments will depend on overcoming challenges such as operator training, infrastructure readiness, and the financial capacity of firms to adopt advanced technologies.

B. *Technical contributions of the model*

The modular design of the proposal, structured into three components, provides technical versatility to address root causes of inefficiency. SMED reduced mold changeover times by 48.90%, transforming internal into external tasks and standardizing workflows. The integration of Digital Twin with FMEA enabled a 73.48% reduction in electrical failures, confirming the potential of real time monitoring and predictive maintenance. Meanwhile, SPC and ANDON together stabilized the thermal range, improving final product quality. From a technical integration perspective, the digital model requires data synchronization between IoT sensors, machine interfaces, and parameter optimization. This integration reinforces the practical feasibility of implementing hybrid Lean Industry 4.0 systems in plastics manufacturing.

C. *Sustainability and replicability*

This model not only seeks to improve production efficiency but also promotes sustainable practices by reducing waste, reprocessing, and downtime. The model's modular architecture makes it replicable in other industrial processes with similar characteristics, especially in industries where mold changes, unplanned downtime, and product thermal quality are determining factors. Long-term sustainability can be achieved by integrating this methodology into continuous improvement programs and digital monitoring systems.

D. *Critical considerations and future directions*

Although the results technically validate the proposal, it is important to recognize that the simulation was conducted in a controlled environment. The variability of human factors, real-life maintenance, and physical conditions are not fully modeled. Furthermore, the implementation of technologies such as Digital Twin or SPC with advanced sensors may require investments that not all companies are willing or able to afford. In this regard, as a future step, we suggest implementing a real-life pilot program to evaluate the model's performance in the plant, as well as incorporating automatic prediction algorithms and data analysis to strengthen the model's digital component.

VI. CONCLUSIONS

The results obtained after implementing the improvement proposal reflect a substantial and consistent improvement in all key performance indicators of the injection molding process. Equipment availability increased significantly, from 85% to 94%, while product quality rose from 93% to 97%, and operational efficiency improved from 91% to 97%. This set of improvements led to an increase in Overall Equipment Effectiveness (OEE) from 71.68% to 89%, surpassing the global standard and translating into a tangible increase in production, with an increase in manufactured benches from 241 to 257 units, along with a notable reduction in defective products, which decreased from 15 to 7 units. These results demonstrate a comprehensive optimization of the production process, with direct positive impacts on efficiency, quality, and productivity, confirming the technical and operational effectiveness of the project.

Additionally, detailed analysis and simulation validation confirmed the feasibility and effectiveness of the Lean and technological tools implemented to address the root causes identified in the diagnosis. Mold changeover time, one of the main bottlenecks, was reduced from 32.37 minutes to 16.54 minutes, approaching the target of 15 minutes through the application of the SMED methodology. Likewise, electrical failures, which represented a significant obstacle, decreased considerably from 36.35 minutes to 9.64 minutes, exceeding the established goals thanks to the integration of FMEA with Digital Twins, which enabled more effective predictive and preventive management. Finally, the variability in injection temperature, controlled through SPC techniques and the ANDON system, showed a reduced and more stable range (from 188°C to 212°C), improving the thermal consistency of the process and, consequently, the quality of the final product.

These results validate the proposal as a viable and operationally sound technical solution, demonstrating how the strategic combination of Lean methodologies with advanced digital technologies can solve critical problems in the plastics industry, contributing to improved competitiveness and sustainability of the production process.

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