International Journal of Engineering Trends and Technology
ISSN: 2231-5381/ https://doi.org/10.14445/22315381/IJETT-V74I5P101

Volume 74 Issue 5, 1-16, May 2026

Original Article

Improvement Proposal to Increase the Availability of Napkin Production Machinery Through Planned Maintenance, IoT, and SMED

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Received: 15 July 2025 Revised: 02 February 2026 Accepted: 11 March 2026 Published: 30 May 2026

***Abstract* - *In recent years, the paper and cardboard industry has grown globally, with China and India leading production at approximately 30% and 15% of the global total, respectively. However, the situation in Peru is different, as the sector's contribution to GDP declined by 6.6% in 2023, and many factories barely utilized 11% of their installed capacity. Even so, demand for tissue paper increased, and the industry is expected to grow by 8.83% in 2024. The biggest obstacle for a local tissue paper producer is the low availability of their equipment, which reaches only 62.71%. Because maintenance is reactive, failures are addressed after they occur, causing constant interruptions and increasing costs. To change this scenario, a model was proposed that combines three strategies: SMED to reduce setup time, planned maintenance to prevent failures, and IoT sensors to monitor conditions in real time and act predictively. The model was validated using historical data and expert review, with availability as the key indicator. As a result of its implementation, availability improved to 86.02%, representing a gain of 23.31 percentage points. Economically, the impact of downtime decreased by 9.78%, and annual savings of S/ 5,251.95 are estimated thanks to fewer repairs, better use of spare parts, and increased productive hours. In short, combining lean techniques with Industry 4.0 tools can significantly improve plant performance, even in small- to medium-sized operations.*

Keywords* - *Machine Availability, SMED, TPM, Industry 4.0, IoT.

1. Introduction

Over the decades, the paper industry has changed for the better. Demand has been driven by e-commerce, increased consumption of sanitary products, and the demand for sustainable packaging. The industry has surpassed $500 billion and is expected to grow by 3.4% annually for the next seven years, reaching $500 billion. Compared to the 6% paper consumption of the rest of Latin America, Brazil and Mexico lead the way, but Peru's situation is changing. In 2023, the paper component of Peru's manufacturing GDP fell by 6.6%. This is a result of poor logistics, low industrial automation, and a stagnant industry. Furthermore, 89% of companies are operating below capacity. The biggest obstacle is downtime resulting from mechanical failures and inadequate predictive maintenance. Therefore, modernizing systems and reducing downtime are critical to restoring productivity.

The problem is particularly severe in medium-sized firms that operate with thin margins and rely on equipment over ten years old, which demands frequent maintenance. According to the Society for Maintenance and Reliability Professionals, manufacturers lose about 5% to 20% of annual output to unplanned failures [3]. In Peru, paper mills have recorded unplanned events causing downtime of up to 90 hours per month [4]. This lost time reduces sales, disrupts schedules, and pushes costs up through overtime and wasted materials. To address this, plants use proven methods. SMED cuts changeover time by separating what can be done while the machine runs from what must be done when it is stopped, reaching reductions of up to 34% in recent packaging and manufacturing cases [5]. TPM involves operators in basic care and early detection, which raises availability, in some cases from 70% to 95% [6]. Moreover, combining these practices with simple visual checks, standard work, and a short daily review helps sustain gains.

Therefore, a staged rollout starts on one line, measures results, then scales to lower risk and builds a clear case for future digital upgrades. In recent years, traditional improvement tools have been strengthened by industrial digitalization. Industry 4.0 technologies, IoT sensors, cloud dashboards, cyber-physical systems, and simple predictive models create new options to manage maintenance in real time. For example, vibration, flow, and temperature sensors connected to plant networks can flag abnormal patterns and prevent failures before they occur, with reports of up to a 95% drop in critical incidents in sectors such as automotive and food [7]. Likewise, platforms like SAP Predictive Maintenance or IBM Maximo, and even open-source stacks in Python, can mix historical and live data to trigger alerts and plan work ahead of time [8]. However, adoption in Peru remains limited, especially in mid-sized mills, because teams lack trained staff, operations and maintenance work in silos, and there is no simple model that ties lean routines to digital tools. In addition, budget limits, weak connectivity, and concerns about data and cybersecurity slow decisions. Even so, falling sensor costs and wireless options make low-risk pilots feasible if the scope is focused and roles are clear.

Despite these advances, few studies test the joint use of SMED and IoT-based predictive maintenance in tissue production, particularly in emerging economies. Most papers treat them apart: SMED to cut changeovers, IoT to watch equipment health. This separation leaves a gap in how their integration can raise both setup efficiency and machine availability at the same time. As a result, small and medium manufacturers struggle to size the real gains from “Digital Lean.” A practical way forward is to design integrated pilots with a short list of indicators, changeover time, availability, OEE, and maintenance cost measured before and after the rollout. In sum, an integrated approach can show clear cause–and–effect links and build the evidence needed to scale.

This research proposes and validates an integrated improvement model that blends SMED and TPM with Industry 4.0 tools, IoT sensors, and predictive monitoring. The combination enables real-time data capture, detection of setup bottlenecks, and early prediction of failure conditions before stoppages. Unlike studies that assess these tools in isolation, the model builds a simple, synergistic framework tailored to Peruvian tissue mills. Moreover, it links daily lean routines with digital alerts and clear response rules, so teams can act before a stop, shorten changeovers, and learn from each cycle.

The study applies the model to a napkin production line. It first identifies the most critical machines, then maps activities with long waits or preparation times. Next, it sets a small set of indicators: setup time, availability, unplanned downtime, and maintenance cost to track impact. The rollout includes quick-change practices, standard work, operator-led basic care, and a light condition-monitoring layer (vibration, temperature, flow). In addition, simple alert logic and a weekly review sustain results. Therefore, the expected effect is fewer unplanned stops, shorter changeovers, and higher operational availability, with improvements that can be scaled line by line as evidence accumulates.

This research is relevant because it can cut the economic impact of unplanned stoppages by up to 9.78%, with estimated annual savings of about USD 5,251; moreover, it helps close the technology gap in medium-sized plants by showing a simple way to combine lean routines with basic digital monitoring that can be replicated across other tissue lines and, later, other mills in the country, so benefits do not remain in one site; therefore, the work is organized in five sections state of the art on industrial maintenance and digitalization, methodology and model design, validation and results on a real line, technical and economic analysis, and conclusions with practical recommendations aiming to deliver a clear, applicable solution that strengthens productivity and competitiveness in the national paper industry.

2. Literature Review

2.1. Paper Sector

The global paper and cardboard industry plays a vital role in the international economy because its operations generate significant impacts across environmental, economic, and social spheres [2]. Today, China leads with about 30% of global supply, while India provides roughly 15% and is expected to grow about 7% per year [1]. Therefore, efficient resource use is essential to sustain this scale and keep performance strong.

Industrial growth can be economically supported through the conversion of waste paper. Furthermore, the cost-effectiveness of the paper industry increases by 20% through the implementation of process engineering combined with waste management [3]. Socially, the greatest challenge for the paper industry is the heterogeneity of the human resources involved. In this case, a predominance of paper industry technologists may be insufficient to sustain the paper sector in local communities economically. It also suggests that the increased availability of integrated paper machines may indirectly lead to increased energy consumption [2].

In terms of sustainable development, the relationship between the paper industry and the energy sector is clearly established. More frequent use of renewable energy sources is being encouraged in the paper industry [1]. The paper recycling industry also tends to have a more positive environmental impact compared to other technologies, based on environmental assessments. These findings reflect the most recent stage of development of the global paper industry and the trend toward further development.

2.2. Machine Availability

Availability is a key yardstick of efficiency and competitiveness. It shows the share of planned time when equipment is ready and running. When mechanical faults appear and unplanned stops occur, the plant loses time and money. Consequently, responsiveness drops and production goals slip [5]. Comprehensive maintenance programs, above all, TPM can lift equipment availability. Its planned maintenance pillar sets regular inspections, preventive tasks, and defined corrective actions to cut failures. In manufacturing SMEs, reported gains exceed 20%, mainly due to less downtime and tighter control of machine condition [7]. At the same time, cutting setup or changeover time with SMED raises availability by freeing more run time and limiting interruptions. Reported gains reach 488 minutes, down from 1,418 to 930, bringing lower costs and quicker response [9].

Finally, IoT boosts availability by streaming and logging key signals, such as vibration, temperature, and humidity, among others. With early alerts and just-in-time work orders, plants reduce spare-parts stock by up to 30% and lift fleet availability [9]. However, budget, skills, and change-management gaps still slow adoption in SMEs; therefore, context-adapted plans are needed to balance costs and benefits.

2.3. Total Productive Maintenance (TPM)

TPM is a broad method to raise equipment efficiency by engaging every level of the organization in maintenance. Its focus is prevention and steady improvement. The Planned Maintenance pillar anticipates failures through simple, scheduled routine inspections, lubrication, and calibration so unplanned stops fall and assets last longer [7].

Technology strengthens TPM. With IoT and basic AI, plants watch operating conditions in real time and decide with data. For example, one case lifted availability from 51.48% to 93.16% after combining TPM and IoT, with operational savings above USD 6,683.71 [6]. In sum, disciplined routines plus live monitoring turn maintenance into a predictable, high-impact process. TPM gains when SMED is added. Shorter setups and changeovers keep planned maintenance on schedule and away from production peaks. The result is smoother flow, less waste, and lower cost [5, 9]. Effective TPM needs a structured, participatory rollout of operators, supervisors, and senior leadership aligned on roles and daily routines. With Industry 4.0 tools, sensors, basic analytics, and clear alerts, the culture strengthens: teams see conditions in real time, plan work before failures, and respond faster to surprises. In sum, the TPM–SMED–IoT mix lifts efficiency and safeguards competitiveness in global markets [8].

2.4. Single Minute Exchange of Die (SMED)

SMED is a lean method aimed at cutting tool or setup changes to under ten minutes. By shortening these pauses, a plant gains flexibility, loses less time, and improves flow. In hygiene product lines, structured SMED projects have reduced changeovers by about 16.5%, which frees capacity and lowers direct costs tied to idle machines [10]. In addition, quicker changeovers stabilize quality and raise OEE because settings follow a clear, repeatable sequence.

When SMED works together with TPM, the effect is stronger. In a paper mill, the two methods cut setup time by 34% and lifted capacity by 11%, showing how coordinated routines and standard work reinforce each other [11]. In practice, pre-staging tools, clear roles, and short checklists keep the window for planned maintenance intact and reduce last-minute delays. Likewise, simple time studies or short video timing help find hidden losses and guide the next improvements.

SMED also evolves with Industry 4.0. Under a “SMED 4.0” approach, IoT sensors, data analytics, and artificial intelligence time each step, verify conditions, and suggest the best sequence. Case reports show reductions above 46% and gains in sustainability because energy and scrap fall when changeovers are shorter and more stable [12]. Moreover, digital work instructions, tool ID tags, and e-Kanban for changeover kits make standards easier to follow across shifts.

For SMEs, SMED is a practical way to compete without buying new machines. By separating internal from external work, preparing parts in advance, and adding simple visual aids, the line becomes more agile, and interruptions fall [9]. Low-cost jigs, quick-release fixtures, and compact tool carts help keep the gains, while before-and-after tracking of changeover time and first-piece quality shows impact in a simple way.

In hygiene manufacturing, studies continue to report double-digit reductions in changeover time when teams follow the method with discipline [13]; and when SMED is paired with Lean Six Sigma, reductions above 46.78% have been achieved by removing variation and balancing tasks [14]. Finally, when SMEs add the 4.0 layer sensors, real-time analytics, and even simple digital twins, average reductions near 32% have been documented, together with better traceability, safer practices, and more reliable schedules [12].

2.5. Industry 4.0: Internet of Things (IoT)

IoT is a core Industry 4.0 technology that connects sensors, machines, and systems to enable real-time monitoring and automated decisions. Thus, maintenance shifts from corrective or purely preventive to predictive, detecting failures in advance and cutting unexpected stops [15]. With about 75 billion connected devices expected by 2025, security becomes a priority; therefore, solutions within the same ecosystem, such as artificial intelligence and blockchain, among them, are key to protecting data and ensuring trust. Moreover, pairing IoT with AI methods such as LSTM improves availability and OEE in plants that apply TPM, because alerts and forecasts support just-in-time maintenance and faster root-cause action [16, 17]. In addition, IoT can also speed SMED efforts by flagging constraints and real-time errors during changeovers, with reported reductions of up to 50% in setup time [18]. To make this reliable on the shop floor, simple enablers help: edge processing near the machines, standard protocols like OPC UA or MQTT for interoperability, and basic “zero trust” practices such as strong authentication and network segmentation.

IoT's benefits are not confined to large companies; small and medium firms also report clear gains in machine availability, lower inventories, and better use of assets [19]. Likewise, its adoption in healthcare and education shows it is a versatile, cross-cutting technology that adapts to different settings.

By linking everyday objects, devices, and systems, this technology enables remote monitoring and control in homes, services, and industry, widening its practical reach [20]. In addition, sensor data viewed through dashboards and basic analytics supports faster, evidence-based decisions, which strengthen sustainable, resilient, and continuously improving operations [21].

2.6. Synergies in Integrated Management

Integrating Planned Maintenance (TPM), SMED, and Industry 4.0 tools, particularly IoT, creates a coordinated and efficient production system. Together, they raise equipment availability, cut downtime, and increase operational flexibility. For example, reducing changeover times with SMED not only lifts effective capacity but also opens short windows to carry out planned maintenance without disrupting production [15, 22].

IoT sensors enable real-time tracking of equipment. They identify signs of wear, abnormal vibrations, and likely failures so that maintenance can be scheduled early and costly stops are avoided. Meanwhile, predictive analytics adapts interventions to actual operating conditions, making actions more precise and lowering costs [23].

Recent evidence indicates that integrating these practices can raise availability by more than 20% while lowering operating costs and the burden of unexpected stoppages [24]. In addition, adopting new digital tools strengthens sustainability: resources are assigned with greater precision, waste decreases, and the response to contingencies becomes faster [25].

Thus, applying TPM, SMED, and IoT in a coordinated way adjusted to each plant's context raises uptime, cuts unplanned stops, and builds a proactive maintenance culture. At the same time, it pushes process digitalization, two pillars for the transition to Industry 4.0.

3. Proposal Model

3.1. Rationale

The model tackles the core bottlenecks: long changeovers (9.27 minutes), recurring breakdowns (2.73 hours), supply delays (4.53 hours), and low availability (62.71%). Therefore, it applies two levels: Planned Maintenance backed by IoT for live condition tracking and early failure alerts, and SMED to trim changeover time through simple, standard steps. In addition, short daily checks and tighter spare-parts coordination stabilize the line and cut surprises. Evidence in small and medium firms shows these practices raise availability and everyday efficiency [26]. Likewise, combining TPM with Lean, where SMED is central, has reduced setup times by about 25% and improved reliability markers such as MTBF and MTTR [27]. Applied to the rewinder, SMED standardizes calibration and adjustments; therefore, changeovers shrink, unplanned pauses drop, and overall productivity rises.

The model has two components, as shown in Figure 1. First, Planned Maintenance (PM) minimizes unplanned stops through proactive routines, automated spare-parts ordering, and continuous skills training.

Second, SMED reduces setup by separating internal and external work and by optimizing the sequence of activities. To keep results, the rollout uses a small KPI set availability, changeover time, MTBF, and MTTR, plus a brief weekly review with clear roles and simple visual controls.

3.2. Comparative Advantages

The model takes a complete route: it links IoT-enabled planned maintenance with the lean SMED method to attack the two main causes of low uptime, unplanned stops, and long changeovers. Unlike approaches that treat these issues separately, it handles both at once, so actions reinforce each other and efficiency rises. Moreover, the use of ThingWorx replaces manual or partial steps with a single, real-time layer, which is a clear advantage.

Furthermore, the HBM T12 and SKF CMPT 2310 sensors, installed according to industrial protocols, enhance monitoring accuracy and accelerate fault detection compared to lightweight, non-integrated assemblies. Simultaneously, a training program with periodic evaluation ensures adoption and sustains the results over time [28, 29].

3.3. Originality, Contribution, and Relevance of the Proposal

This proposal stands out for a comprehensive, context-fit path to raising availability in manufacturing, especially in the paper sector. Its key originality is the joint use of IoT-based planned maintenance, automated spare-parts management, and SMED on the rewinder to identify the bottleneck. Rather than treating these levers separately, the model applies them at the same time, so actions reinforce each other and efficiency climbs. Moreover, it is replicable in SMEs with tight budgets, proving that advanced practices can be deployed without heavy investment while still lifting productivity and cutting downtime. Its relevance is further amplified by addressing local issues such as unplanned shutdowns and lengthy setup times. With this integration, the plant can schedule interventions before a failure occurs, reducing changeovers and stabilizing operations; consequently, it improves performance and maintains long-term competitiveness.

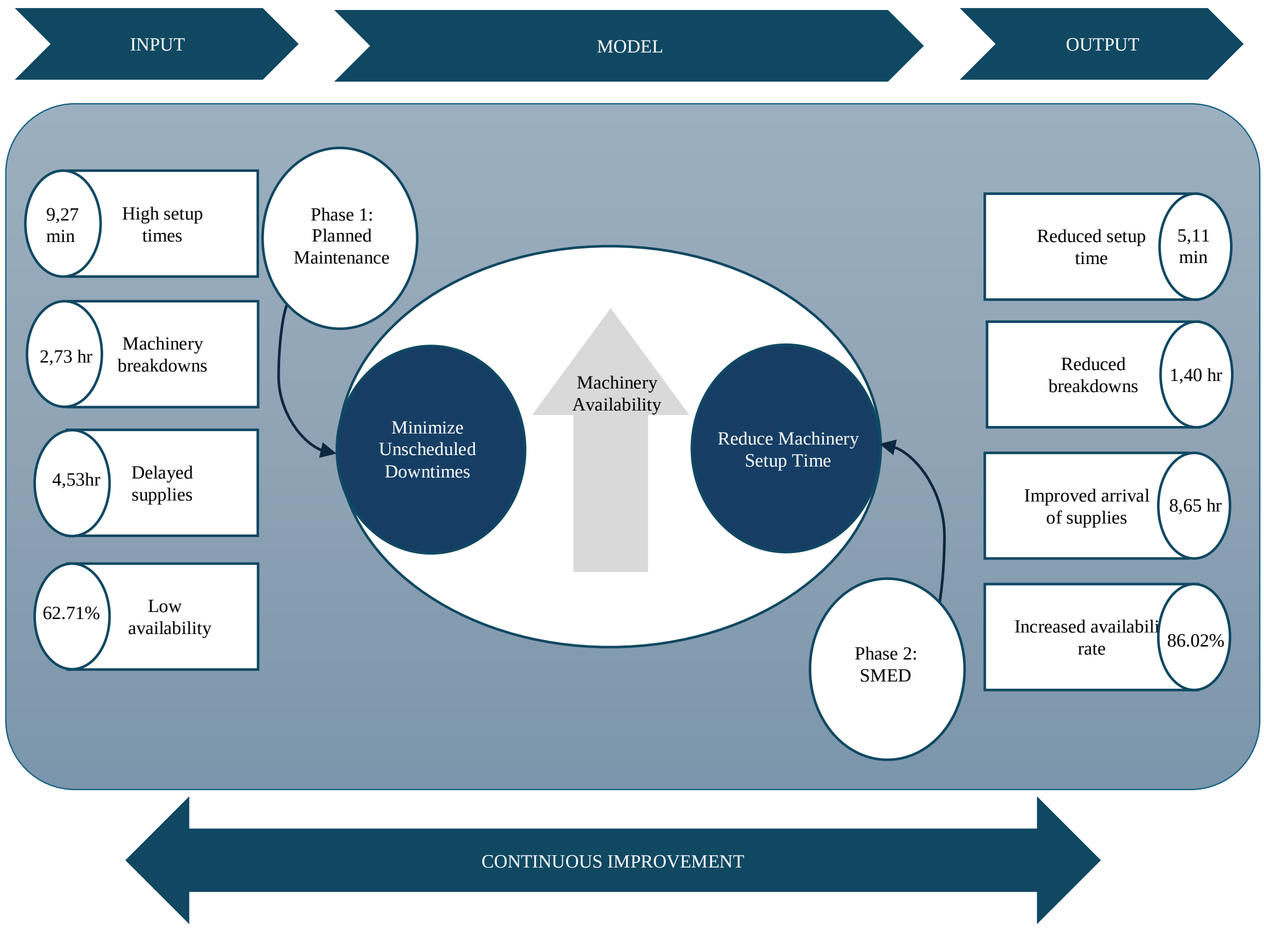

Fig. 1 Proposal model

3.4. Structure of the Proposed Model

3.4.1. Phase 1: Implementation of Planned Maintenance

Planned Maintenance supported by IoT starts with a focused diagnosis of the critical machines, especially the rewinder, so real-time signals can feed predictive software and guide timely interventions, reducing failures and unplanned stops. At the same time, linking the model to the spare-parts system supports automatic ordering, which helps prevent waiting time due to missing components. In addition, staff training and ongoing follow-up strengthen correct use and allow the model to improve as more data and experience are collected.

Stage 1: Initial Diagnosis and Criticality Analysis

In this stage, the condition and criticality of the napkin line machines previously managed mainly with corrective maintenance were assessed. Criteria such as economic impact, reliability, dependency on spare parts, and ease of cleaning were reviewed, and equipment was grouped into criticality levels. The rewinder was ranked as the most critical asset; therefore, an FMEA was conducted to map failure modes, identify causes and effects, and score risks using the Risk Priority Number. As a result, moderate- and high-risk failures were prioritized for immediate action and monitoring.

Stage 2: Installation of IoT Sensors and predictive Analytics Software

Next, two sensors were selected and installed on the rewinder: the HBM T12 digital torque sensor to track tension and torque changes, and the SKF CMPT 2310 to monitor vibration in rotating components. These signals were connected to ThingWorx to enable real-time visualization and automatic alerts for predictive maintenance through edge devices. Moreover, using standard industrial protocols such as OPC UA or MQTT improves integration and scalability, allowing the system to expand to additional machines as the model proves its value (Figure 2, 3).

Stage 3: Integration with the Spare Parts Management System

In this stage, the maintenance schedule is adjusted with real-time tension and vibration data in ThingWorx, so interventions become condition-based and are triggered only when thresholds or trends deviate. Thus, unnecessary downtime falls and availability rises. By learning wear patterns, the team can focus on the most critical assets and reserve parts in advance. In addition, linking alerts to the spare-parts module enables automatic reservations, min–max updates based on lead times, and simple e-Kanban signals to prevent stockouts and shorten waiting time.

Fig. 2 Sensor Deployment Zone 1

Fig. 3 Sensor Deployment Zone 2

Stage 4: Technical Staff Training

The training plan prepares maintenance and operations personnel to use Planned Maintenance and IoT tools in daily work. It covers ThingWorx navigation, reading tension and vibration signals, basic edge alarms, and the link with the spare-parts system. Modules are short and hands-on, with job aids, standard operating procedures, and on-the-line practice, so participants can apply what they learn immediately and support stable, efficient interventions across shifts. To measure how well the training works, a structured form is applied that rates key skills on a 1-to-5 scale. This review highlights gaps, guides reinforcement, and helps staff reach autonomy in the use of the new technologies.

Stage 5: Monitoring and Continuous Improvement

At this stage, a full audit of Planned Maintenance and the IoT system is carried out to confirm that the processes in place work as intended and align with the goals of predictive maintenance and spare-parts control. In addition, the audit verifies policy compliance, finds opportunities for improvement, and protects the results over time. The audit reviews core points. First, it checks compliance with the maintenance plan: tasks must be done on time and properly recorded. Then, it examines logs and work orders, inspects the condition of each machine, and assesses whether preventive and corrective actions achieved the expected results. In this way, it validates execution discipline and the real impact of the program.

3.4.2. Phase 2: SMED Implementation

The team maps the rewinder setup from end to end. Each auxiliary task is timed and labeled as internal when it needs to stop, or external when it can be done while the line is running. Then, wherever possible, internal work moves outside the stop, cleaning, tool preparation, and preset tweaks shift to before or after. As a result, the stop becomes shorter and more stable. Next, the method is tightened and made repeatable. Procedures are written in clear steps, required tools and fixtures are defined, and simple visual checks are added. Times are taken again to verify the gain. If results hold, the new method becomes the standard: the team documents it, trains operators, and sets regular reviews to keep setups fast and consistent in future runs.

Stage 1: Current Situation Analysis

In this first stage, a cross-functional team set out to reduce changeover on the napkin rewinder using SMED. The group mapped the work and listed 30 distinct steps. The full changeover lasted 149.04 minutes. This review clarified who does what and when. As a result, the team obtained a clear baseline to improve the process, prepare some tasks in advance, remove waste, and standardize the remaining work.

Stage 2: Transformation and Reduction of Activities

The team separated all steps into internal tasks done with the machine stopped and external tasks done while it runs. Then it shifted several internal steps, cleaning, minor adjustments, and preset preparations so they could happen before or after the roll change. In total, 41.54 minutes were spent outside the stop window. As a result, the changeover no longer needs the machine to be idle for those actions, and the setup time drops. However, some work must stay internal to protect quality. Tension settings and roller calibration still occur with the machine stopped to keep stable winding, correct dimensions, and safe operation. In summary, the process now reserves stoppage only for what is truly critical, while the rest is prepared in advance to shorten and standardize the changeover.

Stage 3: Strategy Design and Implementation

The team adopted simple rules: standard tools and steps, parts prepared in parallel, quick-adjust devices, automation of key settings, and the next roll ready before the swap. Used together, these actions cut total setup from 149.04 to 87.9 minutes, a 41% drop (61.14 minutes saved). The largest gain came from automating calibration, which removed long pauses and lowered rework. In short, the process now keeps the line moving and stops the machine only for what is truly necessary.

Stage 4: Monitoring and Continuous Improvement

Three digital formats were introduced to track each changeover: a log for recurring issues, a history of changes, and a duration summary to spot assets with higher variability. Furthermore, a brief daily review assigns owners to top losses, a control chart monitors setup time, and a monthly audit checks tool readiness and step compliance. KPIs setup time, first-pass yield, availability, and waiting time for parts trigger escalation when limits are exceeded, ensuring corrections are made quickly and the gains remain stable.

4. Methodology

4.1. Problem Analysis (Before)

To understand the issues on the napkin line, the team ran a full diagnosis centered on three visible symptoms: shipment delays, low equipment availability, and product returns. A cost-based Pareto (Figure 4) ranked their impact and showed where losses concentrated; penalties, lost sales, and rework were the largest buckets. In practice, long waits and recurrent stops delayed orders, stretched downtimes, and cut productive capacity; moreover, weak handoffs between areas made recovery slower than planned. The analysis focused on the napkin production line, the company’s main source of income.

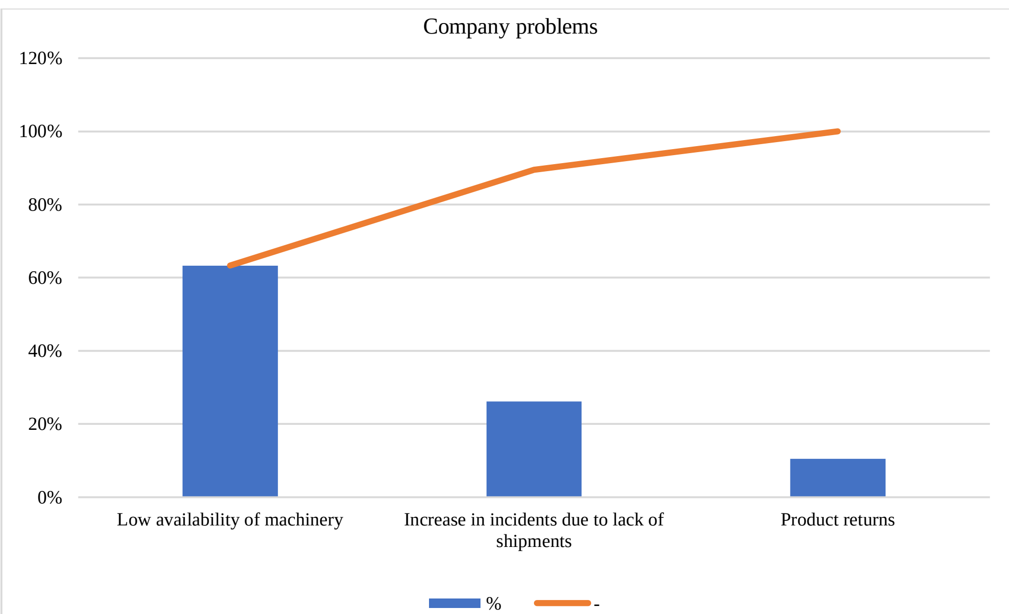

Fig. 1 Pareto of company problems

A quantitative approach was used, drawing on maintenance records and failure logs from 2023 (Figure 5). In this way, the study pinpointed the key causes of the problem: long waits for spare parts, extended calibrations during changeovers, unplanned stoppages, and recurring equipment failures. As part of the diagnosis, machine availability was used as the main metric.

It was calculated from effective operating time over total scheduled time and supported by three indicators: setup time, MTTR, and MTBF. In sum, the results pointed to a clear need to combine IoT-based monitoring with Planned Maintenance and continuous-improvement methods such as SMED and TPM to stabilize performance and reduce stoppages.

4.2. Developed Validation Method (After)

To test the model's effectiveness, the study used a computer simulation in Simio, a widely used tool in industrial improvement because it can represent real and complex systems in motion. This method is valuable in production since it allows trials of different scenarios without consuming physical resources or interrupting ongoing operations. Two cases were built: the current state (AS-IS) and an improved state (TO-BE). The TO-BE case integrated the proposed actions, planned maintenance, SMED to shorten changeovers, and IoT sensors for real-time monitoring and failure prediction, so results could be compared clearly against the baseline. The validation offered a clear picture of how the system's variables interact and how the proposal affects key metrics availability, setup time, MTTR, MTBF, and the cost of unplanned stops. In this context, simulation within Industry 4.0 helps anticipate outcomes before touching the plant, providing objective support for decisions.

The simulated results showed higher availability, shorter calibrations, and fewer failures, which translate into greater operating efficiency. Moreover, the IoT layer proved its predictive value: early alerts improve maintenance planning, reduce downtime, and sustain the continuity of production [30]. It is important to note that the validation used bibliographic sources only. Input data came from published empirical results and standard indicators, not from direct plant measurements. These values served as benchmarks to configure the TO-BE in Simio and compare it with the AS-IS. Therefore, results should be seen as a best estimate; the next step is to calibrate parameters with CMMS/SCADA logs, run face-validation sessions with operators, test extreme conditions, and re-simulate. Thus, the model can be tuned to site reality and the projected benefits converted into a simple ROI for management approval.

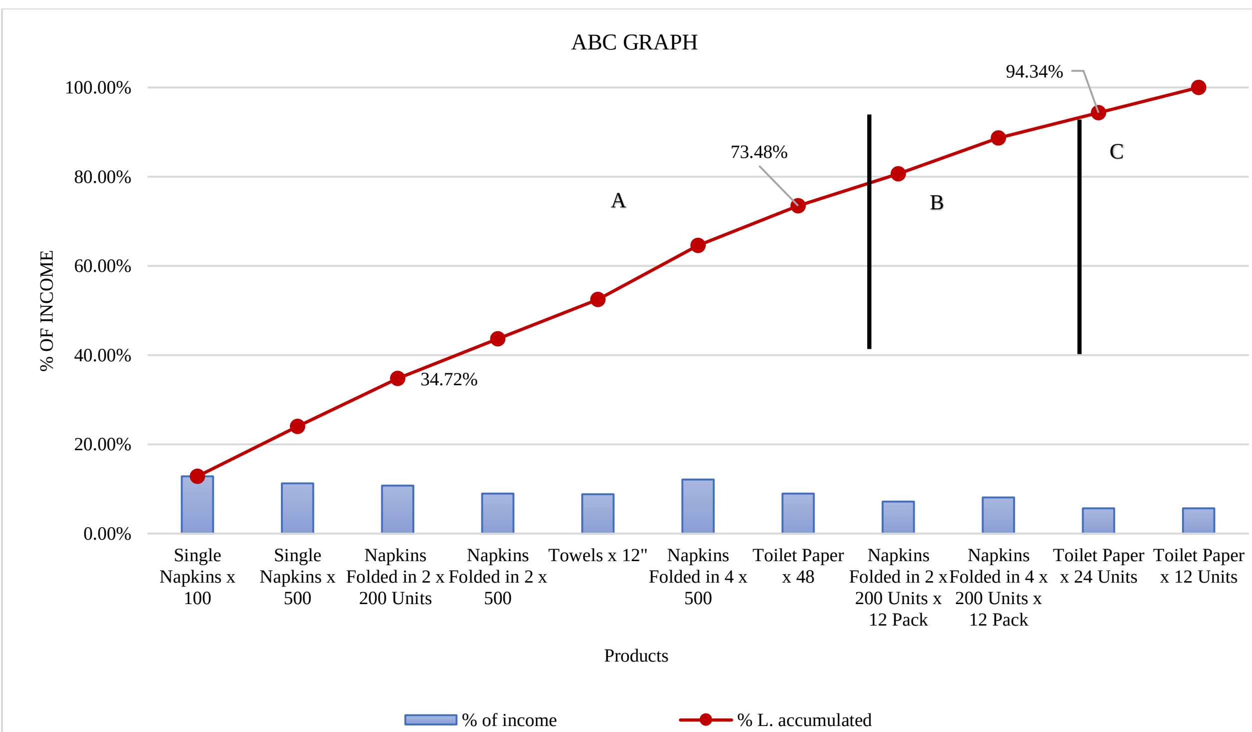

Fig. 5 ABC

4.3. Planned Maintenance + IoT Improvement

One improvement in the TO-BE model is a planned maintenance approach supported by IoT sensors. The goal is to cut unplanned stops from sudden failures and long waits for critical parts by shifting from reactive fixes to condition-based decisions. With real-time data and simple alerts, interventions are scheduled only when the machine's condition requires it, not by a fixed time. In addition, linking alerts to the spare-parts module creates early reservations and shortens lead times, so maintenance windows start on time and idle hours fall. The parameters used in this simulation came from bibliographic sources, not on-site measurements. Values from prior studies were adapted to the napkin line's operation so the model stayed realistic. The results are consistent with reported gains: MTBF improves by about 16.34% and MTTR drops by roughly 11.47% [7]. In summary, integrating TPM with IoT monitoring increases reliability and enables earlier and more accurate failure prediction. In the Simio model, the seven machines operate under reliability rules that use MTBF and average MTTR as the main inputs. The model flags abnormal conditions before a breakdown. Maintenance is then planned before failure, so repairs take less time and happen less often.

This approach is supported by evidence from industry [31]: condition-based maintenance with IoT cuts MTTR by about 25% through earlier diagnosis and better planning of technical and logistical resources. At the same time, MTBF rose as patterns were detected and corrected sooner. These findings were used as benchmarks to project realistic gains for the napkin line, considering each machine's duty cycle and part lead times. In addition, linking IoT alerts to the CMMS streamlines work-order creation and follow-up, which helps sustain the improvements over time.

4.4. SMED Improvement

Additionally, a key improvement integrated into the TO-BE model is the reduction of setup time for the rewinder, as part of the SMED strategy. This improvement is based on principles from a study that demonstrated, in a turning line case, that the SMED methodology allows identifying and transforming internal activities into external ones, standardizing repetitive tasks, and applying technical improvements that reduce format change time without compromising quality. The parameters used to model the improvement of SMED were based on a bibliographic reference that reports a 12% reduction in setup time after implementing SMED in a manufacturing process. These results were adopted as reference targets for the simulation [9]. Based on this approach, the calibration procedure was redesigned, implementing actions such as partial automation of paper tensioning, early separations of materials, and external preparation of tools.

4.5. Indicators

During the implementation of the model, four Key Performance Indicators (KPIs) were used, aligned with the established objectives. The selected indicators are Availability, Setup time, MTTR, and MTBF, which will allow for the evaluation of the proposed model's results.

4.5.1. Availability Index

This indicator shows the effectiveness of maintenance processes and the reliability of equipment.

$$Availability\ Index = \frac{T_{funcion} - T_{stop}}{T_{funcion}} \times 100 \tag{1}$$

4.5.2. Setup Time

This indicator improves efficiency, reduces non-productive time, and increases production flexibility by allowing faster product changeovers.

$$Setup\ Time = \frac{TSU_i - TSU_f}{TSU_i} \times 100 \tag{2}$$

TSU_i = Initial setup time
TSU_f = Initial setup time

4.5.3. Mean Time to Repair (MTTR)

Reflects the average time needed to restore equipment to its operational condition after a failure.

$$MTTR = \frac{Total\ Repair\ Time}{Number\ of\ Failures} \tag{3}$$

4.5.4 Mean Time Between Failures (MTBF)

This is the time that elapses from one failure event to the next.

$$MTBF = \frac{Available\ Producion\ Time}{Total\ Number\ of\ Failures} \tag{4}$$

5. Results

5.1. Results of the Problem Analysis

The initial diagnosis of the napkin line, using 2023 records, showed low operational availability and weak maintenance practices that hurt efficiency and response to demand. In summary, average availability was 62.71%, clearly below the expected ≥85% benchmark, a gap of about 22.29 percentage points, so orders faced delays and the plant lost productive hours. Therefore, the baseline confirmed the need to act on failure prevention and faster setups at the same time.

5.2. Simulation with the software Simio AS IS

The system's logic and operation were modeled from the diagnostic data, including core production steps, setup times, mechanical failures, maintenance downtimes, and material flow. In addition, shift calendars, simple queues, and basic buffer behavior were represented to mirror daily conditions and keep the AS-IS a faithful reference for later comparison.

5.2.1. Step 1: Graphical representation of the process with entities, attributes, and activities

The graphical model in Simio mirrors the plant sequence with six main machines: rewinder, horizontal cutter (cut 1), vertical cutter (cut 2), folder, diverter, and packager. At the attribute level, variables were defined for operating time, setup time, failure probability, Mean Time Between Failures (MTBF), and Mean Time to Repair (MTTR) (Figure 6). Moreover, identifiers for lot size and simple transport times were added to track effects on queues and to link results directly to availability and setup indicators.

5.2.2. Step 2: Data Analysis and Statistical Validation

To model the real behavior of processing times in the system's critical processes, the Input Analyzer software was used, applying a 95% confidence level.

Chi-square and Kolmogorov-Smirnov goodness-of-fit tests were applied, establishing that the distribution assigned to each variable would be accepted if the resulting p-value exceeded the 5% significance level (0.05), thereby ensuring the statistical validity of the distributions for simulation use. First, the study drew pilot samples of 30 observations for each process and treated the source as an infinite population.

With that data, it calculated basic statistics, mean, and variance, and then determined the minimum sample size. The calculation assumed a 5% allowable error, a 5% significance level, and a Z-critical value of 1.96.

5.2.3. Step 3: AS IS Modeling in Simio

To set the starting values for the simulations, the study drew on historical maintenance records to capture spare-part lead times, Mean Time Between Failures (MTBF), setup times, and processing times for each machine. The seven units rewinder, cutter 1, cutter 2, folder, diverter, packer 1, and packer 2 provided the reference data. In this way, the model began with a solid baseline that reflects the real behavior of the production line.

The MTTR analysis considers the entire response chain. First, the failure is logged in the maintenance record; then the clock includes the wait for the technician and the time to obtain spare parts, especially when repairs depend on external suppliers. In the AS IS model, the failure history of the seven machines in the system was used. Also included was the waiting time for spare parts, which, especially for the rewinder, whose MTTR is 5.64 hours due to imported parts, is a large part of the total repair time.

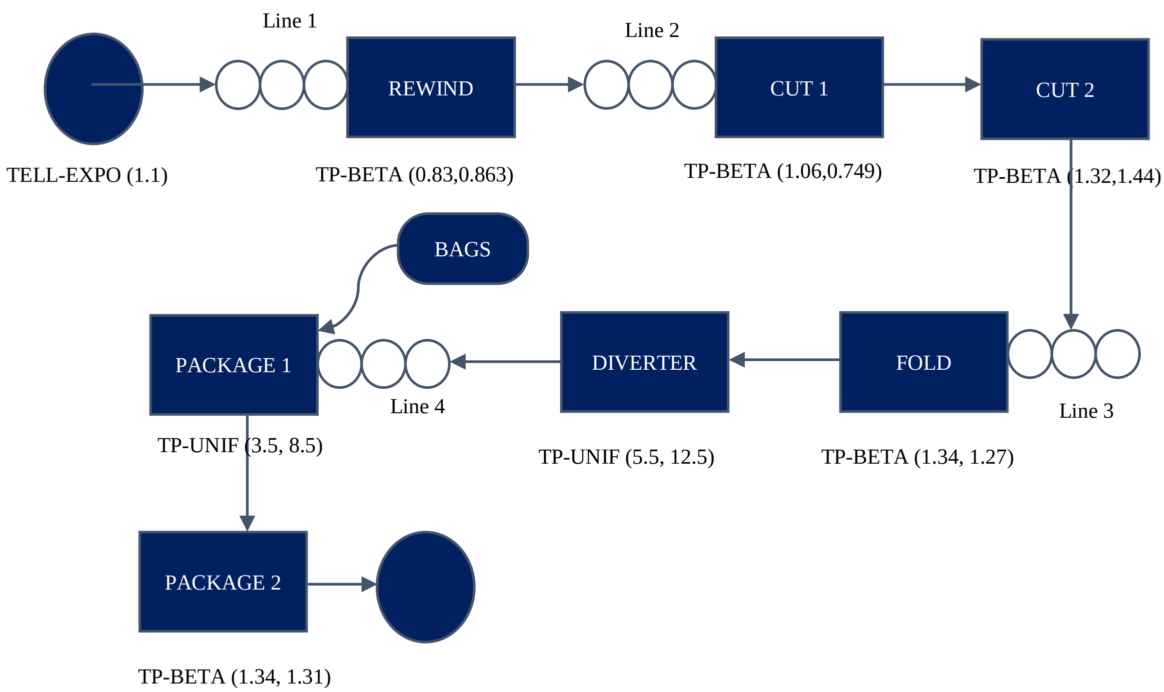

Fig. 2 Representation of Simio

Table 1. Data Analysis

Process	Distrib.	p-val	Hypothesis Test
Rewind	Beta	0.478	H_0 accepted: Fits Beta distribution
Cutter 1	Beta	0.747	H_0 accepted: Fits Beta distribution
Cutter 2	Beta	>0.75	H_0 accepted: Fits Beta distribution
Folder	Beta	0.0804	H0 accepted: Fits Beta distribution
Divertor	Uniform	0.08	H0 accepted: Fits Uniform distribution
Packer 1	Uniform	>0.75 <0.75	H0 accepted: Fits Uniform distribution
Packer 2	Beta	0.468	H0 accepted: Fits Beta distribution

On average, the line records an MTTR of 2.67 hours. The measure begins at the failure report and ends when the machine returns to service, combining travel time, repair work, and parts availability. In Simio, each machine receives these values as reliability inputs through a simple Time to Repair parameter. Thus, the model mirrors current corrective maintenance and allows a clear comparison with the TO-BE scenario.

Table 2. MTTR Time

Code	Time(hr)
Rewinder	5.64
Cutter 1	1.25
Cutter 2	1.52
Folder	2.2
Diverter	2.47
Packer 1	1.24
Packer 2	1.68

To estimate MTBF for the line, the team used maintenance logs for the seven machines. The calculation used the actual running time and the count of breakdowns in the analysis period. Mechanical, electrical, pneumatic, and paper-tension events were included. MTBF was defined as total operating time divided by the number of failures. In this way, the metric reflects the combined behavior of the line and not a single machine.

The average MTBF was 4.73 hours. This value was entered in Simio as the time-between-failures input for each machine so the runs mirror current failure patterns. With this setting, the model reproduces how often stops occur and how they affect flow and availability. Therefore, the AS-IS baseline is realistic and comparable with the TO-BE case.

Table 3. MTBF Time

Code	Time (hr)
Rewinder	18.02
Cutter 1	38.46
Cutter 2	38.88
Folder	27.50
Diverter	40.13
Packer 1	39.81
Packer 2	38.23

Table 4. Set up Time

Code	Time (min)
Rewinder	482.30
Cutter 1	312.60
Cutter 2	327.90
Folder	392.40
Diverter	374.40
Packer 1	207.00
Packer 2	210.00

The model used setup times for each of the seven machines based on direct on-site measurements. These times reflect the work before a new run, adjustments, calibrations, and batch changes. The rewinder showed the longest preparation at 482.3 minutes because it needs paper tensioning, shaft alignment, and quality checks. In contrast, the other machines required shorter windows mainly for packaging settings, while mid-range durations came from blade adjustment, guide alignment, and flow synchronization. The average setup across the line was 322.67 minutes. These inputs were loaded in Simio for each machine so the simulation reproduces real preparation behavior and helps pinpoint the stages where SMED should focus. In Simio, each server object was set up with historical data from the seven Machines' Processing Times, Setup Times, Time Between Failures (MTBF), Repair Time (MTTR), and Spare-Part Lead Times. Thus, a 2,400-minute run yielded 2,691 sheets, a result that mirrors the system's current performance under real operating conditions.

5.3. Results of the Validation To-Be

In a 40-hour Simio run, machine availability rose from 62.71% to 86.02%, a gain of 23.31 points that exceeds the usual minimum for efficient operation. At the same time, setup time fell from 322.67 to 238.86 minutes, smoothing the production flow by reducing idle gaps between batches. Regarding maintenance, the indicators improved clearly: MTBF rose from 4.56 to 9.81 hours, and MTTR fell from 2.67 to 1.55 hours. In other words, the system is more reliable and less dependent on corrective repairs. Production rose from 2,691 to 3,756 napkin stacks in the same period, an increase of approximately 39.6%. In addition, the simulation reported no machine failures, which underscores the stabilizing effect of preventive maintenance on the process.

Table 5. Result of Validation

Indicator	AS IS	TO BE	Improvement
Availability	62.71%	86.02%	+23.31%
Setup (min)	322.67	238.86	-83.81
MTTR (hours)	2.67	1.55	-1.12
MTBF (hours)	4.56	9.81	+5.25

5.4. Results Planned Maintenance + IoT Improvement

In the TO-BE model, all machines showed lower MTTR and higher MTBF than in the AS-IS case. Repair time fell because failures were anticipated and spare parts waits were shortened through tighter inventory control and early reservations. At the same time, MTBF rose across stations, reflecting steadier operation and fewer breakdowns, which raised overall availability. Moreover, real-time alerts helped schedule work in planned windows and align with setup routines, so emergency calls, overtime, and restart losses decreased. Based on this benchmark, the simulation supports planned maintenance with IoT within the Industry 4.0 framework. Real-time decisions and simple predictive logic sustain efficiency, reduce downtime costs, and extend asset life; they also improve schedule reliability and decrease safety risks. In short, it provides practical evidence for scaling digital practices gradually.

As a result, the simulation in the TO BE model showed a reduction in total setup time from 322.67 to 238.86 minutes, representing an approximate 37% decrease. This improvement had a direct impact on the machine's operational availability, with a total accumulated setup time of 156.19 minutes, significantly lower than in the AS IS scenario. The application of the SMED approach, validated by academic literature and reflected in the simulation, supports its effectiveness in improving efficiency in processes with high format variability and elevated preparation times.

Table 6. MTTR and MTBF Time

Machine	MTTR	MTBF
Rewinder	3.83	41.25
Cutter 1	0.47	64.56
Cutter 2	0.52	68.67
Folder	1.45	59.15
Diverter	0.85	76.68
Packer 1	0.58	63.64
Packer 2	0.64	63.67

Table 7. Time and Classifications AS IS activities

Total Time (min)	Activity Classification		Time per Activity	
	Internal	External	Internal	External
149.04	17	13	98.04	51

Table 8. Time and Classification TO BE activities

Total Time (min)	Activity		Time per Activity	
	Internal	External	Internal	External
87.90	9	21	24.70	63.20

5.5. Economic Evaluation

Savings in production, energy, and labor were analyzed using a Capital Opportunity Cost (COC) of 11.03%. The financial evaluation showed a Net Present Value (NPV) of approximately USD15,648.24, confirming that the project would yield returns exceeding the initial investment. Additionally, an Internal Rate of Return (IRR) of 86.64% and a payback period of 16 months reaffirm the short-term viability of the proposal. These results, aligning with recent studies, show that adopting technologies like IoT and SMED can reduce operating costs by up to 30% and increase availability by up to 25% [25].

Table 9. Economic Evaluation

Indicator	Worth
NPV	$15,648.24
IRR	86.64%
RBCF	4.33
PRD (years)	1.38

6. Discussion

6.1 Comparison: Before (Problem) vs. After (Validation)

Previous research on maintenance in manufacturing has shown clear limits, mainly because the solutions are not well connected to each other. For example, when planned maintenance was supported with IoT sensors, availability increased from 62.71% to 86.02% after implementation. This was a great improvement, but it was still affected by two barriers: the lack of simulation tools to test different options in advance and the high initial investment required [31].

In contrast, the present study proposes an integrated maintenance model that combines IoT technologies with simulation and predictive analytics, overcoming several of these limitations. For example, in academic research such as [32], simulation was combined with machine learning, resulting in a 25% reduction in downtime. Similarly, in this study, equipment availability improved by more than 20%, along with a significant reduction in idle time due to unplanned stoppages, demonstrating the applicability of the validated model in real industrial contexts.

The TO-BE simulation showed clear gains in maintenance control. Unlike IoT-only schemes, frequent sensor readings were tied to a live link with the spare-parts inventory. The system identified the part and launched the request at once, so MTTR fell from 2.67 to 1.55 hours, a 48.7% gain. The effect is consistent with [21], yet the model goes further by removing manual calls and follow-ups through automated stock linkage, a point missing in most prior work.

MTBF increased, which signals stronger reliability due to timely maintenance and the removal of repeating faults [14]. Lost hours from failures, repairs, and waiting for parts dropped from 84.6 to 52.3 hours, a 38.2% cut. The change came from more than monitoring. Alerts, digital stock checks, and auto orders sped the response and kept work moving, a flow rarely detailed in prior studies [17].

The setup per batch improved as well. Time fell from 322.73 to 238.86 minutes, a 44.3% reduction. This outperformed results reported in SMED plus IoT trials, which average 25-30% under controlled settings [28]. The edge came from live coordination between maintenance and production plans, which let setups be preconfigured in the system. In practice, digital support moves SMED from reactive steps to planned actions.

Moreover, unplanned stops fell from 12 to 4 per month, a 66.7% drop, an important change given how these events undermine system efficiency [28].

In contrast to Markov models that perform well in simulation but overlook human and logistics effects [33], the proposed model includes operator response time, resource availability, and logistics delays. Thus, it achieves more accurate predictions and results that better reflect real operating conditions.

Overall, these improvements indicate that the validated model provides residual operational benefits and establishes a framework for smart manufacturing transitions for Small and Medium-Sized Enterprises (SMEs). It demonstrates alignment with global sustainability goals by improving resource efficiency, minimizing waste caused by downtime, and providing the opportunity for maintenance planning based on analytical processes. It also attempts to address research gaps highlighted in the Industry 4.0 literature [33, 34].

In summary, the gains come from a hybrid design that links IoT-based predictive monitoring, digital inventory control, and dynamic simulation. This trio speeds failure detection, automates spare-parts readiness, and enables evidence-based optimization before any physical change. Therefore, the approach outperforms methods that rely only on IoT monitoring or only on simulation, and it sets a clear base for scaling with a short KPI set and simple governance.

6.2 Relationship with published articles

This study relates closely to prior work on digital maintenance and Lean methods. The study in [4] applied TPM in a small factory and used simulation to improve availability. However, it did not add real-time monitoring or IoT, so it could not react to sudden failures. In contrast, the present model links IoT sensors with predictive simulation in SIMIO and connects to the inventory flow, so it anticipates faults, reduces idle time, and triggers parts ordering early. In addition, it embeds short SOPs and a simple training loop, with live dashboards and edge alerts to support action on the shop floor elements not covered in [4].

Similarly, [32] proposed an IoT-based predictive system that improved MTBF and MTTR. However, it lacked simulation to test alternative scenarios and demand swings. Here, the dual-layer live data plus modeling explains the stronger results: a 47.6% rise in MTBF and a 48.7% drop in MTTR, with stress tests under different loads and failure rates. Moreover, the model includes basic sensitivity checks and what-if planning (e.g., longer part lead times), which makes resource allocation more proactive and resilient.

A prior study [20] combined TPM, SMED, and RCM in a food processor to lift availability and curb disruptions. It confirmed the value of Lean maintenance in line with frequent changeovers and volatile demand. However, it lacked a real-time digital layer and did not use simulation. By bringing those same methods into a digital setting, the present work delivers stronger quantitative gains and shows that Lean–digital hybridization improves adaptability and speeds learning for continuous improvement. Moreover, recent work from 2024–2025 [33, 34] notes fast progress in predictive maintenance and AI/IoT, yet a clear gap remains in SMEs and in tying these tools to setup-reduction practices such as SMED 4.0 in emerging economies. Therefore, this study helps close that gap by integrating both fronts and proving a practical path that others can replicate.

In the end, the study's stronger results do not come from adopting tools in isolation. Rather, they come from tightly linking data capture, simulation-based validation, and operational design into one system. This closed loop remains uncommon in recent literature, which is why the approach stands out.

In this sense, the study integrates classical maintenance with new technologies inside a robust validation frame. It offers a replicable model for SMEs with tight budgets and real constraints. Unlike other works, it covers seven linked machines, includes human and logistics times, and uses records from peak demand to keep results practical. As a limitation, inputs were bibliographic; next steps are plant calibration and A/B pilots. In sum, dynamic simulation not only validates the proposal before plant changes but also supports informed decisions that reduce risk on the way to predictive maintenance.

6.3. Limitations

While the results are compelling, several limitations should be acknowledged. Firstly, the study was conducted in a single medium-sized tissue production line in Peru, which may limit the generalizability of the findings to other industries or larger -scale manufacturing enterprises. Secondly, although the simulation model incorporated historical downtime, MTTR, and MTBF data from seven machines, real-world implementation may face additional variables such as operator fatigue, supply chain disruptions, or organizational resistance that were not fully simulated. Thirdly, IoT sensors and digital inventory linkage require initial configuration and training, which may present a barrier for non-specialized maintenance teams; the cost and complexity of such deployment in SMEs may inhibit adoption and downtime reduction. Longer-term monitoring (Over multiple years) would be necessary to confirm the durability of the gains and to track potential equipment aging or evolving failure modes.

6.4. Industry Comparisons

From an industrial benchmarking perspective, the results place this study at the forefront of SME-level digital transformation.

In world-class manufacturing standards, OEE values above 85% and availability over 90% are typically achieved by large-scale automated systems such as automotive, semiconductor, or chemical sectors. The present study results of availability of 86%.02% and downtime reduction of 38.20% indicate that an SME can reach near-benchmark performance through targeted digital integration rather than full automation investment [31].

The reduction in setup time was 44.3%, well above the typical range of 25–30% in SMED applications [28]. This indicates that digital adjustments combined with simulation can double the usual Lean improvements and confirms the practical utility of Industry 4.0 when budgets are limited. In economic terms, the project achieves a higher IRR and a shorter payback period than is typical for small industries, where IoT initiatives usually recover in 24–36 months [29]. In environmental terms, fewer stoppages and less maintenance waste reduce energy use and material losses, which supports the company's sustainability goals. In summary, the study closes a methodological and practical gap. It shows that small and medium firms can adopt a Lean IoT simulation framework without high costs and obtain measurable gains in productivity and digital maturity. Likewise, it offers an empirically validated model that is replicable and scalable, bringing together sustainability, efficiency, and technological adaptability in a single system.

7. Conclusion

TPM was selected as the best path to raise availability on the napkin line, where losses came from breakdowns and long changeovers. SMED shortened setup work, and the gradual use of Industry 4.0 tools, real-time IoT monitoring, and simple alerts moved maintenance toward prediction. However, two gaps appeared: there was no standard work in maintenance, and staff needed structured training. With TPM focused on planned maintenance, MTTR fell from 2.67 to 1.55 hours per failure (48.7%). At the same time, MTBF rose from 4.56 to 9.81 hours (90.8%). Therefore, changeovers became faster, flow interruptions eased, and effective run time increased. As a result, availability increased from 62.71% to 86.02%, a gain of 23.31 percentage points that delivered a more stable and predictable operation. Under the SIMIO runs for a 40-hour horizon (optimistic case), output rose from 2,691 to 3,756 napkin sheets, and no failures occurred in the period, which is consistent with the higher MTBF and shorter setups; even so, plant trials should confirm persistence under different demand mixes. Finally, IoT integration reinforced predictive maintenance by enabling continuous condition checks and early alerts. This interaction between TPM, SMED, and IoT transformed asset management in the case study and aligned day-to-day work with Industry 4.0 practices. In sum, the approach is replicable line by line, provided that standard work, focused training, and basic data governance remain in place to keep results over time.

Data Availability

All the simulation models in Simio Simulation can be found in the following link:

https://data.mendeley.com/datasets/462xv5x6t5/1

Conflicts of interest

The authors declared that there is no conflict of interest regarding the publication of this paper.

Acknowledgments

The authors would like to acknowledge. Peruvian University of Applied Sciences, which provided financial and research facilities support through UPC-EXPOST-2025-1, with the knowledge contribution of the University of Arizona, and the participation of the company being studied.

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