Innovation in Smart Maintenance: An IoT-Based Strategy to Improve Packaging Machine Availability in a SME

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Abstract– In the context of the highly competitive food sector in emerging regions, enhancing operational efficiency is essential for business sustainability. This study presents an innovative model aimed at improving the availability of oatmeal packaging machines in a Peruvian company by integrating emerging technologies with industrial engineering methodologies. The proposed approach combines the pillars of Autonomous and Planned Maintenance from the Total Productive Maintenance (TPM) framework with inventory management based on the Supply Chain Operations Reference (SCOR) model, incorporating a smart maintenance strategy through Internet of Things (IoT) sensors connected to a cloud-based platform. This technological solution enables real-time monitoring of machine conditions and supports data-driven operational decision making. The implementation led to an 8.71% increase in machine availability (from 86.64% to 95.36%), a 68.68% reduction in unplanned downtimes, and a 78.78% decrease in stoppage time due to material and spare parts stockouts. Beyond the technical outcomes, this model represents a case of intrapreneurship within the operations team, demonstrating how internal innovation can transform traditional maintenance practices and contribute to the evolution of the business model. The solution is scalable and adaptable to other companies in the Latin American food industry, strengthening industrial competitiveness and promoting sustainable innovation in emerging markets.

Keywords-- Smart Maintenance, IoT, TPM, SCOR Model, Food Industry

I. INTRODUCTION

The food industry in emerging regions faces constant pressure to increase productivity and reduce operational costs in order to remain competitive. In Peru, the industrialized food and beverage sector accounts for 26.2% of the manufacturing GDP and 3.7% of the national GDP, according to the Ministry of Economy and Finance. It comprises over 24,000 companies of various sizes, according to the Commission for the Promotion of Peru for Export and Tourism. Within this sector, companies that produce cereal-based products face difficulties in ensuring continuous production due to the low availability of their equipment.

One of the main issues affecting operational efficiency is the high number of unplanned downtimes, caused by breakdowns, blockages, friction between components, and delays in the supply of materials and spare parts. A Peruvian oat packaging company reported an annual machine availability of 86.64%, below the 90% standard, resulting in losses exceeding $ 68,568 equivalent to 2.61% of its annual revenue.

To address this issue, the study proposes an innovative model that integrates the Autonomous and Planned Maintenance pillars of Total Productive Maintenance [1], [2], [3] with the Supply Chain Operations Reference model to optimize the supply of spare parts and materials [4]. This integration is enhanced by smart maintenance technologies through Internet of Things sensors on the packaging machines connected to a cloud-based platform, enabling real-time monitoring and automated recording of operational data.

The objective of this proposal is to increase machine availability to at least 90%, reduce unplanned downtime by 14.86%, and minimize downtime caused by stockouts by 1.2%, thereby contributing to the sustainable growth of the food industry in Latin America.

This article is organized as follows: Section II presents the state of the art; Section III describes the proposed model; Section IV details the validation through simulation; and Section V discusses the results and conclusions.

II. STATE OF THE ART

The articles selected in the literature review were classified into five categories:

A. Low Machine Availability

The literature on industrial productivity and maintenance highlights the effectiveness of various tools and methodologies. One study emphasized the use of OEE and OBM to identify deficiencies in maintenance management within the cookie industry [5], while another demonstrated how Lean Manufacturing, 5S, and TPM enhance operational efficiency in the textile sector [6]. TPM and CBM have also been integrated to increase the reliability of critical equipment [7], [1]. Additionally, FMEA was employed to prioritize failures [8], and SMED was used to reduce setup times, thereby improving availability [9]. Regarding modernization, Lean 4.0 was applied to streamline maintenance decision-making [10], while other studies utilized advanced techniques for failure prediction and automated monitoring [11], [12]. These studies underscore how such tools contribute to productivity improvements and more efficient maintenance management across various industries.

B. Autonomous and Planned Maintenance Strategies for Operational Optimization

Autonomous Maintenance and Planned Maintenance are key pillars of TPM, playing a critical role in improving productivity and operational efficiency. One study analyzed the implementation of Autonomous Maintenance in the steel industry, reporting improvements in equipment availability and a significant reduction in downtime [3]. Additionally, the impact of Planned Maintenance combined with digitalization resulted in a 15% increase in operational efficiency and reduced inspection times [13]. The integration of Autonomous Maintenance with Axiomatic Design in the textile industry led to a 69.2% reduction in downtime [2], and the implementation of Planned Maintenance increased equipment availability to 90%, exceeding world-class standards [14]. These studies demonstrate that both Autonomous Maintenance, which involves operators in basic maintenance tasks, and Planned Maintenance, which coordinates preventive activities, significantly reduce failures and enhance operational performance. These benefits are further amplified when both strategies are integrated with emerging digital technologies, aligning with the demands of Industry 4.0.

C. Maintenance Optimization through Methodologies and Emerging Technologies

The implementation of TPM aims to optimize industrial efficiency and productivity by minimizing downtime, increasingly supported by emerging technologies and integrated methodologies such as RCM, FMEA, 5S, SMED, and AHP [15], [16]. These approaches have proven to significantly improve OEE and equipment availability, while reducing defects and operational costs [17], [18]. Recent studies show that combining these tools with TPM not only reinforces its pillars but also enables a more preventive and efficient management style, adapting to the current demands of industry and achieving high performance standards [19], [20].

D. Application of the SCOR Model in Supply Chain Improvement

Reviewed studies indicate that the SCOR model is an effective tool for improving supply chain performance across various sectors, although specific adaptations are required depending on the context. Companies aim to enhance financial and operational performance by applying SCOR in conjunction with methodologies such as AHP, ANP, and technological tools like ERP and EDI [21], [22], [23]. Research highlights significant improvements in cost reduction, structured planning, and customer satisfaction, while also identifying challenges such as limited technological integration and the need for contextual adjustments [24], [25]. Overall, the literature concludes that the SCOR model, when complemented with other tools, is essential for evaluating and optimizing supply chain performance, supporting better decision-making and increasing competitiveness.

E. Innovative Industry 4.0 technological applications for Improving Machine Availability and Smart Maintenance Management

The adoption of innovative Industry 4.0 technologies—such as IoT sensors and cloud computing—has transformed industrial maintenance management, significantly improving the availability of critical equipment. In a metalworking SME, implementation alongside artificial intelligence increased cutting equipment availability by over 25% [26], while in an electronics plant, the combination of IoT sensors and hybrid models reduced decision latency by 35% [27]. Other studies report an 18% reduction in downtime and a 22% reduction in maintenance costs thanks to real-time monitoring [28], as well as accurate failure detection using deep learning models [29].

These technologies have shown positive results in various sectors, including agribusiness [30] and technical education [30], leading to reduced unplanned downtimes and extended equipment lifespan. In SMEs, solutions such as machine learning, digital twins, and IoT achieved an 84% reduction in maintenance costs [31], while the use of cloud computing optimized operational costs by up to 31.6% [32]. Even in CNC systems, tool wear detection was achieved with over 90% accuracy [33]. These cases demonstrate that digitalization fosters data-driven decision-making, strengthening operational resilience and advancing smart maintenance.

III. Contribution

The main contribution of this research is the design and validation of an integrated smart maintenance model to increase the availability of oatmeal packaging machines in a Peruvian SME. The proposal combines three complementary elements: (1) the Autonomous and Planned Maintenance pillars of TPM to reduce failures and involve operators in maintenance tasks, (2) the SCOR model to optimize the planning and availability of spare parts and materials, and (3) the use of IoT sensors connected to a cloud-based platform for real-time monitoring and decision-making. Unlike previous approaches, the novelty of this model lies in the integration of maintenance methodologies with supply chain management through emerging technologies, creating a scalable and adaptable framework for SMEs in the Latin American food industry.

Following this introduction of the proposal, the section presents the rationale and a detailed description of each component of the model, highlighting how TPM, SCOR, and IoT-based tools jointly address the root causes of low availability. This is complemented by the current diagnosis of the company under study, as well as the presentation of the *As-Is* and *To-Be* values of the key indicators that demonstrate the expected improvements.

A. Rationale

1) Component 1: Planning and Managing the Planned Maintenance System

The first component aims to reduce downtime caused by failures in mechanical and pneumatic components. To achieve this, the Planned Maintenance pillar of the TPM methodology is implemented, which seeks to establish systematic maintenance management practices based on real data. This approach not only helps prevent failures and extend asset lifespan but also strengthens technical decision-making capabilities through performance analysis of equipment.

2) Component 2: Developing and Managing Autonomous Maintenance

The second component aims to reduce unplanned downtime due to component obstructions caused by residue buildup and friction between components caused by burnt lubricant. This is achieved through the implementation of an autonomous maintenance system. This strategy responds to the need to directly involve operational personnel in the basic care of equipment, promoting a culture of shared responsibility in maintenance management. To this end, the Autonomous Maintenance pillar of the TPM approach is applied, encouraging operators to carry out routine inspection, cleaning, and lubrication tasks, thereby increasing early detection of potential failures. This component seeks not only to improve machine availability, but also to strengthen the standardization of best operational practices and reduce exclusive dependence on the maintenance department.

3) Component 3: Implementing and Managing the Supply System

Finally, the third component aims to reduce the lead time for material supply and outsourced spare parts procurement. For this purpose, an efficient supply system aligned with the SCOR model is implemented, which enables optimization of supply planning, procurement, and control. Through this approach, the goal is not only to maintain adequate inventory levels but also to enhance responsiveness to operational needs by defining clear supply policies, standardizing processes, and continuously monitoring key performance indicators. This strengthens the traceability of material flows, minimizes the risks of stockouts, and promotes proactive management of resources required for equipment maintenance.

B. Proposed Model

The conceptual model presented in Fig. 1 is based on the analysis of critical indicators (inputs) and is structured around the Planned Maintenance, Autonomous Maintenance pillars, and the SCOR model. The proposed strategy incorporates a smart maintenance approach through the installation of wireless sensors on each packaging machine, which capture real-time operational data. These sensors are integrated into an IoT gateway connected to a maintenance management system, where maintenance activities and the inventory of spare parts and materials are recorded. This integration enables continuous monitoring of downtime and ensures availability levels above 90%. This technological architecture, based on smart maintenance, significantly improves output indicators by reducing both unplanned downtimes and inactivity caused by spare parts and material stockouts. As a result, it establishes an innovative link between maintenance functions and inventory management, contributing to increased availability of the packaging line.

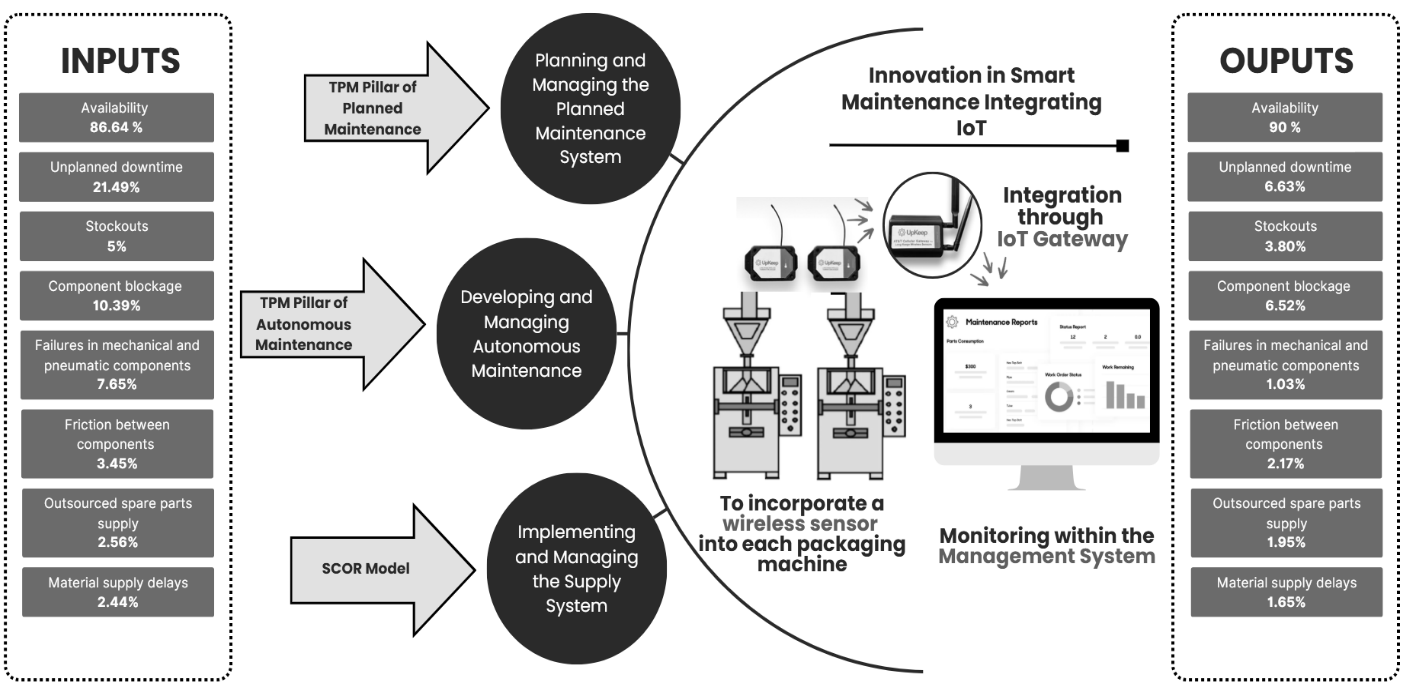

Fig. 1 Conceptual Model

C. Initial Diagnosis

At a SME in the food industry dedicated to the production and packaging of cereal-based products, a significant problem has been identified: low availability of the two machines on the oat-packaging line. The causes are twofold. First, unplanned stoppages arise from component blockages caused by residue build-up, breakdowns in mechanical and pneumatic parts, and friction between components due to burnt lubricant. Second, stock-outs of spare parts and maintenance materials occur because of delays in their supply.

$$\text{Availability} = \frac{\text{TC}-\text{PP}-\text{PNP}}{\text{TC}-\text{PP}} \quad (1)$$

TC: Calendar Time

PP: Scheduled Downtime

PNP: Unplanned Downtime

Figure 2 shows the average annual availability of the production and packaging line; for the latter, the value is 86.64%, below the required 90% threshold [14]. Thus, there is a technical gap of 3.36 % between the standard availability and the current average availability of the packaging line.

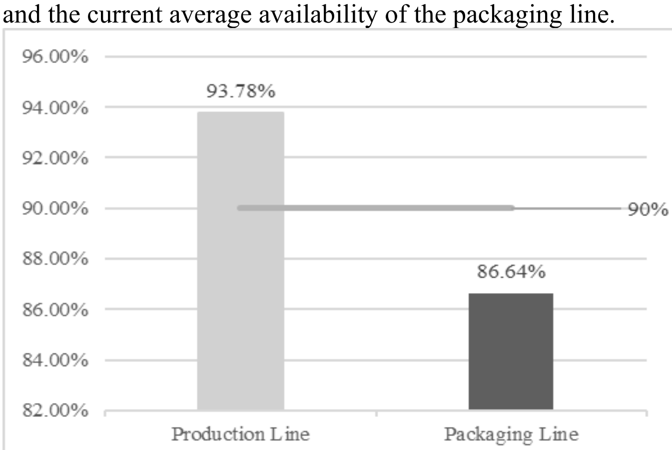

Fig. 2. Average annual availability of the packaging line

The costs associated with low machine availability—penalties, maintenance technicians' man-hour costs, and urgent purchases of spare parts and materials—amount to $ 68,568 representing a 2.61% loss of annual revenue.

D. Model Description

Fig. 3 illustrates the solution model, which sequentially represents the necessary steps for implementing the proposed solution. Each component is subsequently described in detail, along with its corresponding subprocesses and key actions, enabling a comprehensive understanding of the workflow and the logic of integration among the components.

1) Planning and Managing the Planned Maintenance System

The process began with the identification of the root causes associated with failures in critical components, in order to determine the party responsible for addressing each type of failure. Subsequently, it was proposed to install an IoT sensor on each packaging machine to collect real-time operating time and adjust maintenance intervals through the UpKeep Edge management system, as the initial approach considered the MTBF based on historical data.

$$\text{MTBF} = \frac{\text{Calendar Time} - \text{Unplanned Downtime}}{\text{Number of Failures}} \quad (2)$$

Next, a detailed preventive maintenance schedule was designed, including the activities to be carried out by the maintenance supervisor. The relevant information is incorporated into the proposed management system, allowing real-time visualization of the schedule, registration of each intervention performed, and recording of relevant observations. Based on this, the necessary equipment and spare parts for each scheduled intervention were listed.

Finally, key performance indicators were defined to measure the effectiveness of the preventive actions implemented. These indicators are MTBF and MTTR, which will be recorded and monitored through the management software. This platform will allow the supervisor and area manager to perform real-time tracking, facilitating performance evaluation and timely decision-making.

$$\text{MTTR} = \frac{\text{Total Repair Time}}{\text{Number of Failures}} \quad (3)$$

2) Developing and Managing Autonomous Maintenance

The process began with the development of maintenance schedules, leveraging the functionalities of the management system introduced in the first component to program and assign tasks. Next, the equipment required for the execution of the planned activities was identified. Subsequently, it was proposed to train the operators in performing cleaning and lubrication tasks on critical components, as reinforcement of good maintenance practices. Additionally, training was proposed on the use of the management system, which is overseen by the supervisor. The supervisor is responsible for monitoring the tasks carried out, as well as addressing and resolving any observations recorded by operators in the platform during maintenance activities.

3) Implementing and Managing the Supply System

The implementation of the SCOR model began with identifying the required quantity of materials, tools, and spare parts, which were classified into two categories: consumable materials—with high turnover or limited lifespan—and non consumable tools and spare parts—with lower turnover or prolonged usage.

Under these two categories, safety stock and monthly requirements were calculated for the consumable materials. The monthly quantity was determined by multiplying the task frequency by the quantity used per activity, while the safety stock was estimated as 20% of the required monthly quantity.

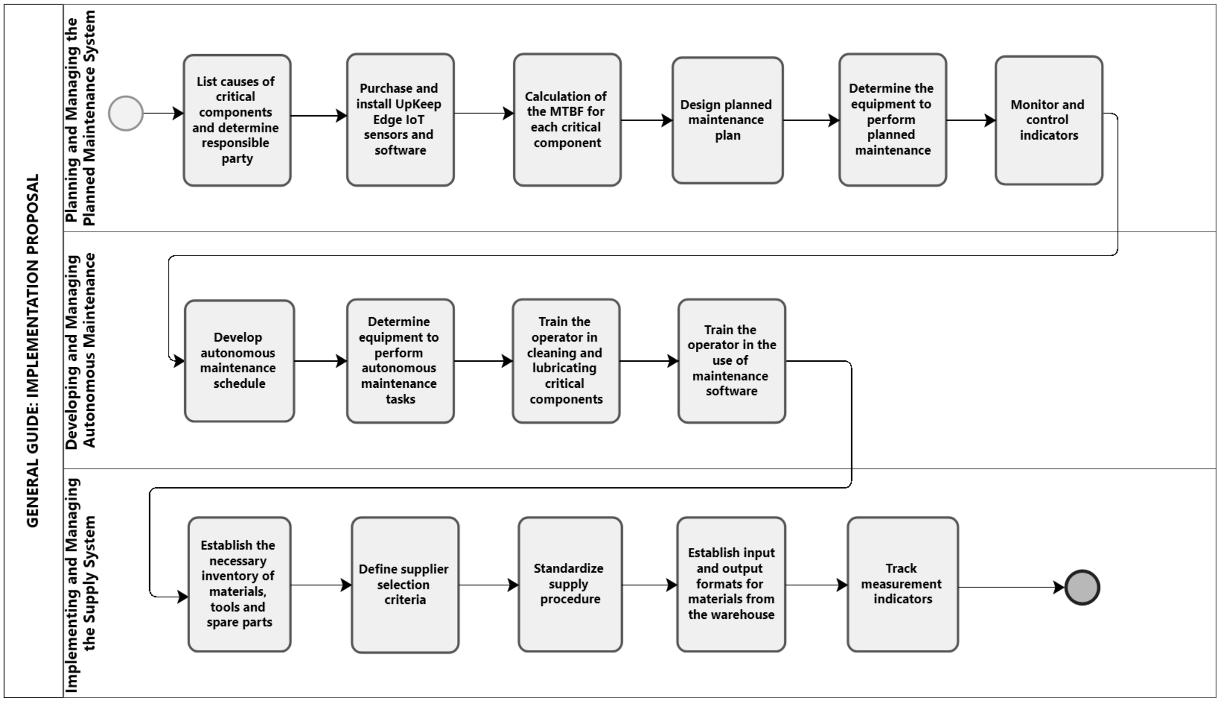

Fig. 3 Solution Model

For non-consumable tools and spare parts, minimum and maximum inventory levels were defined. The minimum level was calculated by dividing the monthly requirement by the duration in months, while the maximum was set directly based on the monthly requirement. These data will also be recorded in the UpKeep Edge platform.

Next, supplier selection criteria were established and evaluated based on key factors such as product quality, delivery times, supply capacity, and customer support and service. Suppliers meeting these criteria satisfactorily and rated as “Qualified” are included in the procurement process. From that point on, they are documented and monitored through performance indicators based on the mentioned criteria, enabling continuous performance tracking and updating their scores according to actual results. This information is also integrated into the management system, enabling the procurement department to make better-informed decisions and optimize supplier selection.

Standardized procedures for the procurement of spare parts, tools, and materials were then established to ensure process efficiency and traceability. Subsequently, inventory entry and exit log formats were implemented to ensure a continuous supply flow. Additionally, performance indicators are constantly monitored, such as delivery punctuality—calculated as the number of on-time deliveries over the total—and average delay, determined by the total number of delayed days among late deliveries. All forms are integrated and indicators are managed through the management system, enabling ongoing monitoring, performance evaluation, and continuous improvement of inventory management.

E. Model Indicators

As shown in Fig. 1, the key indicators used to evaluate the impact of the proposed solution compare the current scenario (As-Is) with the expected scenario (To-Be), in order to assess improvements related to the root causes of the problem. For unplanned downtime, the percentage of downtime hours relative to available time was used. Currently, this value stands at 21.49%, and with the implementation of TPM, it is projected to decrease to 6.63% [14]. In the case of stockouts of spare parts and maintenance materials, the current indicator is 5%, with a projected reduction to 3.80% due to improved inventory management [34].

Among the specific causes, the downtime due to obstruction cleaning is 10.39%, and lubrication due to component friction is 3.45%. By applying the Autonomous Maintenance pillar of TPM, these values are expected to decrease to 6.52% and 2.27%, respectively [14]. For failures in mechanical and pneumatic components, the current downtime is 7.65%, with a projected reduction to 1.03% through Planned Maintenance [35]. Regarding delays due to outsourced supply, current downtime percentages are 2.56% and 2.44%, which could be reduced to 1.95% and 1.85%, respectively [34]. Moreover, the literature indicates that integrating IoT technology with the TPM methodology can further enhance availability [36].

IV. VALIDATION

A. Rationale

Simulation has been widely used in various studies as a validation method for the TPM methodology, allowing improvements to be analyzed without directly intervening in the processes. Research shows improvements in productivity, availability, and maintenance after applying simulation in industrial sectors [1], [37], [38]. In this study, considering that the key indicators include downtime and supply lead times, the SCOR model is validated through simulation to comprehensively analyze the interaction between maintenance and logistics. This decision is supported by research that 5th LACCEI International Multiconference on Entrepreneurship, Innovation and Regional Development - LEIRD 2025 “Entrepreneurship with Purpose: Social and Technological Innovation in the Age of AI” - Virtual Edition, December 1 – 3, 2025 5 demonstrates the effectiveness of combining SCOR and simulation to optimize the supply chain [39].

B. Proposed Model

The appropriate simulation time frame was determined, establishing a one-year horizon. This period corresponds to the time over which unplanned downtimes have been recorded (100,800 minutes per year). The decision to use a one-year basis is justified because the Mean Time Between Failures (MTBF) requires a larger time span to adequately capture system variability and ensure the statistical validity of the simulation model results.

C. Implementation

The model was implemented in Arena software using real production, failure, and maintenance data from the packaging process. Based on this information, the system’s operating parameters were configured. Preliminary simulations were then run to fine-tune downtime durations and system behavior under failure scenarios. Once these adjustments were validated, final simulations were executed, applying the optimal number of replications as determined through statistical analysis in Output Analyzer. This ensured the evaluation of variability in key system indicators within a 95% confidence interval. Finally, the simulation results were compared to actual data to validate model consistency, demonstrating its usefulness for operational decision-making under real working conditions.

D. Model Details

The model was developed following a process-oriented approach. It represented the continuous packaging flow from the entry of raw materials to the exit of the finished product, including breakdowns, corrective maintenance, and effective operation times, as shown in Fig. 4. Entities were defined to represent products in process and machine failures for both packaging machines. To model the system's stochastic behavior, Input Analyzer, a tool within Arena software, was used to analyze historical data and determine the most representative probability distributions for failure, repair, and production times.

The model structure includes process, assignment, and resource blocks configured to simulate interruptions and restarts. Statistical outputs were incorporated to capture key performance indicators. The generated files were subsequently analyzed in Output Analyzer to determine the appropriate number of replications, resulting in 81 replications for the model of Packaging Machine 1 and 56 replications for the model of Packaging Machine 2. This configuration ensured reliable results consistent with the actual behavior of the system.

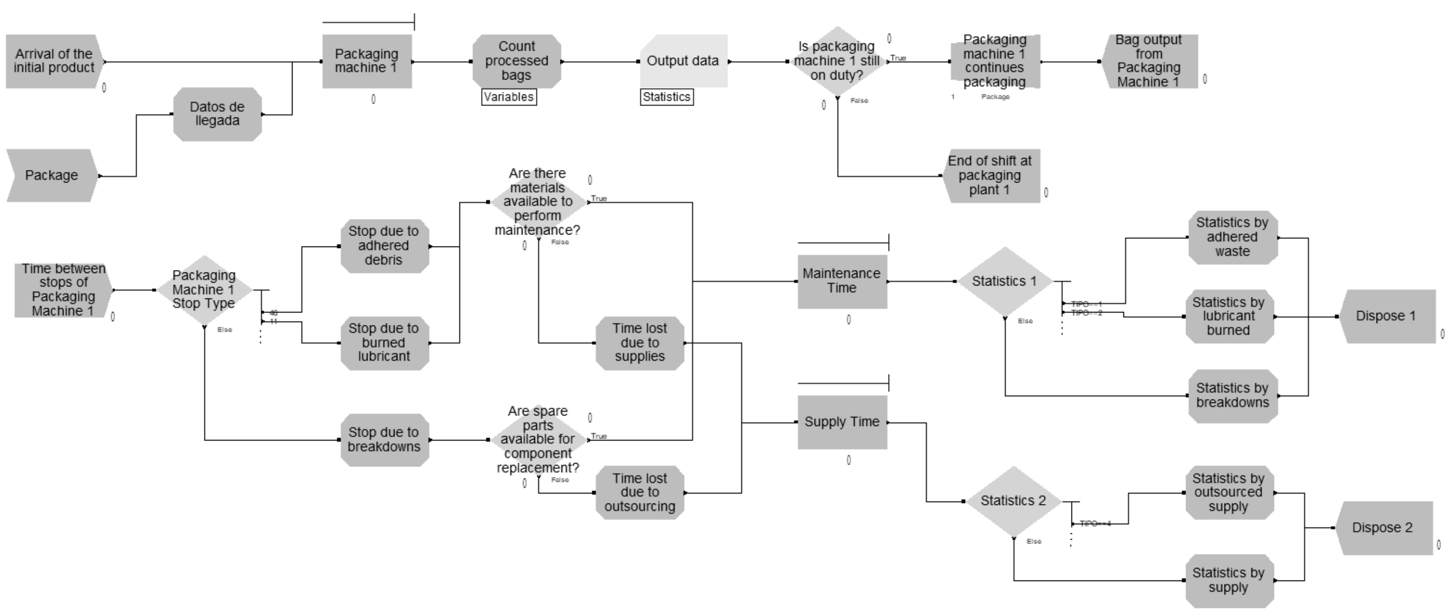

Fig. 4 Simulation Design

E. Proposed Process

For the simulation of the proposed improvement, key variables involved in the system were considered, including both maintenance and supply processes, in order to realistically represent their behavior and interaction. For the To-Be scenario, the available time was set at 1,438 hours per year, which takes into account the scheduled downtime established in the proposed improvement plan.

To estimate the Mean Time Between Failures (MTBF) in the To-Be scenario, previous studies were used as reference. On one hand, a study reported a 118.80% increase in MTBF after implementing TPM, rising from 22.4 to 48.9 hours [40].

The initial MTBF was determined from historical data; however, this value is expected to vary as improvements are implemented. It will be recalculated using real-time and updated data provided directly by IoT sensors through the maintenance management system.

On the other hand, a 76% reduction in time lost due to delays in resource delivery was observed, thanks to efficient supply chain management [34]. Table I presents the distribution of times in the As-Is versus To Be scenarios.

TABLE I
TIME DISTRIBUTION: AS-IS VS TO-BE

Concept	As-Is Distribution (min)	To-Be Distribution (min)
Time between stops of Packaging Machine 1	EXPO(1400)	EXPO(3063)
Time between stops of Packaging Machine 2	EXPO(1344)	EXPO(2941)
Downtime due to outsourced supply for Packaging Machine 1	60+EXPO(46.7)	60+EXPO(9.6)
Downtime due to outsourced supply for Packaging Machine 2	NORM(116, 47.9)	NORM(27.84, 47.9)
Downtime due to supply for Packaging Machine 1	60+EXPO(40)	60+EXPO(11.21)
Downtime due to supply for Packaging Machine 2	60+EXPO(37.9)	60+EXPO(9.10)

F. Results Comparison

Tables II, III, and IV show that the simulation provided key results that will be used to compare the performance of the current system (As-Is scenario) with the projected results after the implementation of the improvement proposal (To-Be scenario).

TABLE II
METRICS-TRAFFIC LIGHTS-RESULTS BY ROOT CAUSES

Cause	As-Is	To-Be	Result
High downtime rate due to component blockage caused by residue buildup	10.39%	6.52%	3.48%
High downtime rate due to recurrent failures in mechanical and pneumatic components	7.65%	1.03%	2.06%
High downtime rate due to friction between components caused by burnt lubricant	3.45%	2.17%	2.90%

TABLE II (continued)
METRICS-TRAFFIC LIGHTS-RESULTS BY ROOT CAUSES

Cause	As-Is	To-Be	Result
High downtime rate due to outsourced spare parts supply	2.56%	1.95%	0.61%
High downtime rate due to material supply delays	2.44%	1.85%	0.63%

TABLE III
METRICS-TRAFFIC LIGHTS-RESULTS BY REASONS

Reason	As-Is	To-Be	Result
High rate of unplanned downtime	21.49%	6.63%	8.45%
High downtime rate due to stockouts	5%	3.80%	1.24%

TABLE IV
METRICS-TRAFFIC LIGHTS-OVERALL RESULTS OF THE PROBLEM

Problem	As-Is	To-Be	Result
Availability	86.64%	90%	95.36%

V. DISCUSSION

A. Main Results

The main results of this research show a significant improvement in the availability of the packaging line following the implementation of TPM's planned and autonomous maintenance pillars and the SCOR model, integrated with IoT sensors and a maintenance management system. Specifically, an 8.71% increase in line availability was recorded. These findings highlight the importance of integrating emerging technologies into maintenance and supply management programs to optimize machine availability.

A. Scenario vs. Results

Before implementation, the packaging line experienced downtime due to blockages caused by residue buildup, friction between components due to burned lubricant, and failures in mechanical and pneumatic components, as well as delays in the supply of materials and spare parts. This situation resulted in an average availability of 86.63% for the packaging line.

After the implementation of TPM and the SCOR model, integrated with IoT sensors connected to a maintenance management system, availability increased to 95.36%. The IoT sensors enabled continuous monitoring of downtime, facilitating proactive interventions and more effective maintenance planning, ensuring availability levels above 90%.

The results analysis showed a 68.68% reduction in unplanned downtime, confirming the positive impact of autonomous and planned maintenance. Likewise, downtime due to stockouts decreased by 78.78% thanks to improved inventory management through the SCOR model, as supported in [35].

Among the specific causes of downtime, significant improvement was observed in the reduction of interruptions due to blockages and supply delays. Friction-related issues due to lubrication showed moderate improvement, suggesting that the frequency of this task may need to be adjusted. As for recurrent failures, although they have not yet reached optimal levels, the trend indicates progressive improvement as maintenance integrated with IoT sensors becomes more established [36].

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CONCLUSIONS

It is concluded that the implementation of the proposed improvement led to an 8.71% increase in the availability of oatmeal packaging machines, rising from 86.64% to 95.36%. Likewise, unplanned downtime was reduced by 68.68%, from 445 hours to 139.4 hours, due to the incorporation of scheduled downtime for the execution of periodic maintenance activities. Additionally, stockouts of spare parts and maintenance materials were reduced by shortening supply lead times by 78.78%, from 84 hours to 17.82 hours.

The investment amount required to implement the improvement proposal is $ 20,881. From a financial perspective, the project proved to be viable, achieving a Net Present Value (NPV) of $ 24,403 and an Internal Rate of Return (IRR) of 72.89%. This study contributes to ongoing research aimed at replacing corrective maintenance through the joint implementation of preventive maintenance, using IoT sensors integrated with a management system.

Moreover, the proposal serves as an example of intrapreneurship within the operations team, demonstrating how internal innovation can transform traditional maintenance practices and provide strategic value to the business model. Given its scalable and adaptable nature, this solution can be implemented in other food industry companies across Latin America, enhancing industrial competitiveness and promoting sustainable innovation in emerging markets.

For future research, it is recommended to explore the implementation of predictive maintenance, utilizing real-time sensors and data analysis to anticipate failures and optimize maintenance resources.

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