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An Automated Model Based on SMED, FMEA, and IoT, Designed for Industry 4.0 to Increase Conformity Rates in a Textile Company: A Case Study

Abstract— **In the textile sector, production efficiency is a key factor for the sustainability and competitiveness of companies. This study analyzes the company Corporación Textil Espain & Espinoza S.A.C., which specializes in the manufacture of circular knit fabrics. In 2024, the company reported a non-conforming product rate of 0.51%, exceeding the contractual limit of 0.4%. This situation had an adverse effect on process performance, associated with downtime, machine failures, and rework. Among the main causes identified are an excessive number of broken needles, at 17.81%, and bobbin tangling, at 14.37%, both related to deficiencies in equipment calibration and maintenance. In response, an automated model is proposed based on the incorporation of IoT sensors and SMED and FMEA methodologies, aimed at minimizing these incidents. This model, framed within the context of Industry 4.0, aims to reduce the frequency of failures, increase product conformity, and optimize changeover times in the circular knitting process.**

Keywords—Lean Manufacturing, Internet of Things (IoT), Textile Industry, SMED, FMEA

I. INTRODUCTION

The textile industry, which accounts for approximately 2% of global industrial GDP [1], is one of the most active manufacturing sectors worldwide. This sector is known for its ability to adapt to international demand for apparel and fashion, as well as for generating millions of direct and indirect jobs. However, recent research shows that disparities still exist in terms of sustainability, productivity, and quality management, particularly in developing nations [2]. Maintaining a balance between costs, quality, and productivity is crucial for production efficiency; weaving defects are one of the most significant factors causing losses in this industry [3], [4].

In Latin America, the textile sector remains a strategic component due to its ability to absorb labor and its presence in global markets. However, it faces gaps in technological modernization and operational control, which reduce its competitiveness compared to nations such as India, China, and Bangladesh [5], [6]. In Peru, the apparel and textile industry has made a significant contribution to economic growth. In 2023, this industry generated more than 400,000 direct and indirect jobs and accounted for 1.3% of manufacturing GDP, with exports exceeding $1.4 billion [7]. However, the loss rate for products that do not meet standards reaches up to 1.5% of total production, which exceeds the international standard of 0.3% [8]. This situation affects the competitiveness of local companies and generates additional costs due to rework, delivery delays, and lost contracts.

In this context, the company Espain & Espinoza S.A.C., which offers custom circular knitting services, is a representative example of the problem at the national level. The company had a total production of 2,177,592 kg of fabric in 2024, with 11,124.83 kg of defective fabric, equivalent to a non-conformance rate of 0.51%, exceeding the established contractual limit of 0.4%. This excess resulted in financial losses exceeding USD 59,112.72, equivalent to 4.85% of annual profits, caused by rework, machine failures, and downtime. Ring winding by Ring winding by bobbin (14.37%) and an excess of broken needles (17.81%) were the primary causes identified, both associated with deficiencies in preventive maintenance, calibration, and operational control.

The technical diagnosis revealed an average gap of 0.21% between the technical limit of 0.3% and the actual percentage of non-conforming products [9]. This difference, although seemingly small, has a cumulative effect on production costs and overall efficiency. The lack of real-time monitoring, late detection of failures, and corrective maintenance increase hidden costs and process inefficiency.

Therefore, the application of Lean methodologies and tools for continuous improvement—such as SMED, TPM, and 5S—is proposed to enhance production efficiency. These methods reduce downtime and standardize operations [10], [11]. Furthermore, the inclusion of emerging technologies such as the Internet of Things (IoT) and machine vision systems [12], [13] would enable constant monitoring of circular knitting machines, which would improve early detection and traceability of faults. With this objective in mind, this analysis aims to identify the technical and operational factors that impact the efficiency of the circular knitting process at Espain & Espinoza S.A.C., in order to support solutions focused on improving the productivity and sustainability of the Peruvian textile production system.

This article consists of five parts, in addition to the introduction. First, Section 2 covers the literature review. Second, Section 3 focuses on the specific research contribution. Next, Section 4 explains the method used to validate the results. The results obtained after implementing the model are discussed and analyzed in Section 5. Finally, the study's conclusions are presented in Section 6.

II. STATE OF THE ART

To develop the State of the Art, a detailed review of scientific articles addressing proposals aimed at reducing excess finished goods was conducted. To this end, selection criteria such as the journal's quartile, the recency of the publication, the relevance of the study, and its theoretical contribution were applied, which allowed for the precise filtering of the most relevant research. This filtering process made it possible to gather solid information that supports the analysis of the problem under study. Based on this review, categories were identified that explain the problem, both in terms of its main causes and the alternative solutions proposed in the literature.

A. Single Minute Exchange of Die *(SMED)*

The SMED methodology is a useful tool for reducing setup and changeover times in manufacturing environments, as it allows for the distinction between internal and external activities, the streamlining of operations where possible, and the standardization of setup tasks. Studies indicate that the implementation of SMED focuses not only on restructuring activities but also on eliminating unnecessary actions, improving material organization, and optimizing the operational sequence [14], [19], [23], [24]. Similarly, the SMED approach expands on this perspective by enabling a joint analysis of changeover time reduction and risks associated with the setup procedure, prioritizing essential tasks that impact operational reliability [15].

On the other hand, the main conclusions of the analyzed studies show that SMED significantly improves process efficiency, reducing downtime and increasing the ability to respond to variations in demand. The authors agree that its effectiveness increases when it is integrated with other tools for improvement, standardization, and operational participation [15], [23]. The literature generally supports SMED as a fundamental method for contributing to the continuity of the production system, optimizing setup time, and increasing operational flexibility [14], [19].

B. Total Productive Maintenance (TPM)

In Total Productive Maintenance (TPM), the reviewed research indicates that this methodology aims to increase equipment reliability and availability through the active participation of operational staff in maintenance work. The authors agree that its implementation helps reduce unscheduled interruptions, optimize autonomous maintenance, and increase the overall performance of the production system. Furthermore, certain studies extend this framework by combining it with equipment condition monitoring and reliability standards, which enables more accurate breakdown management and more effective scheduling of interventions [1], [15], [26], [27].

Regarding its most relevant conclusions, the literature indicates that TPM promotes operational continuity and fosters a culture of continuous improvement within the plant. The reviewed analyses affirm that its results are more sustainable when combined with methods focused on monitoring failures and prioritizing maintenance activities. In general, this approach is presented as an important option for increasing operational stability and strengthening the efficiency of the production process [1], [15], [26].

C. 5S Methodology

In the analyzed studies, the 5S methodology is described as a tool focused on optimizing order, cleanliness, and standardization of the workspace with the aim of reducing waste and reinforcing operational discipline. Its implementation has a positive impact on operational performance and helps eliminate activities that do not add value to the production process [19], [24]. Similarly, the literature highlights those practices related to order and organization make it possible to prioritize losses, optimize plant efficiency, and promote the standardization of procedures [23], [21].

On the other hand, the most relevant conclusions in the literature agree that the 5S method not only optimizes the physical conditions of the work environment but also helps maintain a culture of discipline and continuous improvement. Furthermore, a review of the studies indicates that its use, whether individually or in conjunction with other lean tools, improves process organization and contributes to operational stability [19], [21]. In summary, this methodology serves as a significant foundation for reducing downtime, maintaining appropriate conditions in the plant, and improving the efficiency of the production system [23], [24].

D. Failure Mode and Effect Analysis (FMEA)

Failure Mode and Effect Analysis (FMEA) is a systematic procedure that facilitates the identification of failure modes, the analysis of their causes and consequences, and the prioritization of improvement actions based on risk criteria. To define intervention priorities, it is essential to break down the process, identify critical functions, and evaluate each failure. This tool directs maintenance plans toward critical components and helps reduce machine downtime, thereby improving availability [17], [20]. Furthermore, its integration with other improvement approaches extends its scope to more precise control and prevention decisions [27], [25].

Furthermore, it has been demonstrated that FMEA improves process reliability by preventing risks and prioritizing actions before failures have a severe impact on operations. According to studies, the most significant contributions are the reduction in the recurrence of failures in critical components and the increased ability to respond to operational issues [20], [27]. Similarly, when combined with methods aimed at optimizing configuration, this tool helps reduce post-intervention errors and strengthen process control [17], [25].

E. IoT Sensors and Machine Vision Systems

Machine vision systems and IoT sensors are essential technologies for improving the control and monitoring of the production process. On the one hand, machine vision based on deep learning enables the automatic detection of defects in fabrics with high accuracy and in real time, even when there are changes in speed or lighting [3], [21]. On the other hand, the implementation of IoT sensors in industrial machines allows for the continuous collection of operational variables, such as current, motion, and temperature. This contributes to the advancement of data-driven monitoring and maintenance schemes [4], [22], [23].

Furthermore, it has been demonstrated that the incorporation of these technologies helps prevent errors, reduce unexpected downtime, and optimize the decision-making process on the factory floor. IoT sensors enable real-time monitoring of equipment status and allow for improved maintenance interventions [22], [20]. For their part, machine vision systems strengthen quality control and reduce reliance on manual inspection [21].

F. Continuous Improvement and Lean Manufacturing Approaches

Continuous improvement and lean manufacturing approaches are presented as a managerial foundation that seeks to implement sustained and progressive changes in processes, fostering collaboration across every organizational level to detect problems, apply countermeasures, and standardize the improvements achieved. In this context, it is recognized that tools such as 5S, SMED, TPM, work standardization, and value stream maps can be integrated into a single system to reduce waste associated with waiting times, rework, and unnecessary movements [19], [23]. These methods also enable operational improvements to be aligned with a broader perspective on process control and efficiency [24], [22].

Furthermore, it is evident that the joint implementation of these approaches not only improves productivity but also the long-term sustainability of the gains. When diagnostic, implementation, and monitoring activities are carried out continuously and in a structured manner, studies agree that their effectiveness increases [23], [24]. Furthermore, combining them with specific lean tools strengthens operational discipline and fosters more consistent improvements in production [19], [22].

G. Reliability-Centered Maintenance (RCM)

The Reliability-Centered Maintenance (RCM) methodology focuses on determining the most appropriate maintenance strategy based on equipment functions, failure modes, and the consequences of each functional loss. Its implementation makes it possible to identify critical assets, define risk-based maintenance intervals, and select preventive, corrective, or predictive tasks based on operational impact [25], [26]. Furthermore, its implementation in industrial settings facilitates better resource prioritization and more accurate planning for highly critical equipment [20], [24].

Furthermore, it has been observed that this approach helps reduce unplanned downtime and increase the reliability of the production system when combined with maintenance programs and equipment condition monitoring [26], [20]. Furthermore, its inclusion in broader decision-making systems makes it possible to strengthen operational continuity and optimize the effectiveness of procedures in situations where interventions must be determined based on risk [25], [27].

III. CONTRIBUTION

The contribution of this research will be presented through a detailed diagram that accurately and comprehensively represents the stages involved in addressing the case study. Figure 1 provides a diagram that, in addition to facilitating visual understanding of the procedure, will enable the identification of the essential steps in each phase. Similarly, it will help structure the workflow and illustrate the methodology employed.

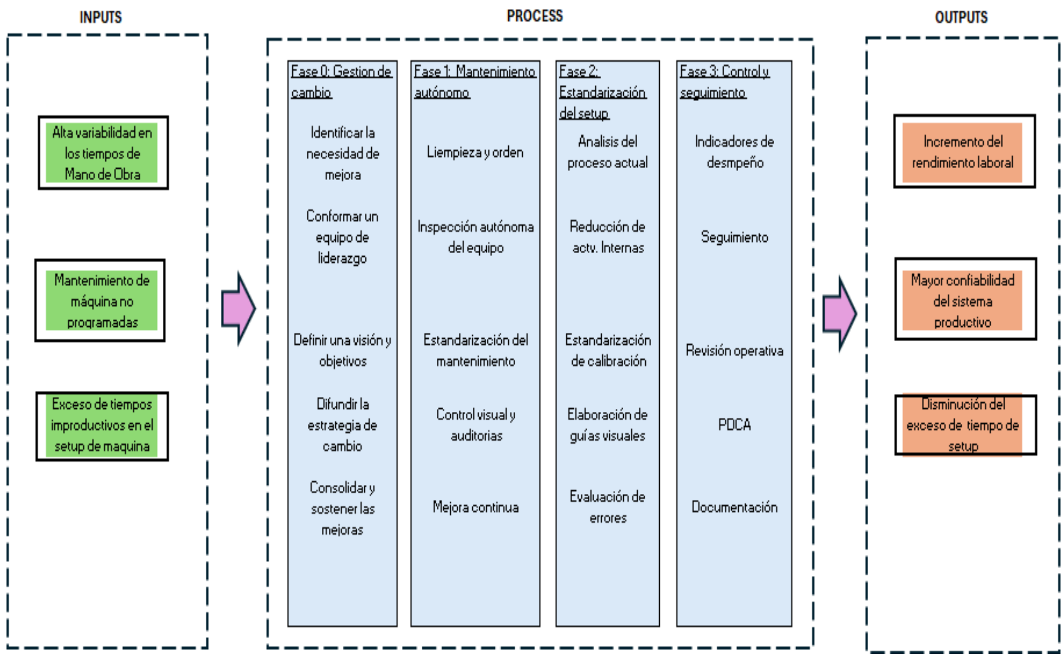

Fig. 1 Proposed Model

A. *Rationale*

The proposed model is based on the automated textile defect detection method [21], which posits that early detection of product defects provides more accurate data regarding the issues that compromise quality. This approach is related to the implementation of failure mode and effects analysis [20], as it allows defect detection to help prioritize critical causes and direct maintenance actions toward the highest-risk elements. Additionally, the use of lean tools focused on order, cleanliness, and waste elimination [24] is included so that these measures can take place in a more stable environment, as such conditions make it possible to reduce losses caused by disorganization and simplify operational control. On this basis, predictive monitoring via IoT sensors [22] is included to track operational variables in real time and anticipate problems before they cause unplanned downtime. Finally, the model incorporates the integrated approach of SMED and FMEA [15] to standardize format changes and reduce setup errors. In this way, the model aims to reduce non-conforming products, increase equipment reliability, and enhance the stability of the production process.

B. *Proposed Model*

As outlined above, there is a clear need to directly address the operational issues affecting production efficiency, particularly those related to downtime, unscheduled stoppages, and variability in machine setups. Resolving these issues will yield significant benefits for the company, such as increased equipment availability, reduced costs associated with failures and rework, and improved overall process performance. Together, these benefits will strengthen the company’s competitiveness and responsiveness in the face of a highly demanding textile market. To this end, this study identified root causes such as maintenance deficiencies, lack of standardization, recurring mechanical failures, and delays in model changes. Based on this diagnosis, a comprehensive model was designed to reduce these impacts, optimize operational performance, and ensure a more stable and efficient production flow.

The proposed model offers an integrated perspective in which the inputs are related to the root causes identified throughout the process, while the implementation is structured in stages focused on change management, autonomous maintenance, configuration standardization, and performance control and monitoring. This structure combines tools such as IoT, 5S, TPM, SMED, and FMEA. Their combined use enables a gradual intervention on the operational deficiencies that have been detected [15], [22], [24], [26], [27]. The innovative model does not propose isolated actions, but rather a series of structured activities that connect diagnosis, implementation, evaluation, and constant monitoring. Thus, it is anticipated that the initial causes of the problem will be transformed into optimized results, which will manifest as improved labor productivity, increased reliability of the production system, and a reduction in excessive setup time. Fig. 1 illustrates, in accordance with the above, the relationship between the inputs of the proposed model, its process phases, and the expected results, as well as its conceptual design.

C. *Initial Diagnosis*

The initial diagnosis of the problem is based on indicators that facilitate the assessment of the company's current operational performance and demonstrate the need for improvements. Equipment availability—the percentage of time that equipment is operating without interruptions—is considered the primary indicator. This indicator directly shows how mechanical breakdowns and unplanned downtime affect the production process. Additionally, supporting indicators that enrich the performance analysis are taken into account, such as setup time, which provides insight into the duration of model changes, and the defect rate, which allows for an analysis of the quality of the fabric produced. Together, these indicators facilitate appropriate monitoring of the stability and efficiency of the production process. The selected indicators, along with their initial values, are shown in Table I.

TABLE I
INITIAL STATUS OF THE INDICATORS

Indicador	AS IS
Tasa de Productos No Conformes (NCR %)	0.51% no cumplen especificaciones
MTBF – Tiempo Medio Entre Fallas (horas)	32 horas promedio entre fallas de máquina circular.
MTTR – Tiempo Medio Para Reparar (minutos)	95 minutos por falla (mantenimiento reactivo).
Cumplimiento 5S (%)	Auditorías actuales: 65% (promedio anual).

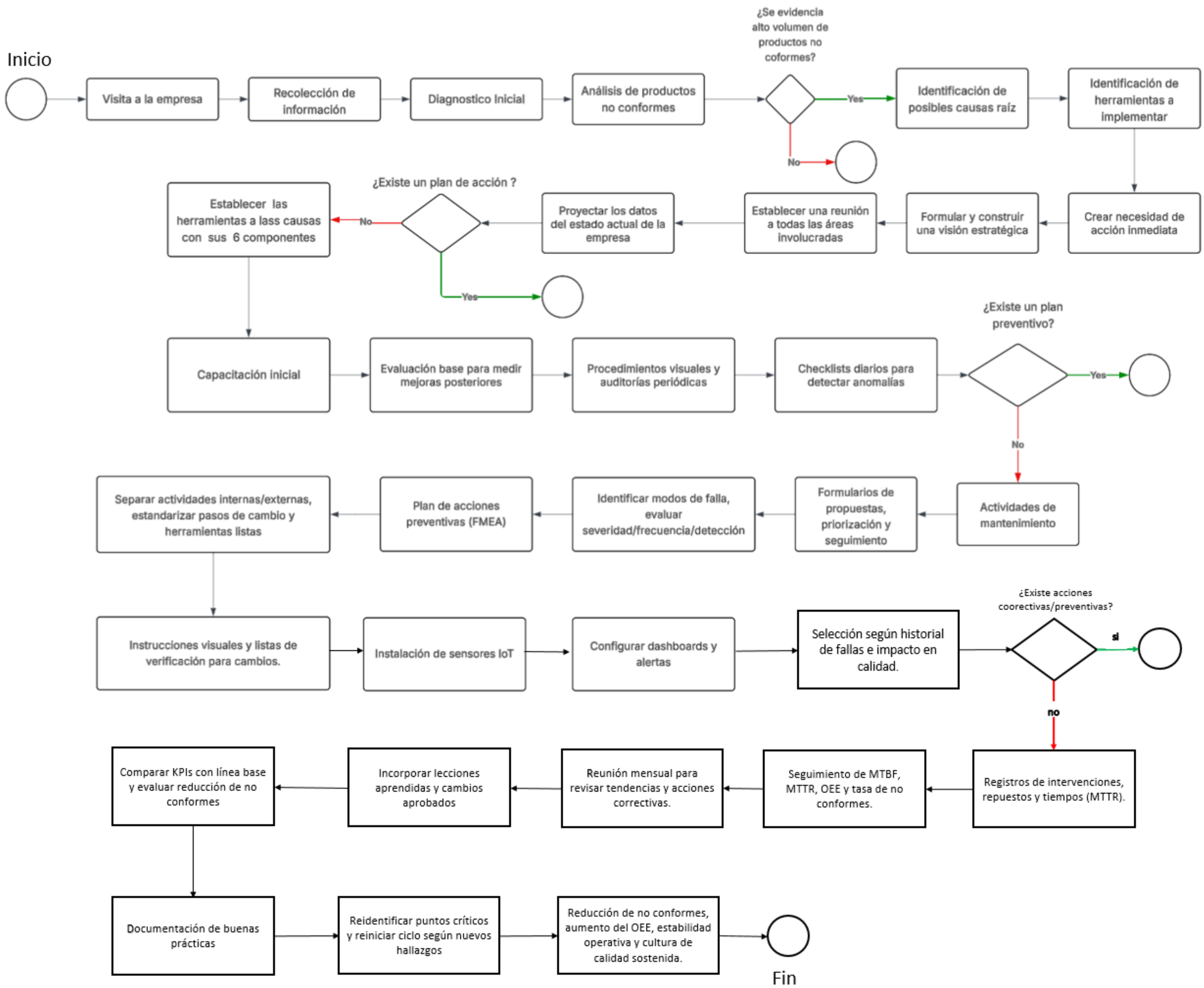

Fig. 2 Flowchart

D. Development

The proposed model is implemented in three interconnected stages, the purpose of which is to optimize operational efficiency, equipment reliability, and the stability of the production process. Phase 1 focuses on establishing the basic conditions for system stability by implementing initial autonomous maintenance and the 5S methodology. In this phase, the objective is to eliminate clutter, reduce search times, optimize cleanliness, and ensure an environment conducive to constant inspection. The application of 5S creates a standardized and solid operational foundation that reduces losses due to disorganization and makes it easier to identify faults in advance, enabling clearer control over the essential components of the process [22]. Additionally, initial TPM activities aimed at autonomous maintenance are implemented. In these activities, operators perform routine lubrication, inspection, and basic cleaning tasks, which reduces the occurrence of minor failures and promotes greater accountability regarding the condition of the machines [26]. The objective of this stage is to establish a controlled and stable environment that enables the reduction of variability in operations and subsequently the optimization of cycle times.

Phase 2 focuses on the systematic management of failures and on improving operational flow through the use of SMED and FMEA. First, using FMEA, failure modes can be identified, their impact assessed, causes determined, and corrective actions classified according to risk level. This methodology reduces uncertainty in operations and enables maintenance resources to focus correctly on the most problematic causes, which improves machine reliability and reduces the frequency of significant failures [20], [25]. SMED is additionally applied to improve setup times by separating external and internal activities, eliminating unnecessary steps, and standardizing adjustment processes. Research shows that its use can significantly reduce downtime associated with changes in machine models and configurations in textile processes [14], [15]. In this way, the company increases its operational adaptability and reduces bottlenecks that hinder production continuity. Reducing interruptions, optimizing workflow, and increasing overall process efficiency are the main objectives of this stage.

Finally, the third phase incorporates IoT-based technological tools, following an approach of monitoring and automatic response to the production process. In this stage, an industrial machine vision camera is installed on the machine itself, one meter from the fabric exits, to continuously monitor the produced fabric and detect defects associated with needle breakage. When the system identifies an anomaly, the captured information is immediately processed to activate a warning light and, simultaneously, trigger the machine's automatic shutdown, thereby preventing the continuation of defective production. In this way, the IoT system not only performs a detection function but also captures, processes, and takes action on the process, allowing for more timely intervention in the face of failures that affect fabric quality [22], [26]. The incorporation of this system strengthens operational control, improves process traceability, and contributes to the development of more stable and technologically advanced production. The flowchart shown in Fig. 2 corresponds to the development of the proposed model.

E. Final Diagnosis

The final diagnosis demonstrates progress in the company's key indicators of reliability, quality, and operational stability. Regarding the primary indicator, the non-conforming product rate (NCR %) currently stands at a high value of 0.51%. Therefore, it is anticipated that after implementing the phases of the proposed model, this rate will decrease to a percentage equal to or less than 0.3%. Similarly, regarding the supporting indicators, the objective is to increase the MTBF to improve the mean time between failures and enhance machine reliability. It is also anticipated that the MTTR will decrease through the implementation of intervention protocols and setup optimizations, which will enable a more agile response to operational failures. Finally, it is anticipated that 5S compliance, which currently stands at 65%, will increase to at least 90%, thereby establishing superior conditions in terms of cleanliness, order, and operational discipline. Overall, these anticipated results will make it possible to reduce downtime, minimize waste, and strengthen the stability of the production system. The expected results of the indicators included in the proposal are shown in Table II.

TABLE II
EXPECTED INDICATOR RESULTS

Indicador	AS IS (valor actual)	TO BE (meta)
Tasa de Productos No Conformes (NCR %)	0.51%	≤ 0.3%
MTBF — Tiempo Medio Entre Fallas (horas)	32 h	≥ 70 h
MTTR — Tiempo Medio Para Reparar (minutos)	95 min	≤ 45 min
Cumplimiento 5S (%)	65%	≥ 90%

IV. VALIDATION

To validate this research, we will ensure that the results presented are accurate, reproducible, and reliable through the proper implementation of the improvement model applied to the circular knitting process at Espain & Espinoza S.A.C. To this end, we will describe the scenario, the phases of the model's implementation, and how the proposed tools improve the performance of the production system.

A. Scenario Description

This solution model is based on the implementation of four development phases that will be validated through a pilot test and simulation using FlexSim software. In Phase 0 (change management), staff adaptation to the new operational practices will be evaluated. Phase 1 (TPM) and Phase 2 (IoT) will be validated through field application, demonstrating improvements in machine maintenance and real-time monitoring of the production process, using FlexSim software to analyze system behavior. Finally, Phase 3 (RCM) will be validated through simulation in FlexSim, allowing for the evaluation of system performance under a reliability-based maintenance approach.

B. Model / Implementation

1) Change Management Validation Model

For the validation of Phase 0, 5 of the 8 steps proposed by Kotter will be adopted, with the aim of facilitating the implementation of the improvement model in the circular knitting process at Espain & Espinoza S.A.C. To this end, a pilot team was selected consisting of the general manager, production coordinator, maintenance manager, and operators.

Subsequently, training sessions were conducted, and the pilot was implemented through five meetings. In the first meeting, a sense of urgency was established regarding the issue of non-conforming products; in the second, the change leadership team was formed; in the third, the strategic vision of the model was defined; in the fourth, this vision was communicated to all employees; and finally, in the fifth meeting, the initial results were evaluated and adjustments were made to ensure the sustainability of the proposal.

2) Autonomous Maintenance Validation Model (Phase 1)

For the validation of Phase 1, a meeting was held with the board of directors to present the issues with the circular knitting process, characterized by needle wear, a lack of preventive maintenance, and the absence of control over bobbin inspection. Based on this, guidelines were defined for the implementation of TPM through a pilot plan applied to knitting machines.

Subsequently, a pilot group of 5 circular knitting machines was selected, on which autonomous maintenance activities were implemented, such as shift-based cleaning, needle inspection, bobbin checks, and the use of operational checklists. These actions were complemented by staff training and the standardization of procedures, ensuring their proper execution and sustainability on the shop floor.

In the current state (AS IS), the machines had an average of 8 failures per period, with an MTBF of 31 hours and an MTTR of 2.0 hours, reflecting low reliability and a high frequency of downtime. After implementing TPM (TO BE), failures were reduced to an average of 4.6, MTBF increased to 55.2 hours (+78%), and MTTR decreased to 1.16 hours (-42%), demonstrating a significant improvement in operational stability and continuity.

Likewise, an approximate 45% reduction in the frequency of failures was observed, along with an improvement in machine conditions—evidenced by less lint buildup and better control of critical components—as well as an increase in maintenance compliance from 40% to 90%.

Finally, these results demonstrate that the implementation of TPM significantly improved equipment reliability, reduced downtime, and optimized the circular knitting process, validating its effectiveness. [26], [27].

3) Validation model for setup standardization

For the validation of Phase 2, a simulation model was implemented using FlexSim software, based on the construction of a digital twin that replicates the behavior of a jersey machine in the circular knitting process. This approach allowed for the analysis of the impact of incorporating an IoT system, specifically through an image sensor (machine vision camera), without the need for physical implementation on the factory floor [17].

The model was built using real parameters from the production process, such as a shift of 86,400 seconds, a daily production of 2,000 meters of fabric, and a frequency of 8 needle breakage failures per day. In the current scenario (AS IS), fault detection is manual, with an average time of 302.4 seconds, during which approximately 7 meters of defective fabric are produced for each fault.

In the improved scenario (TO BE), the image sensor was incorporated as part of the IoT system, enabling automatic defect detection in 43.2 seconds, which reduces the generation of defective fabric to approximately 1 meter per failure. This represents a significant improvement in the system's ability to respond to critical events.

The simulation showed that the amount of defective fabric was reduced by 85.71%, demonstrating a substantial improvement in process quality. Additionally, there was an increase of 43 meters in compliant production, equivalent to a 2.33% improvement in production system yield.

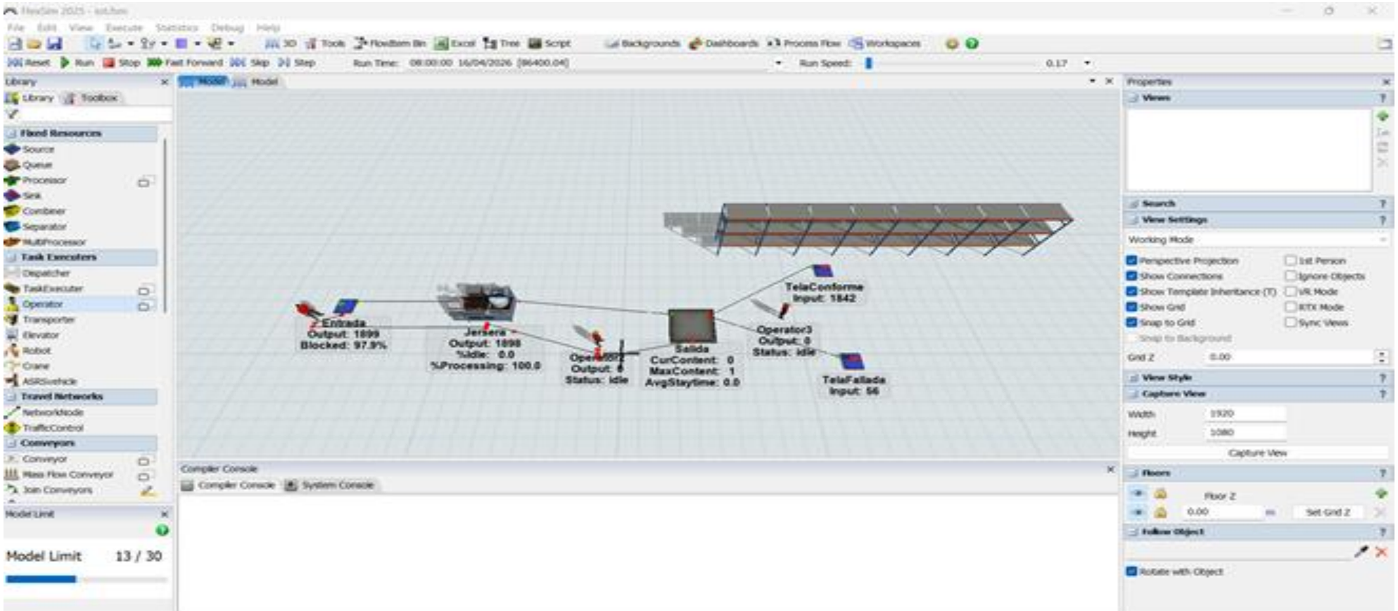

Fig. 3 Simulation model proposed in FlexSim

The model validation was carried out on three levels. First, conceptual validation was performed, verifying that the model's logic accurately represents the actual behavior of the production system. Second, operational validation was conducted, comparing the results of the AS-IS scenario with the company's actual historical data. Finally, experimental validation was performed through multiple simulation runs, allowing for an analysis of the consistency of the results and the variability of the system [17], [18].

Additionally, performance indicators such as the number of failures, defective meters, and reaction time were evaluated, showing sustained improvements in all cases. The repeatability of the results and their consistency with real data confirmed the model's reliability.

Finally, the results demonstrate that the implementation of an IoT system based on image sensors significantly reduces the production of non-conforming products, improves process efficiency, and optimizes real-time decision-making, thereby validating its effectiveness in the company's circular knitting process. [17], [27].

TABLE III

COMPARISON OF DIGITAL TWIN RESULTS

Indicador	Escenario actual	Escenario mejorado
Tela fallada	56	8
Reducción absoluta de tela fallada	0	48
Reducción porcentual de tela fallada	0.00%	85.71%
Tela conforme	1842	1885
Incremento absoluto de tela conforme	0	43
Incremento porcentual de tela conforme	0.00%	2.33%

4) Control and Monitoring Validation Model

For the validation of Phase 3, the RCM approach was implemented with the aim of ensuring the sustainability of improvements in the circular knitting process, focusing on critical components such as needles, bobbins, and calibration parameters.

The implementation consisted of developing a reliability-based maintenance plan, including preventive activities, inspection frequencies, responsible parties, and control forms, which enabled structured maintenance monitoring.

In the current state (AS IS), the system relied on reactive maintenance, with an average of 8 failures per period and a maintenance compliance rate of 40%. After the implementation of RCM (TO BE), failures were reduced to 4.6 (-42.5%), unscheduled downtime decreased by 35%, and maintenance compliance increased to 90%, demonstrating an improvement in operational stability.

Validation was performed by comparing indicators before and after implementation, using failure records and on-site monitoring.

Finally, the results demonstrate that RCM improves system reliability, reduces the recurrence of failures, and ensures the continuity of improvements over time, validating its effectiveness at Espain & Espinoza S.A.C. [22], [23].

C. Model Indicators

After carrying out the various validations of the proposed solution in each of its phases, the following results were obtained in relation to the previously established indicators.

TABLE IV

COMPARISON OF INDICATORS

Tool	AS IS	TO BE	Actual	Variation (%)
TPM	**8.0**	**4.5**	**4.6**	**-42.5%**
IoT	**56**	**8**	**8**	**-85.7%**
RCM	**40%**	**90%**	**90%**	**+125%**

The model's indicator table shows a comparison between the current state (AS IS), the proposed state (TO BE), and the actual results obtained after validating the TPM, IoT, and RCM tools. In the case of TPM, there was a 42.5% reduction in the number of failures, reflecting an improvement in equipment reliability. Meanwhile, the implementation of IoT using image sensors reduced the generation of defective fabric by 85.7% due to the early detection of anomalies in the process. Finally, the use of RCM increased maintenance compliance from 40% to 90%, ensuring the sustainability of the improvements and control of the production system. Taken together, these results demonstrate a significant improvement in the operational efficiency and quality of the circular knitting process. [11], [26], [27]

V. DISCUSSION

A. New Scenarios vs. Results

The results obtained align with the expectations set forth and with the reviewed literature [26], [27], demonstrating improvements in fault reduction and control of the production process. This allows us to infer that the proposed model is not only effective in the case study but also has the potential for application in other industrial environments with similar challenges.

1) Mining industry

The model would improve the reliability of heavy machinery through TPM, while IoT would facilitate real-time monitoring of critical variables and RCM would optimize maintenance planning, reducing unscheduled downtime [17], [18].

2) Fishing industry

The model would help reduce failures in production processes through TPM, while IoT would enable control of operating conditions and RCM would ensure process continuity [17].

3) Plastics industry

The model would improve machine stability through TPM, while IoT would enable real-time monitoring of critical parameters and RCM would optimize maintenance, reducing downtime [18], [19].

4) Metalworking Industry

Applying the model would improve equipment reliability through TPM, while IoT would facilitate fault detection and RCM would ensure efficient maintenance [25].

B. Analysis of Results

The results obtained in the model validation are highly relevant, as they demonstrate the effectiveness of the tools implemented in the circular knitting process. As observed, the analyzed indicators show significant improvements compared to the initial state, aligning with the expected values according to the literature and demonstrating the positive impact of the proposed model. The main results are detailed below:

1) Reduction of failures in the production process

The application of TPM reduced the number of failures from 8.0 to 4.6 per period, representing a 42.5% decrease. This result demonstrates an improvement in the reliability of knitting machines, due to the implementation of autonomous maintenance, periodic inspections, and control of critical components.

2) Reduction in non-conforming products

The implementation of the IoT system using image sensors reduced the production of defective fabric from 56 m to 8 m, achieving an 85.7% reduction. This demonstrates that early fault detection allows for timely intervention, preventing the spread of defects in the production process.

3) Improved maintenance control

The use of the RCM approach increased maintenance compliance from 40% to 90%, ensuring proper planning and execution of preventive activities. This helped reduce the recurrence of failures and improve the system's operational stability

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