

Smart Manufacturing: Lean-TPM 4.0 Model with IoT and AI to Improve Innovation and Efficiency in the Refractory Industry

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Abstract– *Low efficiency in refractory production is a critical problem affecting the profitability and sustainability of manufacturing processes. This study proposes an innovative model integrating Total Productive Maintenance (TPM 4.0) and Lean Manufacturing tools, supported by Internet of Things (IoT) and Artificial Intelligence (AI) technologies. The research follows an applied research typology with a pre-experimental design, utilizing non-probabilistic purposive sampling focused on the critical equipment of a refractory crucible manufacturer. The methodology evaluates the "before-and-after" impact of integrating automated data collection and predictive analytics. The model aims to increase operational efficiency, reduce equipment downtime, and mitigate high rework rates. After implementation, significant improvements were observed: the porous crucible rate was reduced by 57.69% (from 18.20% to 7.70%); the Mean Time Between Failures (MTBF) of the press increased by 25.33% (from 173.06 h to 216.91 h), while the MTBF of the mixer increased by 50.44%. Likewise, the internal setup time through Single Minute Exchange of Die (SMED) decreased by 27.58%, from 83.60 h to 60.54 h. Finally, the results demonstrate that the model is scalable and flexible, providing a practical framework for other industrial environments seeking to transition toward Smart Manufacturing. These findings validate the integration of Lean-TPM 4.0 as a robust solution for enhancing global efficiency in traditional industries.*

Keywords– *Smart Manufacturing, Lean Manufacturing, TPM 4.0, Internet of Things (IoT), Machine Learning (ML).*

I. INTRODUCTION

In Peru, the refractory industry plays a strategic role in the mining and metallurgical sectors, by supplying materials capable of resisting high temperatures during metal smelting, such as refractory crucibles. In 2023, domestic production of refractory materials decreased by 6% compared to the previous year, mainly due to the lower manufacture of high-alumina products. However, the production of basic refractories increased by 52%, reflecting the growing demand for essential materials for the transformation and processing industries.

In parallel, mining continues to be the country's main economic engine, accounting for approximately 63.4% of total exports in 2023. In 2024, mining exports reached a record US\$ 47,701 million, with copper and gold as the main products, concentrating 49% and 32% of the value exported, respectively [1], [2].

Despite this favourable context, the refractory sector faces production efficiency problems, mainly due to reprocesses, non-productive times and the lack of preventive and/or

predictive maintenance, which causes equipment breakdowns and significant economic losses [3], [4]. Addressing this situation is essential to improve the productivity and sustainability of processes.

In recent years, different manufacturing companies have implemented innovative preventive maintenance models based on digitalization and emerging technologies. In particular, the use of the Internet of Things (IoT) has proven effective in optimizing resources and reducing downtime [5], [6]. Likewise, the standardization of work and the Single Minute Exchange of Die (SMED) methodology are consolidated as key tools to reduce changeover times and increase operational efficiency [7], [8].

The integration of SMED with IoT-based predictive maintenance represents a transformative opportunity, enabling more accurate maintenance management and failure prevention [2], [9]. However, the adoption of these tools remains limited in many Small and Medium-sized Enterprises (SMEs), which shows a technological gap compared to more advanced industries.

In this context, the purpose of this research is to analyse how a model based on the standardization of work, SMED and Total Productive Maintenance (TPM 4.0) can improve the level of efficiency in production processes within a refractory company. To this end, IoT technology is integrated for real-time monitoring of the condition of equipment and AI, specifically Machine Learning (ML) algorithms, for failure prediction, along with the application of SMED to reduce changeover times [3], [10], [11].

This approach proposes a comprehensive model that can be adapted to other manufacturing companies, aimed at reducing downtime and operating costs [6], [12].

The structure of the article is as follows: Section 1 addresses the theoretical foundations on SMED, process standardization and TPM 4.0; section 2 presents the methodology applied in the case study, including the implementation of the IoT and the standardization of work; the third section presents the results obtained and their practical implications; the fourth presents the discussion and validation of the tools; and finally, Section 5 develops the conclusions for the application of the model in other similar manufacturing companies.

II. STATE OF THE ART

A. SMED implementation to improve and reduce equipment set-up times

The SMED methodology is a key tool in manufacturing aimed at reducing the time needed to make reference changes or preparation between operations. Its objective is to minimize downtime and improve operational efficiency, which are decisive aspects to achieve production flexibility. This approach is integrated with the principles of Lean Manufacturing, focused on eliminating waste and promoting continuous improvement. Thus, SMED allows you to optimize changeover times and adapt quickly to variations in demand, especially in environments where agility is critical [13]–[15].

Recent studies show that its application in different industrial contexts generates significant reductions in preparation times and increases productivity by eliminating activities that do not add value [10], [16], [17]. In specific sectors, its use has optimized the preparation of machinery and tools, with notable improvements in tandem press lines [18], [19]. Similarly, in companies with lean manufacturing systems, the SMED has managed to reduce changeover times by about 30%, confirming its versatility [20].

In more comprehensive approaches, models have been developed that combine SMED with methodologies such as the Johnson method and TPM, increasing productivity in the production of flexible packaging in SMEs in the plastics sector, and demonstrating its potential within multifunctional solutions [4], [14].

The effectiveness of the SMED depends on a structured and participatory implementation. Its success lies in correctly differentiating internal and external activities, involving operational personnel and carrying out a prior diagnosis of the process. Subsequently, worthless tasks are eliminated, internal activities are transformed into external ones, and procedures are standardized using visual tools and checklists. These actions reduce wasted time and increase the overall availability of equipment, consolidating SMED as an essential strategy in modern maintenance and production management.

B. TPM 4.0: Preventive and Predictive Maintenance with IoT and Machine Learning (ML)

TPM 4.0 emerges as the evolution of traditional maintenance towards a digital and intelligent approach, aligned with the principles of Industry 4.0 and Smart Manufacturing. This vision integrates technological tools such as the IoT, ML, data analytics and cloud computing, allowing teams to be able to self-diagnose, predict failures and optimize their maintenance routines in real time [12]. These trends not only seek to increase the availability and reliability of machines, but also to promote more sustainable, efficient operations based on the decision process with real data. In this scenario, TPM 4.0 represents a synergy between the Lean philosophy and digital technologies, consolidating itself as one of the key strategies for the digital transformation of manufacturing in the last decade [15], [21].

As for preventive maintenance, this is defined as the practice of carrying out regular inspections and adjustments to equipment or systems in order to avoid unforeseen failures [10]. Its main purpose is to ensure efficient and safe operation, reducing the likelihood of breakdowns and accidents. Within the framework of Industry 4.0, predictive maintenance has reached a greater degree of sophistication thanks to technologies such as the IoT, which allow real-time data collection, and the implementation of predictive systems based on ML [8]. These tools optimize maintenance planning and execution, enabling interventions before critical failures occur, reducing operational disruptions and extending equipment life [12]. For example, in the case of lean machines, a predictive system trained with ML algorithms and optimized using cross-validation techniques achieved 92% accuracy in classifying stops in real time [13]. These results demonstrate the feasibility and effectiveness of integrating IoT and ML to improve the efficiency and profitability of industrial maintenance operations [21], [22].

For its part, the application of the preventive maintenance pillar of TPM 4.0, supported by standardized protocols and schedules based on mean time between failures (MTBF), has shown progressive improvements in operational efficiency [23]. In one documented case, the initial availability of 62.33% and production efficiency of 39.01%, considered "very low", were significantly increased after the implementation of the program, validating the effectiveness of combining planned strategies with smart technologies [8], [15], [24].

In relation to predictive maintenance, this is consolidated as one of the most advanced pillars of TPM 4.0, as it allows the anticipation of failures through the analysis of historical data and the real-time monitoring of critical variables such as temperature, vibration, pressure or energy consumption [21]. Unlike preventive maintenance, which operates under fixed intervals or hours of use, predictive maintenance acts based on the actual condition of the equipment, using IoT sensors to capture information and analytical or ML models to estimate the probability of failure before it occurs. This approach optimises intervention planning, avoids unnecessary maintenance and maximises machine availability [19].

In industries such as metalworking and plastics manufacturing, it has been shown that incorporating ML-based prediction models—such as neural networks and logistic regression algorithms—can increase equipment reliability by 25% to 45%, as well as reduce annual maintenance costs by up to 30% [8]. These advances have been possible thanks to the integration of cloud platforms and intelligent SCADA systems, capable of collecting large volumes of data and transforming it into useful information for strategic decision-making.

Likewise, vibration analysis has established itself as a fundamental technique within modern predictive maintenance. By using acceleration sensors or ultrasonic microphones, it is possible to detect anomalous patterns associated with imbalances, misalignments, or wear in rotating components, such as motors and pumps. Spectral analysis and signal

processing using Fast Fourier Transform (FFT) allow faults to be detected with more than 90% accuracy, anticipating failures in electric motors, centrifugal pumps and industrial compressors up to 72 h before their occurrence, which significantly reduces the Mean Time to Repair (MTTR) [8], [13].

The current trend focuses on autonomous predictive systems with self-diagnosis and self-calibration capabilities, characteristic of intelligent cyber-physical equipment that integrates IoT, artificial intelligence, and digital twins to simulate operating conditions, generate early warnings, and optimize maintenance, thereby improving reliability and sustainability. However, their implementation faces challenges in contexts such as Peru due to limitations in connectivity, lack of data standardization across equipment, and resistance to technological change, which drives the need for adaptive, low-cost solutions, particularly for manufacturing SMEs.

C. Standardization of work to optimize processes

Work standardization is an essential principle in manufacturing that consists of defining specific methods to execute each task within a process, in order to minimize variations, reduce errors and maintain constant quality [25]. This approach seeks to ensure that all operators follow the same documented procedure, optimizing time and resources, and receiving adequate training to ensure its correct application [16].

Their implementation, often combined with the anthropometric design of the stations, has shown significant and measurable improvements. In one study, the reduction in ineffective actions and improper postures went from 230 to 78, simplifying tasks and improving ergonomics. Likewise, the standard time to assemble a box decreased from 244 to 199 seconds, reflecting a substantial increase in operational efficiency [16], [19].

These improvements in cycle times and ergonomics have a direct impact on productivity. The standardization of work made it possible to increase daily production to 229 units in one line, eliminating overtime and optimizing the use of personnel and resources [16]. Similarly, another study showed an increase in weekly production from 61.75 to 128.75 units, equivalent to a 108.5% improvement in line performance [19]. These results demonstrate the feasibility and positive effect of work standardization on the efficiency, productivity, and sustainability of industrial operations.

III. CONTRIBUTION

In this part, the central contribution of the research work is presented: an innovative model that seeks to optimize the production process of the case under study, the Lean method applied in the refractory industry. The particularity of the model lies in adapting industry 4.0 tools to a context little explored in the academic literature, which constitutes a significant contribution to scientific knowledge in this field.

A. General model

Fig. 1 shows the proposed solution model to optimize production efficiency, with its phases, components and sequential implementation. The model is comprehensive and is designed based on the main root causes (input) identified in the production process. This model is structured in three complementary components: (1) the standardization of work, aimed at optimizing mixing, drying and calcining conditions to reduce operational variability and reduce the index of porous crucibles; (2) the application of SMED together with a preventive maintenance plan, in order to reduce setup times and reduce unplanned failures in crimping machines; and (3) the implementation of a Smart Monitoring system based on IoT and ML, which allows predictive maintenance to be carried out through the early detection of anomalous vibrations in the mixer. Together, these three components seek to increase the

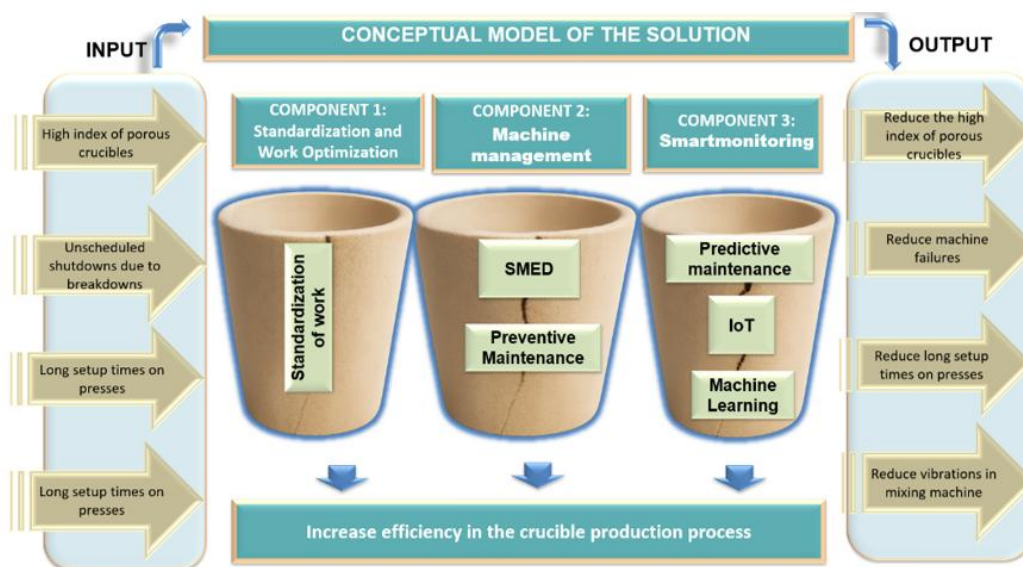


Fig. 1. Conceptual solution model

overall efficiency of the process, ensuring greater operational continuity, reduction of defects and a more competitive production response.

B. Detailed model

Each of the stages that make up the proposed optimization model is explained in detail below.

1) Standardization of work:

Phase 1: Analyse Activities.

In this first stage, the activities of the mixing, drying and calcining process using the Process Analysis Chart (DAP) are analysed and documented in detail, promoting standardization as a continuous practice. In crucible manufacturing, this allows for reduced variability, errors, and rework, improving productivity and reducing costs.

Phase 2: Action plan.

After the initial diagnosis, an action plan was developed to analyse and classify each activity of the three processes mentioned above according to the value it brings to the product, using the Value-Added Analysis - Process Analysis Chart (AVA-DAP) tool. This made it possible to identify unnecessary tasks, prioritize improvements, and optimize workflow, reducing waste and increasing process efficiency.

Phase 3: Design standard procedures.

After analysing the previous activities, a standard procedure for mixing, drying and calcining was developed, transforming the plant observations into a practical guide for the staff. This instruction seeks to standardize the process, improve efficiency, reduce errors and facilitate training, promoting a culture of quality and continuous improvement.

Phase 4: Process Performance Evaluation.

Finally, the percentage of rework in the mixing area is measured to objectively identify the efficiency of the process and verify the impact of standardization. This measurement confirms whether rework has been reduced, validates corrective actions, and serves as a basis for future improvements, optimizing quality and plant resources.

2) Single Minute Exchange of Die:

Phase 1:

In the first phase of SMED, the current state of the pressing machines was analysed, and their preparation activities were measured using the DAP. The tasks were classified as follows: internal and external, identifying that 80% of the time corresponded to internal activities and only 20% to external activities.

Phase 2: Conversion of internal to external activities

The Eliminate, Combine, Rearrange, and Simplify (ECRS) technique was applied to convert internal to external activities in the pressing machines, allowing tasks to be carried out without stopping the machine. This allowed six internal activities to be transformed, significantly reducing downtime during mold changes.

Phase 3: Curating and Implementing Proposals.

Applying SMED and ECRS principles, various internal tasks were transformed into external ones to minimize press setup time. Improvements include off-line cleaning, pre-inspections, mold release automation and parameter presetting. These actions reduced vacuum testing and significantly decreased downtime in mold changes.

Phase 4: Measure indicators and standardize processes.

Finally, after the application of the tools, a notable reduction in the preparation time of the pressing machines was identified. This result is attributed to the immediate availability of implements and a better organization of the work area. Fig. 8 presents a detailed checklist for each setup activity, indicating the reduced times or, where they are maintained, the reference values for standardizing the process.

3) TPM 4.0:

Phase 1: Preparing a Maintenance Plan.

The preparation stage is critical to implementing effective preventive maintenance, as it allows for a thorough understanding of the current state of equipment and processes through detailed diagnostics. Operating conditions, recurring failures, and history are evaluated through audits, and key indicators (KPIs) are analysed to identify performance gaps. Subsequently, a pilot line is selected to validate the methodology and reduce risks before its full application. Finally, a cause-effect analysis is performed to identify the true roots of failures and inefficiencies, and not just their symptoms.

Phase 2: Planning.

In this phase, the diagnosis becomes a concrete action plan for maintenance. Specific activities are defined, clear roles are assigned according to responsibilities and competencies, and a team of facilitators is formed to lead the change. In addition, a master plan with Specific, Measurable, Achievable, Relevant, and Time-bound (SMART) objectives is drawn up to guide the entire implementation. Once the team is formed, the functions are distributed considering the position, experience, technical skills and availability of each member. The details of these assignments are presented on the following tab.

Phase 3: Preventive maintenance implementation stage.

In this phase, a schedule of training given by a specialist was developed, along with the standardization of cleaning and a training program. The plan ranges from preventive to predictive maintenance with IoT and is applied to the pressing machines, recording tasks and failures in daily files for follow-up.

Phase 4: Architecture Design for Predictive Maintenance.

In this phase, a comprehensive monitoring system is implemented for the mixer motor, using vibration sensors connected to a Programmable Logic Controller (PLC) and a Human-Machine Interface (HMI) for local control. The data is sent to the cloud (Google Cloud) via an IOT-2040 and visualized on a dashboard, allowing real-time conditions to be monitored and predictive maintenance to be supported.

Phase 5: Configure Servers and Mount.

It refers to the comprehensive configuration of the software and hardware necessary to ensure the correct functioning of all the programs involved. This involves the installation,

adjustment and customization of computer systems, as well as their integration and connection with each other, guaranteeing coordinated and efficient work that allows the defined objectives to be achieved.

Phase 6: Measuring indicators and continuous improvement.

In this last stage, it will be evaluated whether the implementation of the tool has produced the expected results. If the goal is not met, the results obtained will be reviewed and corrective actions will be defined. This procedure is explained in more detail in the following graphic.

4) Proposed Process:

Fig. 2 presents the actions contemplated in the proposed model to improve efficiency in the manufacture of refractory crucibles, showing how the different stages and the tools used are related. Implementation begins with the planning phase, where the corresponding goals, teams, and timelines are defined. Subsequently, in the standardization stage, the work is responsible for examining and recording the activities, eliminating those that do not add value. Within the SMED approach, methods are used to reduce set-up times by converting and simplifying internal and external tasks. Finally, TPM 4.0 incorporates preventive and predictive maintenance strategies supported by IoT and real-time data analysis, which allows failures to be anticipated and reliability to be increased. Overall, the model integrates management, standardization and digitalization to achieve more agile, sustainable and competitive processes.

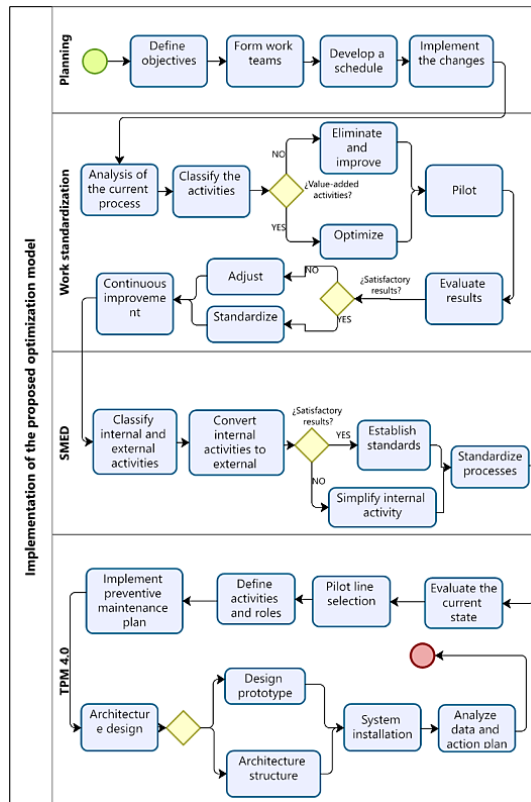


Fig. 2. Proposed model.

5) Indicators:

The following Table I presents the project's monitoring indicators. In it, the values of both the current scenario (As-Is) and those of the expected scenario (To-Be) are shown, based on the success stories analysed in the literature review.

TABLE I
INDICATORS

Indicator	As - Is	To - Be	Ref.
Production efficiency	63.46%	76.92%	[12].
Porous crucible rate	18.20%	4.15%	[19].
MTBF Press	69.58 h	134.26 h	[26].
Internal configuration	83.60 h	58.52 h	[17].
MTBF Mixer	72.50 h	139.88 h	[20].

IV. VALIDATION AND DISCUSSION

A. Discussion

The proposed model is based on the joint application of three fundamental elements: process standardization, SMED methodology and TPM 4.0 combined with IoT and ML technologies. Each of these components is supported by recent scientific literature, which confirms their ability to enhance operational performance, reduce the periods in which equipment does not produce and increase its level of availability [26], [27].

Work standardization is supported by studies that show significant reductions in process variability, human error, and cycle time when standardized instructions and ergonomic job design are applied [16], [19]. In addition, the SMED methodology has proven to reduce changeover times by 25% to 45% through the correct separation of internal and external activities, the elimination of non-value-added tasks and the reorganization of the work area [17], [28].

For its part, the TPM 4.0 pillar is based on the ability of IoT and ML to identify deterioration patterns, diagnose anomalies and predict failures with accuracy levels greater than 90%, as demonstrated by recent studies in industrial predictive maintenance [13]. Vibration monitoring makes it possible to anticipate failures in motors and rotating systems following the criteria established in ISO 20816, reducing MTTR and increasing Mean Time Between Failures (MTBF).

The integration of these 3 engineering tools constitutes the foundation of the validated model, allowing standardization to control variability, SMED to reduce preparation time and TPM 4.0 to anticipate failures, thus generating a robust, synchronized system supported by technical evidence.

B. Proposed model

The validation of the model was developed following exactly the flow proposed in the "Proposed Process" section. To do this, each of the phases of the model was applied in the areas of mixing, drying, calcining, pressing and mixing, using the artifacts defined in the "Model Detail": DAP sheets, checklists,

operating standards, SMED matrices, IoT architecture, vibration dashboards and TPM plan.

First, the standardization pillar was applied through the analysis of activities, their AVA-DAP classification and the design of standard procedures. The SMED was then run on the presses, transforming internal tasks into external ones and directly evaluating how this influenced set-up times. Subsequently, TPM was implemented in its preventive component through training, the use of formats, scheduled execution and periodic inspection. Finally, the predictive module was validated by connecting vibration sensors to the PLC and the IoT-2040, sending data to Google Cloud and training a Random Forest model for fault detection.

C. Commissioning

1) Validation of the Standardization of work:

To validate the standardization proposal, a pilot was carried out in the mixing, drying and calcining stages, selected for their direct influence on the porosity of the crucibles. We worked with two similar production batches and a total sample of 300 units, which made it possible to identify the technical gap and verify that standardization reduces defects due to porosity, improving the consistency and quality of the production process.

TABLE II
CURRENT AND STANDARDIZED CONDITION

Stage	Current condition	Standardized condition
Mixed	25 min average, no humidity control	30 - 40 min average, humidity control at 6%
Drying	1-3 calendar days + 12 h at 220 °C	5-6 calendar days + 12 h (temperature ramps) max. 220°C
Calcined	1200°C for 12 h	1300°C – 1400°C for 13 h

First, the dosage of materials was carried out according to the formula established by the company. For validation, we worked with two similar production batches and a total sample of 300 crucibles. In Lot A (current conditions) 150 units were produced under traditional parameters, while in Lot B (standardized conditions) 150 crucibles were made applying parameters defined from the literature review and good industrial practices. This comparison made it possible to identify the technical gap and quantify the impact of standardization on the reduction of porosity defects, demonstrating the effectiveness of the method to improve the consistency and quality of the process.

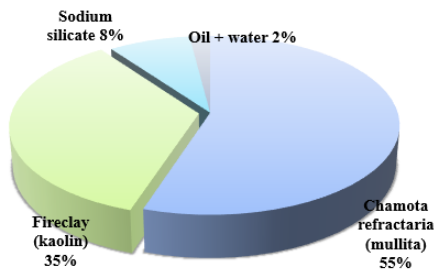


Fig. 3. Current Mixing Modification.

In Lot B, weight control was reinforced, and they incorporated calcined alumina (Al_2O_3) and fine silica (SiO_2), in accordance with ISO 10081-1 and UNE 61014-61015 standards, in addition to previous experimental studies. These improvements generated a denser and more resistant mixture, reducing porosity and increasing the thermal stability of the crucibles, results consistent with what has been reported for Al_2O_3 - SiO_2 combinations [29].

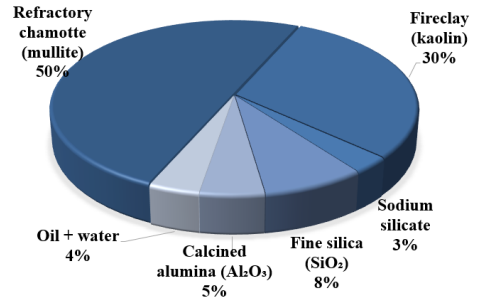


Fig. 4. Proposed dosage.

During the mixing stage, Batch A was processed for 25 minutes without humidity control, while Batch B was mixed for 35 minutes, applying spray of atomized water to 6% humidity, verified with a portable sensor. Subsequently, both batches went on to drying: Batch A maintained the current procedure (three days at room temperature and 12 h in the oven at 220 °C), while Lot B underwent natural drying of five days and 12 h in the oven with temperature ramps up to 220 °C.

Finally, in calcining, the crucibles of Lot A were fired in a conventional oven at 1100 °C for 10 h, while Lot B followed a controlled cycle of 13 h with a maximum temperature of 1330 °C and gradual ramps of increase, achieving a more complete and stable sintering of the material.



Fig. 5. Refractory crucibles in calcining area.

The results of the final quality control showed notable differences between both batches.

TABLE III
RESULT AFTER THE PILOT

Indicator	Current	Standardized	Improvement
Porous Crucibles (%)	18.2%	7.7%	57.69%

2) Validation of Predictive Maintenance + IoT and ML:

To validate the predictive model tools, the prototype data was processed using a ML algorithm trained to recognize normal and anomalous patterns in the machine's operation, anticipating unusual vibrations. The process included three phases: collection of historical data on vibration and motor current;

training the model in Python with the Random Forest algorithm, chosen for its accuracy and classification capacity; and a pilot test where the system was connected to the IoT gateway to issue real-time predictive alerts in the event of anomalous behaviour.

The Model Configuration and Evaluation Protocol, the predictive maintenance model was designed to classify the operational condition of the mixer motor into two states: Normal operation and Anomalous vibration condition. The objective of the model was to predict abnormal vibration behaviour that could indicate the early stages of mechanical failure. The input features used for model training were extracted from the vibration and electrical signals collected through IoT sensors. The main features included “Root Mean Square” (RMS) vibration (mm/s), peak vibration amplitude, average motor current (A), and vibration trend variation over time windows of 60 seconds. These variables were selected based on the International Organization for Standardization (ISO) 20816 vibration severity criteria and their relevance in detecting unbalance, misalignment, and mechanical wear.

The dataset consisted of vibration and motor current records collected over 720 h of continuous monitoring. The data were labelled according to ISO 20816 vibration severity thresholds into normal and anomalous conditions. The dataset was divided into 70% for training and 30% for testing to ensure independent validation of the model.

A Random Forest classifier was implemented in Python using the Scikit-learn library. The model was configured with 100 decision trees, maximum depth of 10 levels, and Gini impurity as the splitting criterion. Hyperparameters were selected based on empirical testing to balance model accuracy and computational efficiency. The performance of the model was evaluated using standard classification metrics, including Accuracy, Precision, Recall, and False Alarm Rate. The model achieved an accuracy of 92%, with a precision of 0.91 and recall of 0.89. The False Positive Rate (false alarms) was estimated at 6%, indicating a low number of unnecessary maintenance alerts. Additionally, the False Negative Rate was maintained below 5%, ensuring that critical faults were rarely missed.

These evaluation results confirm that the proposed predictive maintenance system provides reliable early detection of abnormal vibration patterns, supporting timely maintenance decisions and reducing unexpected equipment downtime.

The validation was carried out according to the ISO 10816 standard (currently ISO 20816), which defines the acceptable Root Mean Square (RMS) velocity ranges (mm/s) for diagnosing rotating machines and classifying their operating status.

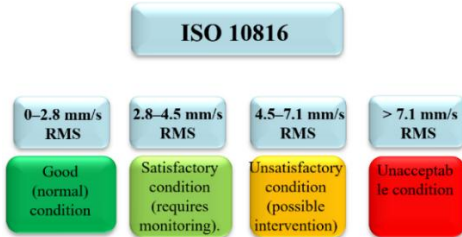


Fig. 6. Vibration ranges according to ISO 10816

After implementation, the collected data was stored in Comma-Separated Values (CSV) files and processed by the ML model for real-time analysis and learning. The system recognized the vibrations of the engine and determined its operating status, generating automatic alerts in the event of anomalous conditions. 720 h of observation were recorded, equivalent to one month of continuous monitoring of the mixer motor.

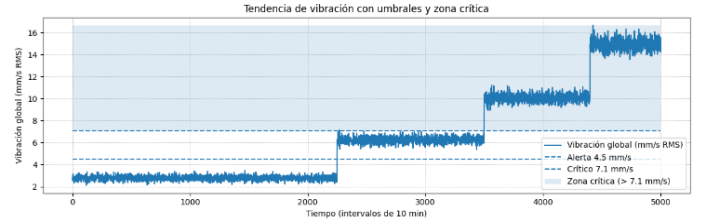


Fig. 7. Mixer vibration register.

During the simulation, the dashboard showed the behaviour of the motor in real time, with three vibration peaks close to the critical level, of which only one required preventive action. The start table detailed the operating times and the condition of the engine, while the control panel presented the average vibrations of the last 24 h, facilitating monitoring and decision-making.

TABLE IV
REAL ENGINE TIME STATUS

Date	Event	Value (mm/s)	Severy
2025-09-29 17:08:31 UTC	Vibration entered CRITICAL	2.43	GOOD
2025-09-29 16:52:31 UTC	Vibration entered UNSATISFACTORY	4.88	GOOD
2025-09-29 16:38:31 UTC	Vibration entered CRITICAL	2.96	GOOD
2025-09-29 16:30:31 UTC	Vibration entered UNSATISFACTORY	4.69	WARNING
2025-09-29 16:24:31 UTC	Vibration entered UNSATISFACTORY	2.5	GOOD
2025-09-29 12:32:31 UTC	Vibration entered CRITICAL	3.41	GOOD
2025-09-29 12:08:31 UTC	Vibration entered UNSATISFACTORY	5.21	WARNING

The table below summarizes the results generated from the simulation of the prototype, as well as the reference values obtained from the specialized literature. Together, these data confirm that the validation process achieved significant improvements in the indicators evaluated.

TABLE V
VALIDATION OF THE RESULTS

Indicator	As-Is (h)	To-Be (h)	Result (h)
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MTBF	72.50	139.88	109.07
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3) SMED Validation:

A pilot plan was applied in the refractory crucible pressing area to validate the SMED methodology. First, the staff was trained for an hour at the end of the working day, guaranteeing the understanding and correct execution of the method without affecting production. Then, the conversion of internal to external activities was evaluated in real conditions, measuring their impact on preparation time and equipment availability.

Improvements included early cleaning of the die and work area, external mold inspection, automated mold release application, use of pre-centring systems for mold alignment, and preloading of operating parameters (pressure, speed, and temperature) prior to changeover. These actions reduced downtime and increased process efficiency, validating the effectiveness of the SMED approach.

TABLE VI
SUMMARY OF ACTIVITIES AFTER THE CHANGE

Activity	As-Is	To-Be
External	11.70%	95.65%
Internal	88.30%	4.35%
Total	100%	100%

The results showed a more efficient and safer work sequence, optimizing the team's preparation. The graph showed a notable reduction in machine set-up time, confirming the improvement in process efficiency after pilot implementation.

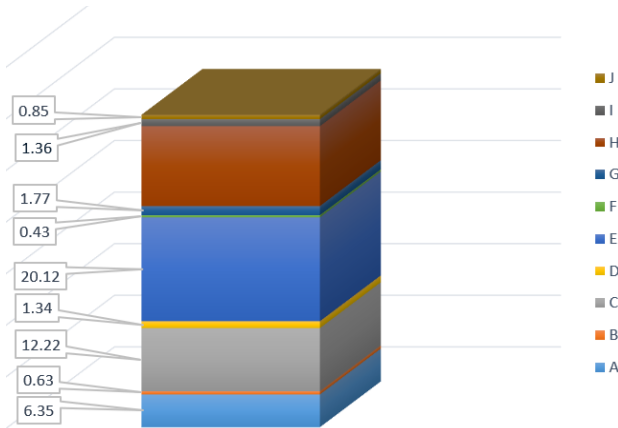


Fig. 8. Standardized setup of the press machine.

After applying the SMED, the *setup* time decreased from 83.60 h to 60.54 h, achieving an improvement of 27.70%. This result shows greater efficiency in format change thanks to the standardization and conversion of internal to external tasks [30].

TABLE VII
SUMMARY OF ACTIVITIES AFTER THE CHANGE

Indicator	As-Is (h)	To-Be (h)	Result (h)
Setup Time	83.60	58.52	60.54

4) Validation of preventive maintenance:

As a first stage, the staff of the press area, made up of four operators and the maintenance supervisor, was trained in a two-hour session aimed at explaining the fundamentals and changes of the preventive maintenance pillar of the TPM. A week later, the pilot was executed, preparing and disseminating the procedures and technical sheets in the communication area of the area. This facilitated access to information, understanding of the stages of the process and the correct application of the programmed activities, guaranteeing an orderly and effective execution of preventive maintenance [31], [32].



General inspection of the press



Checking the hydraulic oil/lubricator level



Cleaning the hydraulic cylinders



Cleaning of critical components

Fig. 9. Preventive maintenance procedures.

The operator in charge used a checklist to record the operating status of the crimping machine, documenting anomalies and critical aspects. For four weeks, the supervisor reviewed the forms to ensure their correct completion, strengthening traceability and the basis for preventive maintenance decisions. After the pilot, with evaluations every three days, performance was measured, comparing the initial state, the expected state according to the literature and the final result achieved.

TABLE VIII
RESULTS AFTER THE MAINTENANCE PILOT PLAN

Indicator	As-Is (h)	To-Be (h)	Result (h)
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MTBF	173.06	333.93	216.91
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The table shows the results after the implementation of the proposals for improvement in the main problems detected during the diagnosis, showing progress in all indicators. The percentage of porous crucibles was reduced from 18.20% to 7.7%, with an improvement of 57.69% thanks to the standardization and control of critical parameters. Regarding unscheduled shutdowns due to ring breakage, MTTR decreased from 6.97 h to 4.14 h and MTBF increased from 173.06 h to 216.91 h, improving by 40.52% and 25.33%, respectively, due to preventive maintenance. Likewise, the setup time in the presses decreased from 83.60 h to 60.54 h (27.58 % improvement) using the SMED methodology. Finally, in the mixer, the MTTR was reduced from 7.30 h to 5.82 h and the MTBF increased from 72.50 h to 109.07 h, with improvements of 50.44%, validating the effectiveness of predictive maintenance based on vibration monitoring.

TABLE IX
SUMMARY OF RESULTS

Indicators	As-Is	To-Be	Results	%
Production efficiency	63.46%	76.92%	75.32%	+18.69%
Porous crucible rate	18.20%	4.15%	7.7%	-57.69%
MTBF Press	173.06 h	333.93 h	216.91 h	+24.34%
Internal configuration	83.60 h	58.52 h	60.54 h	-27.58%
MTBF Mixer	72.50 h	139.88 h	109.07 h	+50.44%

V. CONCLUSIONS

The integration of Lean tools - SMED, work standardization and TPM 4.0 with IoT and ML proves to be an effective strategy to increase production efficiency in the refractory industry. The results obtained reflect significant improvements: reduction in corrective maintenance costs, increasing operational efficiency by +18.69%, thus reducing the existing gap. This model transforms traditional maintenance methods by processing data instantaneously, anticipating failures and extending the life of equipment.

The study provides a technical and academic advance by adapting Industry 4.0 technologies to a little-explored sector, achieving an effective integration between predictive maintenance, standardization and reduction of preparation times. The validation of the model confirmed its effectiveness: standardization decreased inefficient movements and cycle times; IoT and ML achieved 92% accuracy in stopping classification; and SMED reduced changeover times by 30%. Data reliability, correct algorithm selection, and staff training are identified as critical variables to sustain these improvements.

In the mixing, drying and calcining processes, standardization reduced the porosity of the crucibles by 57.69%, improving their density and thermal stability. Likewise,

predictive maintenance with Random Forest made it possible to anticipate failures in accordance with the ISO 20816 standard, increasing the MTBF from 72.50 h to 109.07 h and reducing the MTTR from 7.30 h to 5.82 h. Finally, the synergy between SMED and TPM 4.0 evidenced an increase in MTBF from 173.06 h to 216.91 h and a reduction in setup time from 83.60 h to 60.54 h. These results confirm that the proposed model is a scalable and sustainable solution, capable of strengthening the competitiveness and operational reliability of the refractory industry under the principles of Industry 4.0.

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