Sensor-Based Predictive Maintenance Prototype to Reduce Non-productive Time in Brick Manufacturing SMEs

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Abstract

Low production efficiency in brick manufacturing small and medium-sized enterprises (SMEs) is mainly caused by unplanned downtime and the absence of real-time operational monitoring. This paper presents a sensor-based predictive maintenance prototype designed to reduce non-productive time and improve system availability in a brick production process. The proposed solution integrates low-cost sensors and an automated control mechanism to monitor operational conditions and support timely maintenance actions. The prototype was experimentally validated through a comparative AS-IS and TO-BE analysis under controlled operating conditions. The results show a reduction in non-productive time to 3.28%, an increase in system availability to 96.7%, and a noticeable stabilization of the production flow. These results demonstrate that sensor-based predictive maintenance solutions are technically viable and suitable for implementation in resource-constrained manufacturing SMEs.

1 Introduction

The Peruvian brick manufacturing sector plays an important role in the construction industry and local economic development. However, micro and small enterprises (MSEs) in this sector commonly operate with low production efficiency and reduced equipment availability, mainly due to unplanned downtime and corrective maintenance practices [1]. According to industry reports, brick manufacturing SMEs frequently operate below their nominal production capacity, which negatively impacts productivity and operational costs [1].

In raw-brick production lines, non-productive time is strongly associated with corrective maintenance interventions, calibration issues, and non-standardized setup activities. Becerra-Flores et al. report that corrective maintenance activities can account for more than 40% of total downtime in small-scale brick manufacturing processes [2]. The same study indicates that setup and adjustment operations contribute between 20% and 30% of production losses, significantly affecting production continuity [2]. The impact of maintenance inefficiencies is further reflected in equipment availability levels. Mendes et al. report availability values below 60% in conveyor-based production systems operating under predominantly corrective maintenance strategies [3]. Although the study focuses on material-handling systems, similar operational patterns are observed in raw-brick production lines due to comparable continuous-process characteristics [3].

To address these limitations, this paper presents a sensor-based predictive maintenance prototype aimed at reducing non-productive time and improving system availability. The proposed solution integrates low-cost IoT sensors and automated data acquisition to monitor equipment operating time and stoppage events. The system was experimentally evaluated through an AS-IS and TO-BE comparison, using quantitative indicators such as downtime, availability, and production efficiency.

The main contribution of this work lies in the experimental validation of a low-cost monitoring solution that improves production performance without requiring complex digital infrastructure. Similar sensor-based maintenance implementations have reported availability improvements ranging from 15% to 30%, demonstrating the potential impact of affordable monitoring technologies in resource-constrained manufacturing environments [5].

2 State of the Art

Recent research in industrial engineering highlights the effectiveness of Total Productive Maintenance (TPM) in reducing unplanned downtime and improving asset availability. Becerra-Flores et al. demonstrate that TPM implementation in brick manufacturing SMEs leads to substantial reductions in corrective maintenance frequency and measurable improvements in operational stability [2]. These results confirm the suitability of TPM for continuous production systems with limited automation. Additional evidence from metalworking SMEs shows that TPM implementation can increase equipment availability from initial values below 65% to levels exceeding 80%, while improving Overall Equipment Effectiveness (OEE) [4]. These findings highlight the role of structured maintenance planning and operator involvement in improving production reliability [4].

The Single-Minute Exchange of Die (SMED) methodology has also demonstrated strong quantitative impacts on manufacturing performance. Flores and Vega-Alvites report setup-time reductions of up to 48% following SMED implementation in SME environments, mainly through task standardization and internal-to-external task conversion [6]. These reductions directly contribute to improved production flow and reduced non-productive time [6].

More advanced SMED implementations supported by analytical techniques show even greater improvements. El Belghiti et al. report changeover-time reductions exceeding 50% through the integration of Lean Six Sigma and fuzzy logic approaches in injection molding processes [7]. Similar results are reported by Sonsanam et al., who achieved significant setup-time reductions in plastic injection systems through structured SMED-based interventions [8].

The integration of Industry 4.0 technologies has further strengthened maintenance and setup optimization strategies. Mendes et al. demonstrate that IoT-based monitoring combined with TPM enables downtime reductions between 20% and 30%, while improving maintenance response times and system availability [5]. These results confirm the value of real-time data acquisition in maintenance decision-making.

The application of machine learning techniques to sensor-based monitoring data has shown promising results in predictive maintenance. Varalakshmi and Kumar report downtime reductions of up to 40% in industrial IoT networks through the use of reinforcement learning models applied to streaming data [9]. Similarly, Zhang et al. demonstrate high fault detection accuracy in conveyor systems using deep learning-based monitoring approaches [11].

Despite these advances, Habeeb highlights that most predictive maintenance implementations are focused on medium or large-scale industries, limiting their applicability in micro and small enterprises due to cost and infrastructure constraints [13]. This gap emphasizes the need for low-cost, scalable solutions specifically designed for MSE manufacturing contexts.

In this context, the present study contributes by proposing and validating a hybrid TPM-SMED approach supported by low-cost IoT-based monitoring, tailored to the operational characteristics of small-scale brick manufacturing processes. The proposed solution enables quantitative performance evaluation through AS-IS and TO-BE analysis, focusing on availability improvement and non-productive time reduction.

3 Proposed System

The proposed system is designed to reduce non-productive time and improve operational availability in brick manufacturing micro and small enterprises (MSEs) through the integration of structured maintenance methodologies and low-cost Industry 4.0 technologies. The system combines Total Productive Maintenance (TPM) and Single-Minute Exchange of Die (SMED) with real-time monitoring enabled by Internet of Things (IoT) sensors, addressing recurrent operational issues such as unplanned downtime, lack of setup standardization, and limited visibility of equipment performance.

3.1 Conceptual framework

The conceptual framework of the proposed system is based on two complementary improvement mechanisms. First, TPM is applied to enhance equipment availability through preventive and autonomous maintenance activities, including routine inspection, cleaning, lubrication, and early detection of abnormal operating conditions. Second, SMED is used to reduce setup and restart times by identifying, separating, and standardizing internal and external activities associated with machine configuration and adjustment tasks.

These methodologies are integrated within a continuous improvement cycle supported by digital data acquisition. Operational data collected during production are used to support maintenance planning and setup optimization, enabling a transition from reactive maintenance practices toward a data-driven and predictive maintenance approach consistent with Industry 4.0 principles. The conceptual structure of the proposed system and the interaction between TPM and SMED are illustrated in Fig. 1.

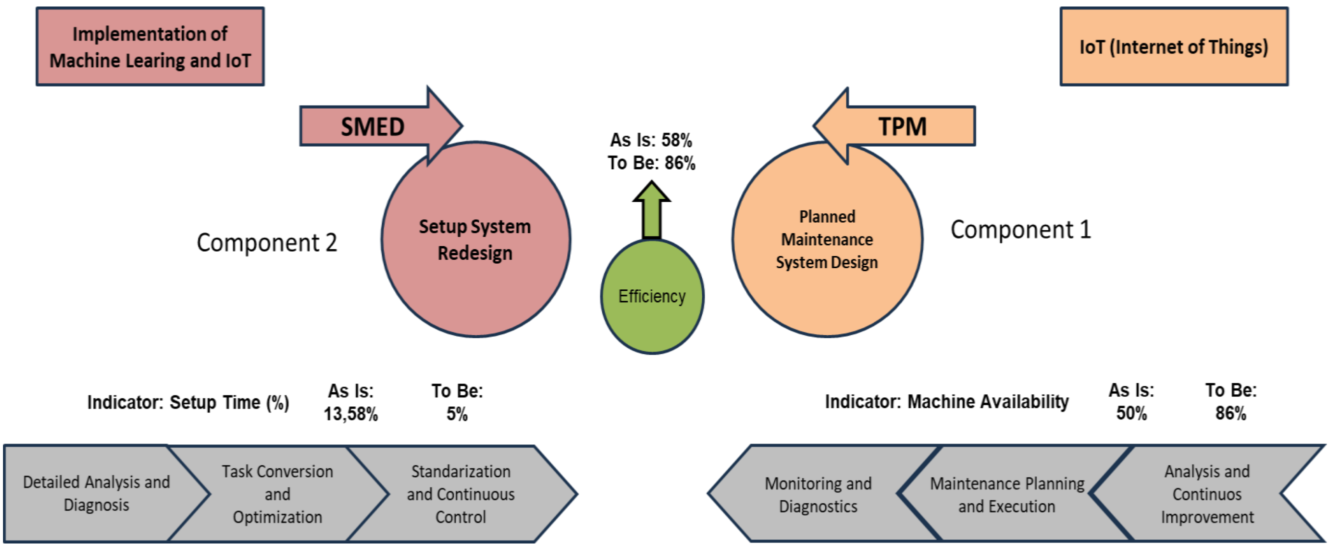

Fig. 1 Conceptual model integrating TPM and SMED supported by Industry 4.0 technologies.

3.2 System architecture

The system architecture follows a hybrid physical-digital structure designed for low-automation manufacturing environments. At the physical level, the raw-brick production line is instrumented with sensors that monitor key operational variables such as conveyor speed, operating time, and stoppage events. These sensors are installed at critical points of the production process to capture data related to equipment condition and operational interruptions.

At the digital level, the data collected are transmitted to a centralized processing unit where they are stored and analyzed in real time. The system enables automatic logging of machine stoppages and setup durations, providing objective and traceable information for maintenance and operational decision-making. This architecture supports the gradual adoption of predictive maintenance practices while maintaining low implementation and operational costs, which is critical for MSE environments. The physical-digital architecture of the proposed system and the data flow between sensors and the processing unit are illustrated in Fig. 2.

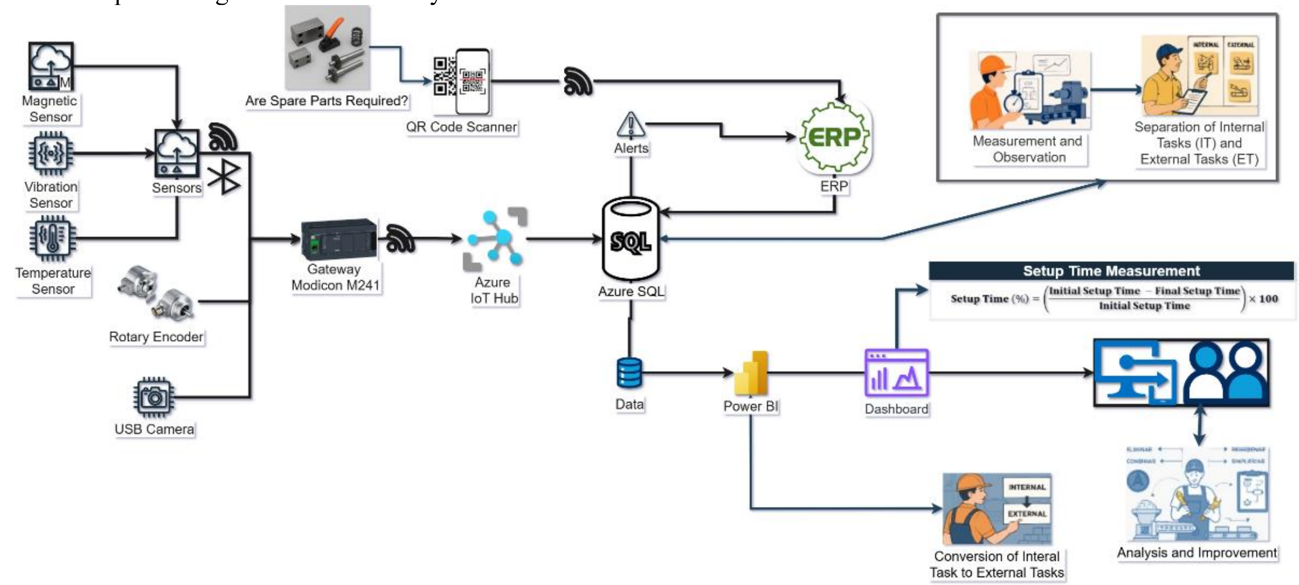

Fig. 2 Sensor-based system architecture for real-time monitoring and maintenance decision support.

3.3 Functional components

The proposed system is implemented through two main functional components:

Planned Maintenance Component (TPM-based): This component classifies equipment according to its operational criticality and establishes preventive maintenance routines based on monitored operating conditions and historical stoppage data. Continuous sensor-based monitoring supports early detection of abnormal behavior, reducing unexpected failures and improving equipment availability.

Setup Optimization Component (SMED-based): This component focuses on reducing non-productive time associated with setup and restart activities. Setup tasks are identified and standardized, and their execution times are automatically recorded through the sensor system. This enables continuous evaluation of setup performance and supports data-driven improvements aligned with SMED principles.

The proposed system operates under two comparative scenarios. In the AS-IS scenario, production relies on manual inspection and reactive maintenance. In contrast, the TO-BE scenario incorporates sensor-based monitoring and automated data logging, enabling faster detection of anomalies and more efficient operational recovery.

Overall, the proposed system provides a scalable and technically viable solution for improving production efficiency in brick manufacturing MSEs, integrating structured maintenance methodologies with accessible digital technologies without requiring complex infrastructure or high investment costs. A functional sensor-based prototype was implemented to support the proposed components and validate the AS-IS and TO-BE operational scenarios, as illustrated in Fig. 3.

Fig. 3 Functional sensor-based prototype.

4 Experimental Results

The proposed system was validated through a controlled experimental setup designed to compare the operational performance of the production line before and after the implementation of the sensorized TPM-SMED model. Two operational scenarios were evaluated: an initial AS-IS scenario, characterized by the absence of automatic monitoring and reliance on manual inspection, and a TO-BE scenario, in which the proposed system was fully implemented.

During the AS-IS scenario, the production process exhibited frequent unplanned stoppages, high non-productive time, and unstable operational flow. Performance measurements were manually recorded, and anomaly detection depended entirely on the operator's visual inspection. As a result, downtime accounted for a significant portion of the operating cycle, directly affecting system availability and process continuity.

In contrast, the TO-BE scenario incorporated real-time monitoring through sensorization and automatic event logging. The system continuously measured conveyor speed, operating time, and stoppage duration, enabling the early identification of abnormal operating conditions and faster maintenance intervention with reduced dependence on human supervision. This cause-effect relationship between condition monitoring, anomaly detection, and timely intervention explains the observed improvements in operational performance.

Representative condition-based anomalies were detected and corrected during the TO-BE scenario. Sensor data revealed abnormal fluctuations in conveyor speed and repeated short-duration stoppages, indicating mechanical resistance and alignment deviations in the transport system. Early corrective actions were performed before these conditions evolved into longer unplanned downtime events. Additionally, abnormal increases in setup and restart durations were identified through deviations from standardized time thresholds, revealing inconsistencies in adjustment procedures. The application of SMED-based standardization reduced setup variability and stabilized recovery times after stoppages.

The experimental results demonstrate a substantial improvement in operational performance. Non-productive time was reduced to 3.28%, representing a reduction of approximately 90% compared to the initial condition. System availability increased from 77% to 96.7%, indicating a significant enhancement in equipment utilization and production continuity. Additionally, the average conveyor speed increased to 1.42 m/s, resulting in a more stable and predictable operational flow.

The automatic detection mechanism achieved a detection efficiency of 80%, confirming the system's ability to identify anomalies and prevent prolonged stoppages. Although the detection rate did not reach full accuracy, the results validate the technical feasibility of the proposed approach and highlight its potential for further improvement through algorithm refinement and sensor calibration.

Overall, the experimental validation confirms that integrating TPM and SMED with low-cost IoT-based monitoring significantly improves production efficiency in brick manufacturing environments. The observed reductions in downtime and increases in availability demonstrate that the proposed system effectively addresses the operational limitations identified in the initial diagnosis. The quantitative comparison between the AS-IS and TO-BE operational scenarios is summarized in Table 1.

Table 1 Comparison of operational performance between AS-IS and TO-BE scenarios

Variable	AS-IS	TO-BE	% Improvement
Average speed (m/s)	1.07	1.42	+33.33%
Operating time (s)	5.59	7.15	+27.91%
Downtime (s)	2.61	0.21	-91.95%
Availability (%)	77%	96.7%	+25.58%
Detection efficiency (%)	0%	80%	+80%

5 Conclusions

This paper presented a sensor-based predictive maintenance system integrating Total Productive Maintenance (TPM) and Single-Minute Exchange of Die (SMED) methodologies, supported by low-cost Industry 4.0 technologies, to improve production efficiency in brick manufacturing micro and small enterprises (MSEs). The proposed system was designed to address recurrent operational issues such as unplanned downtime, lack of setup standardization, and limited real-time visibility of equipment performance.

The experimental validation demonstrated that the implementation of the proposed system significantly reduced non-productive time to 3.28% and increased system availability to 96.7%, confirming a substantial improvement in equipment utilization and operational continuity. The integration of sensor-based monitoring and automated event logging enabled faster anomaly detection and more efficient operational recovery compared to the initial AS-IS condition.

The results confirm that combining structured maintenance methodologies with accessible digital technologies constitutes a technically viable and scalable solution for resource-constrained manufacturing environments. Unlike approaches that require high levels of automation or complex infrastructure, the proposed system prioritizes simplicity, low implementation cost, and adaptability, making it suitable for replication in similar production processes.

Although the anomaly detection mechanism did not achieve full accuracy, the obtained detection efficiency validates the feasibility of the approach and highlights opportunities for future enhancement through improved sensor calibration and algorithm refinement. Overall, the proposed system effectively bridges the gap between traditional maintenance practices and digital manufacturing, contributing to the practical adoption of predictive maintenance strategies in small-scale industrial contexts.

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