Model for Improving OEE in the Metalworking Sector through TPM, RCM, SMED, and Integration of Industry 4.0 Technologies: Big Data and Machine Learning

Hetzibá Benavides-De la Cruz[1], Johan Lázaro-Enriquez[1], José Velásquez-Costa[1], Javier Torres-Zavala[1] and Baldomero Mendez-Pallares[2]*

[1]*Faculty of Engineering, Universidad Peruana de Ciencias Aplicadas, Lima, Peru*
[2]*Faculty of Engineering, Universidad Piloto de Colombia, Colombia*
**pcinjosv@upc.edu.pe*

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Abstract

In the metalworking industry, machinery is central to production continuity and productivity. However, the sector faces low overall equipment effectiveness (OEE) due to unplanned stoppages, recurrent failures and deficient maintenance management, generating losses that may reach 10.65% of annual turnover. To address this problem, this study proposes an integrated improvement model combining Total Productive Maintenance (TPM), Reliability-Centered Maintenance (RCM) and Single-Minute Exchange of Die (SMED), supported by Industry 4.0 technologies. Big Data enables the collection and analysis of sensor and operational data to identify losses, optimize changeover times and support data-driven decisions. Machine Learning strengthens RCM by enabling predictive strategies capable of anticipating failures and improving equipment reliability. The model was validated using a reduced-scale functional prototype with IoT monitoring of temperature, vibration and operating status. The results show an OEE increase of approximately 20 percentage points, reaching at least 82%, together with economic feasibility based on reduced downtime, corrective maintenance costs and quality losses. The proposal contributes to maintenance digitalization and operational competitiveness in metalworking environments.

1 Introduction

The metalworking industry is a strategic pillar of industrial development due to its role in supplying components, equipment, and technological solutions to key sectors such as mining, construction, automotive, and energy [1]. Its relevance lies not only in its economic contribution but also in its dependence on high-precision machinery, where operational continuity directly impacts productivity and competitiveness. National industrial reports indicate that the sector represents approximately 1.5% of Gross Domestic Product (GDP) and supplies more than 60% of intermediate goods required by strategic industries [2], [3].

Despite its importance, the metalworking sector faces persistent challenges related to low equipment efficiency caused by unplanned stoppages, frequent failures, and insufficient maintenance management [4]. These inefficiencies negatively affect availability, performance, and quality, the three core components of OEE, leading to increased operational costs and reduced competitiveness [5], [6], with economic losses exceeding 10% of annual revenue in some cases [7]. To address these challenges, companies have adopted continuous improvement methodologies such as TPM, RCM, and SMED, complemented by Industry 4.0 technologies including Big Data analytics and Machine Learning, which enhance maintenance decision-making through predictive strategies and real-time monitoring [8], [9]. In this context, this research aims to develop and validate an integrated improvement model that combines TPM, RCM, and SMED with advanced digital technologies to increase OEE in the metalworking sector.

Although TPM, RCM, and SMED have been widely studied individually, the literature reveals a lack of integrated models that align these methodologies within a unified framework explicitly linked to OEE components. In addition, Industry 4.0 technologies are frequently addressed in isolation, without clearly defining their role as enablers of maintenance decision-making across availability, performance, and quality dimensions. This gap is particularly evident in project-based metalworking environments, where high production variability and frequent equipment failures demand coordinated and data-driven maintenance strategies.

The main contributions of this paper are: (i) the development of an integrated maintenance improvement model that systematically links TPM, SMED, and RCM to the three components of OEE; (ii) the conceptual integration of Industry 4.0 technologies, where Big Data supports TPM and SMED through operational data analysis, while Machine Learning reinforces RCM as a decision-support mechanism for predictive maintenance; and (iii) the experimental validation of the model using a reduced-scale functional prototype representative of typical failure conditions in metalworking machinery, complemented by technical and economic performance evaluation. The remainder of this paper is organized as follows: Section 2 reviews the related literature, Section 3 presents the proposed model, Section 4 describes the validation and results, Section 5 discusses the findings, and Section 6 concludes the paper and outlines future research directions.

2 Literature Review

Industrial machinery failures remain a major source of productivity loss in manufacturing systems, and preventive and predictive maintenance strategies have proven effective in reducing unplanned downtime and optimizing resource utilization [10]. Current approaches emphasize risk-based analysis, historical failure data, continuous monitoring, and the incorporation of machine learning techniques to enhance predictive maintenance through early failure detection and data-driven decision-making [11]. Within this context, Total Productive Maintenance is widely recognized for improving equipment availability and operational stability through operator involvement and planned maintenance activities [12].

Reliability-Centered Maintenance focuses on identifying critical failure modes and prioritizing maintenance actions to ensure system reliability at minimal cost [13], while SMED targets the reduction of setup and changeover times, significantly improving production flexibility and equipment utilization in metalworking environments [14], [15]. Recent research highlights that isolated maintenance strategies often provide limited results when applied independently, particularly in complex manufacturing environments such as the metalworking sector, whereas the integration of preventive, predictive, and organizational approaches generates more sustainable improvements in operational performance [12], [14]. In this sense, the integration of TPM, RCM, and SMED constitutes a comprehensive framework capable of simultaneously addressing equipment availability, failure prevention, and process flexibility, reducing the gap between maintenance planning and production execution.

Big Data platforms facilitate the analysis of historical and operational information to detect inefficiencies and recurring failure patterns, while machine learning algorithms improve predictive maintenance accuracy [8]. This technological convergence reinforces traditional maintenance methodologies and supports the transition toward data-driven maintenance systems, particularly in industries characterized by high operational variability.

Despite the extensive literature addressing TPM, RCM, and SMED as individual or partially combined approaches, most studies focus on isolated performance improvements or specific operational contexts, without mapping their contributions to the three OEE dimensions. Similarly, Industry 4.0-enabled maintenance studies often emphasize data acquisition or predictive capabilities, lacking structured frameworks that align digital technologies with established maintenance methodologies. Consequently, a gap remains regarding comprehensive, OEE-oriented models that integrate TPM, RCM, and SMED under a unified decision-making structure supported by Industry 4.0 technologies, particularly in project-based metalworking environments with high variability and frequent equipment failures.

3 Proposed Model

The proposed model integrates TPM, SMED, and RCM into a unified maintenance improvement framework explicitly aligned with the three components of Overall Equipment Effectiveness (availability, performance, and quality). Unlike traditional approaches that apply these methodologies independently, the model establishes a structured interaction between them, ensuring that each methodology contributes directly to specific OEE losses within a continuous improvement cycle supported by Industry 4.0 technologies.

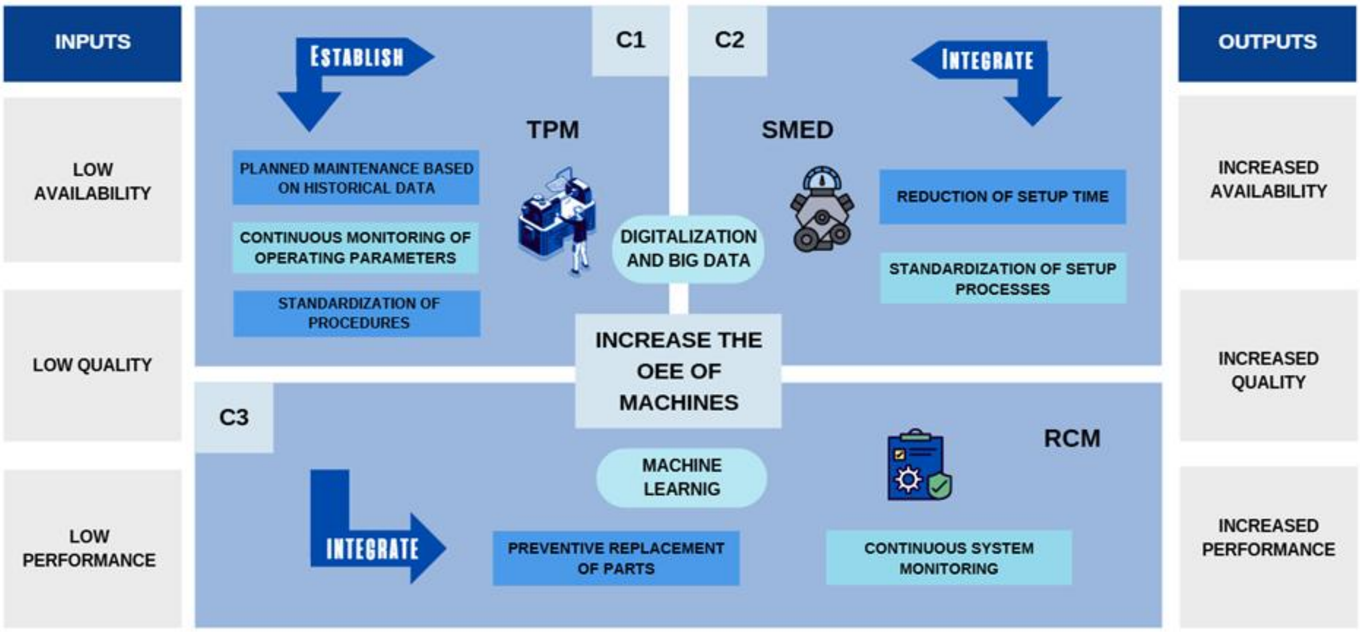

Fig. 1 Integrated TPM, SMED, and RCM improvement model supported by Industry 4.0 technologies

TPM focuses on maximizing equipment availability through autonomous maintenance, operator training, and planned inspections, directly addressing availability losses identified through OEE analysis. SMED reduces non-productive time by optimizing setup and adjustment activities, contributing primarily to performance improvement by minimizing speed and changeover losses. RCM prioritizes maintenance interventions based on equipment criticality and failure risk, supporting quality and availability by preventing recurrent and high-impact failures [13], [14].

The integration of Big Data and Machine Learning enables predictive maintenance, improving reliability, reducing corrective costs, and supporting data-driven decisions across maintenance and production. Fig. 2 presents the main implementation stages of the proposed maintenance model.

The proposed model is framed within the Industry 4.0 paradigm, as its primary objective is the digitalization of maintenance processes through data acquisition, connectivity, and analytics to support operational decision-making. While emerging concepts such as Industry 5.0 and Industry 6.0 emphasize human-centricity, sustainability, and autonomous intelligence, the scope of this study is intentionally limited to Industry 4.0 principles to ensure technological feasibility and practical applicability in current metalworking environments, while remaining compatible with future extensions toward these paradigms.

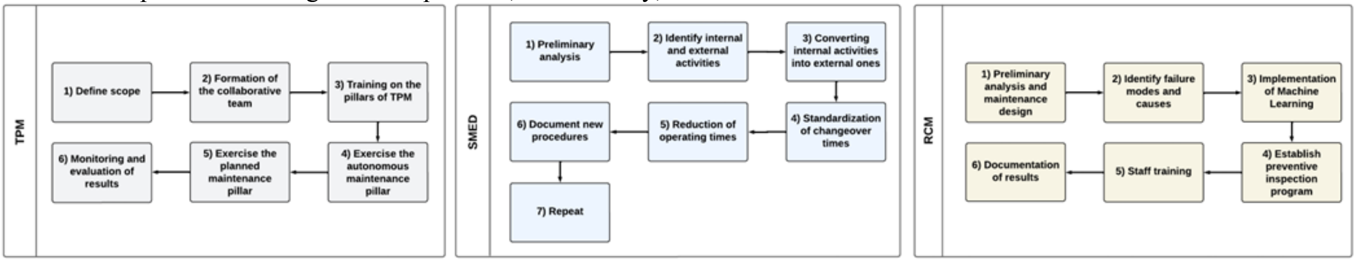

Fig. 2 Implementation stages of the proposed maintenance improvement model

4 Validation and Results

The proposed model was validated through a reduced-scale functional prototype designed to replicate typical failure conditions observed in metalworking machinery. This validation approach enabled controlled experimentation while preserving the representativeness of real industrial environments. The prototype incorporated an IoT-based monitoring system using an ESP32 microcontroller and sensors for temperature, vibration, and operational status, enabling real-time data visualization through an interactive dashboard. Fig. 3 presents the reduced-scale functional prototype and the IoT dashboard used for model validation. The selected variables respond to their direct relationship with common failure modes in metalworking equipment, supporting early detection of abnormal operating conditions and condition-based maintenance decisions within the proposed model.

The use of a reduced-scale functional prototype is justified as it preserves the fundamental failure mechanisms affecting availability, performance, and quality, such as overheating, abnormal vibration, and unplanned stoppages, while allowing controlled experimentation, repeatability, and real-time monitoring. Continuous data acquisition through sensors enabled the identification of abnormal conditions before they evolved into critical failures, improving maintenance planning accuracy and aligning with predictive maintenance frameworks reported in the literature [16].

(a) (b)

Fig. 3 Reduced-scale functional prototype (a) and IoT dashboard used for model validation (b)

The analysis of the individual OEE components provides a clearer understanding of the impact of the proposed model on operational performance. Availability showed the most significant improvement due to the reduction of unplanned stoppages achieved through TPM activities and predictive alerts generated by the IoT monitoring system. Performance gains were primarily driven by reduced setup and adjustment times through SMED, while quality improved due to more stable conditions and early failure detection, lowering defects. These results highlight the synergy of integrating TPM, SMED, and RCM within a unified operational framework.

OEE was calculated using the standard equations [17]:

$$\textit{Availability} = (\textit{Operating time} / \textit{Planned production time}) \times 100\%$$

$$\textit{Performance} = (\textit{Ideal cycle time} \times \textit{Total count} / \textit{Operating time}) \times 100\%$$

$$\textit{Quality} = (\textit{Good count} / \textit{Total count}) \times 100\%$$

$$\textit{OEE} = \textit{Availability} \times \textit{Performance} \times \textit{Quality}$$

Two scenarios were evaluated: an AS-IS scenario with an average OEE of 62%, and a TO-BE scenario after implementing TPM, SMED, and RCM strategies, achieving OEE values close to 82%. This 20-percentage point increase reflects a substantial improvement in equipment utilization and operational stability. These results demonstrate a significant reduction in downtime and improved operational efficiency, consistent with previous studies [7].

Table 1 OEE components before and after implementation

Indicator	AS-IS	TO-BE
Availability	92%	90%
Performance	91%	95%
Quality	98%	99%
OEE	82%	85%

From an economic perspective, the improvements in OEE translated into higher production capacity, reduced corrective maintenance costs, and lower losses associated with defective products and idle time. Economic validation showed that the model is financially viable, with an initial investment of USD 22,775 and estimated annual savings of USD 1.49 million. The Net Present Value reached USD 2,236,824, with an Internal Rate of Return of 107.65%, exceeding the WACC of 19.77%, confirming the model's profitability and applicability in project-based metalworking service companies.

5 Discussion

The results confirm that the combined application of TPM, SMED, and RCM provides a robust framework for improving equipment efficiency in the metalworking sector. TPM increased availability through autonomous maintenance and operator involvement, while SMED reduced setup times and non-productive periods. RCM, enhanced by Machine Learning and IoT technologies, strengthened predictive maintenance capabilities and reduced unexpected failures [12], [15]. These results are consistent with previous studies on integrated maintenance strategies; however, this study extends existing approaches by explicitly aligning each methodology with the three OEE components and supporting their integration through digital technologies. The observed improvement in OEE and the associated economic outcomes demonstrate that maintenance digitalization generates sustainable operational and financial benefits, reinforcing the link between efficiency and competitiveness.

Despite the positive results, this study presents certain limitations. Validation was conducted using a reduced-scale functional prototype, which, although effective in reproducing typical failure conditions, does not fully capture the complexity, scale, and organizational dynamics of real industrial environments. Consequently, performance gains may vary in full-scale applications. Additionally, scaling the proposed model may face challenges such as organizational resistance, the need for operator training, and integration with existing systems. Addressing these challenges requires strong managerial commitment and gradual implementation strategies aligned with the organization's technological maturity.

6 Conclusions

This study demonstrated that integrating TPM, SMED, and RCM within a digitally supported maintenance framework significantly improves Overall Equipment Effectiveness in the metalworking sector. The validated model increased OEE from 62% to approximately 82%, confirming its technical and operational effectiveness. The main contribution of this research lies in the structured integration of established maintenance methodologies with Industry 4.0 technologies, emphasizing their coordinated impact on OEE rather than the development of new analytical or machine learning algorithms. In addition, the incorporation of Big Data analytics, IoT monitoring, and Machine Learning enhanced predictive maintenance capabilities and maintenance decision-making accuracy.

From an economic standpoint, the model showed strong profitability, quick payback, and sustained value, confirming its practical applicability. Future work should validate its scalability in real industrial settings and explore deeper AI integration and improved human-machine interaction to support more sustainable maintenance systems.

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