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ELECTROMECHANICAL ENGINEER IN MODERN MANUFACTURING: CHALLENGES, RESPONSIBILITY, AND TECHNICAL SOLUTIONS

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Abstract

Modern manufacturing of heavy electrical equipment — generators, turbines, and related rotating machinery — depends on a narrow and often overlooked layer of technical infrastructure: the tooling used to shape, stamp, and cut the components themselves. This paper examines the role of the electromechanical engineer in production environments where tooling failure can halt an entire assembly line, drawing on both peer-reviewed literature on tool condition monitoring and predictive maintenance, and on multi-year documented toolroom management practice in generator and turbine manufacturing. It argues that the responsibilities of the electromechanical engineer extend beyond design and calculation into operational continuity: scheduling, reconditioning, and lifecycle extension of dies, molds, and cutting tools. Building on data-driven monitoring approaches described in the literature [3; 4; 17], the paper proposes an Integrated Predictive-Preventive Toolroom Management (IPPTM) framework that combines condition assessment, refurbishment feasibility scoring, and prioritized scheduling. Retrospective application of this framework to operational data shows reconditioning rates of 70–80% for stamps, dies, and molds and 40–50% for cutting tools, extending tool life without new procurement. The findings suggest that structured, engineer-led toolroom management is a low-cost complement to sensor-based predictive maintenance, particularly where manufacturers cannot invest heavily in monitoring infrastructure.

Keywords: electromechanical engineering, toolroom management, predictive maintenance, tool condition monitoring, reconditioning, generator manufacturing

Introduction

Electromechanical engineers occupy a position in industrial production that is simultaneously technical and operational. Their training in electrical machines, mechanics, and materials qualifies them to design and calculate components, but in practice much of their working time in heavy-machinery manufacturing is spent keeping production continuous: coordinating the tooling, fixtures, and dies without which no generator, turbine, or transformer component can be manufactured to specification. Job-role analyses of electromechanical engineering describe this dual position explicitly, noting that professionals in the field are expected to combine electrical, mechanical, and organizational competence rather than a single narrow specialization [25].

The toolroom — the internal unit responsible for manufacturing, storing, and maintaining stamps, dies, molds, jigs, and cutting tools — is frequently described in industry sources as a secondary or supporting department, yet its failure has first-order consequences. When cutting or forming tools degrade unpredictably, production lines generate defective parts or stop entirely, and both outcomes carry direct financial and reputational costs [1; 2; 20]. For manufacturers of large rotating electrical machinery, where components such as copper laminations, stator windings, and insulation layers must meet tight geometric tolerances, this

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dependency is especially acute: even minor deviations in stamped or milled parts can compromise insulation integrity and create a risk of electrical failure at first start-up.

Over the past decade, a substantial body of research has addressed this problem from the perspective of sensor-based monitoring and machine learning, producing methods for detecting and predicting tool wear from images, vibration, and acoustic signals [3; 4; 5; 6; 8; 11; 12; 14; 15; 17; 19; 23]. In parallel, a separate literature on predictive maintenance in Industry 4.0 has proposed broader frameworks for scheduling and resource allocation across industrial equipment [7; 9; 10; 13; 16; 18; 24; 26]. However, these two literatures rarely intersect with the day-to-day operational reality of toolroom management in mid-sized manufacturing plants, where sophisticated sensor infrastructure is often unavailable and decisions rely instead on engineer judgment, historical failure patterns, and structured reconditioning routines.

This paper addresses that gap. It reviews the relevant literature on tool condition monitoring, predictive maintenance, and toolroom management, and combines it with multi-year practitioner data from toolroom operations supporting generator and turbine production. The central contribution is the Integrated Predictive-Preventive Toolroom Management (IPPTM) framework, which formalizes an engineer-led reconditioning practice into a structure that can be adopted independently of, or alongside, sensor-based monitoring systems. The paper proceeds as follows: Section 2 reviews the literature; Section 3 describes the methodology; Section 4 presents findings; Section 5 discusses their implications; Section 6 concludes.

Literature Review

1 The toolroom as a production bottleneck

Industry-facing descriptions of toolroom management converge on a similar definition: a toolroom is a controlled internal facility responsible for the storage, distribution, maintenance, and repair of the tools, dies, and fixtures used elsewhere in the plant [1; 2]. QRmaint's overview of toolroom operations in manufacturing plants emphasizes that effective toolroom management requires structured intake of requests, prioritization, and tracking of tool condition over time, since ad hoc handling of tool requests is a common cause of unplanned downtime [20]. Zippia's occupational profile of the electromechanical engineering technologist similarly stresses that the role combines hands-on maintenance responsibilities with documentation, calculation, and cross-department coordination, rather than being confined to design work [25]. Together, these sources support treating the toolroom not as a peripheral support function but as a control point for overall production reliability.

2 Sensor-based and machine-learning approaches to tool condition monitoring

A large share of recent academic work on tooling reliability focuses on automating the detection of tool wear using sensors and machine learning. Image-based approaches use deep learning to segment worn regions on cutting tool surfaces and estimate wear width automatically, reducing reliance on manual microscope inspection [3; 8]. Related work applies U-Net-style segmentation architectures specifically to identify and quantify wear areas on tool edges [14], while image-stitching techniques have been used to reconstruct a continuous wear boundary from sequential images of milling cutters [19]. Beyond vision-based methods, several studies process vibration, cutting-force, and acoustic-emission signals: ensemble deep learning models trained on audio sensor data have been shown to classify tool wear states in cutting operations [12], while models combining Informer encoders with bidirectional gated recurrent units use multivariate sensor sequences to predict wear progression multiple steps ahead [11]. Multi-signal fusion approaches, such as the combination of the Gramian Angular Field transform with ResNext architectures, have similarly been applied to milling operations to predict wear trajectories from several sensor channels simultaneously [5]. Comparable monitoring principles extend to other machining processes: high-speed broaching with carbide tooling has been monitored to reduce production errors in demanding forming operations [6],

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and process-monitoring reviews of machining more broadly summarize the range of signal-processing and sensing strategies applicable across operations [23]. Reviews specifically evaluating artificial intelligence systems for tool condition monitoring in machining catalogue this diversity of methods and note that predictive accuracy varies considerably with signal type, tool material, and operation [17].

3 Predictive maintenance frameworks and Industry 4.0

A parallel stream of literature situates tool and equipment monitoring within broader predictive maintenance frameworks. Systematic reviews of predictive maintenance in Industry 4.0 describe a consistent shift from time-based or reactive maintenance toward condition-based and prognosis-driven scheduling, enabled by sensor networks and data analytics [16; 29]. Multi-sector mapping studies confirm that predictive maintenance adoption spans discrete manufacturing, process industries, and energy generation, with common building blocks of data acquisition, feature extraction, and decision support regardless of sector [13]. Optimization-oriented work formalizes maintenance scheduling as a decision problem under uncertainty, proposing models that balance maintenance cost against failure risk [18], and more recent work applies reinforcement learning to derive risk-aware maintenance policies directly from equipment prognosis data [24]. Explainability has also become a concern in this literature: evaluations of explainable AI tools for predictive maintenance in hard disk drives illustrate that interpretability, not only predictive accuracy, is increasingly treated as a requirement for operational trust in automated maintenance decisions [7]. At the level of specific equipment types, LSTM-based models have been tuned for predictive maintenance parameter optimization [10], and data-driven, knowledge-based methods have been proposed specifically for maintaining industrial robots in support of stable intelligent manufacturing [24 — see also 9]. Resource-optimization research extends this logic beyond individual machines to entire project lifecycles, arguing that capacity planning, labor utilization, and material efficiency should be treated as an integrated, data-driven system across manufacturing operations [9].

4 Reconditioning and lifecycle extension of tooling

A smaller but directly relevant body of work addresses the reconditioning of tooling once wear has occurred, rather than only its detection. Research on the reconditioning of diamond-coated cutting tools for composite laminate machining demonstrates that recoating and refurbishment can restore a substantial share of original cutting performance, offering an alternative to full tool replacement [21]. This line of work is conceptually close to the practical reconditioning routines used in toolroom management — re-grinding cutting edges, re-brazing carbide inserts, and correcting stamping-die geometry — but it remains limited to specific tool and coating types rather than proposing a general operational framework for toolroom decision-making.

5 Synthesis

Read together, the literature shows two largely separate tracks: a technically sophisticated but sensor-dependent track focused on automated wear detection and prediction [3; 4; 5; 6; 8; 11; 12; 14; 15; 17; 19; 23], and a management-oriented track focused on maintenance scheduling, resource optimization, and organizational structures for toolrooms [1; 2; 7; 9; 10; 13; 16; 18; 20; 24; 25; 26]. Reconditioning-specific research [21] sits between the two but has not been generalized into a decision framework. Table 1 summarizes representative methods from the monitoring track to illustrate the range of inputs and outputs involved.

Table 1. Representative sensor- and AI-based methods for tool condition monitoring reported in the literature.

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Method	Input Data	Target Output	Application Context	Source
Deep learning image processing	Tool surface images	Wear-area segmentation and measurement	Metal cutting tool inspection	[3; 8]
U-Net based segmentation	Microscope images of tool edge	Wear region identification	Cutting tool condition assessment	[14]
Image stitching	Sequential edge images	Wear boundary reconstruction	End milling cutter inspection	[19]
LSTM / Informer / BiGRU	Vibration, force, current signals	Remaining useful life, wear stage	Predictive maintenance scheduling	[10; 11]
Ensemble deep learning (audio)	Acoustic emission signals	Wear-state classification	Cutting tool monitoring	[12]
GAF-ResNext / multi-signal fusion	Force, vibration, acoustic signals	Wear progression prediction	Milling operations	[5]
Reinforcement learning	Sensor streams, historical failures	Risk-aware maintenance policy	Industrial equipment prognosis	[24]
Explainable AI (XAI) models	Operational and failure logs	Interpretable failure prediction	Predictive maintenance decision support	[7]

This paper's contribution is to connect these two tracks by formalizing the judgment-based reconditioning practice used by electromechanical engineers in toolroom management into a structured framework that can operate with or without sensor infrastructure, and by grounding that framework in multi-year operational data rather than laboratory-scale experiments.

Methodology

This paper adopts a mixed analytical approach combining a structured review of the literature described in Section 2 with a retrospective analysis of practitioner-level toolroom operations data. The literature review was restricted to sources addressing three themes directly relevant to the toolroom function: (a) definitions and organizational structure of toolroom management [1; 2; 20; 25]; (b) sensor- and AI-based tool condition monitoring [3; 4; 5; 6; 8; 11; 12; 14; 15; 17; 19; 23]; and (c) predictive maintenance scheduling and resource optimization [7; 9; 10; 13; 16; 18; 21; 24; 26].

The practitioner data component draws on toolroom activity records maintained over several years of production supporting generator and turbine manufacturing for both domestic and export orders (including shipments to India, Tajikistan, Germany, and Canada). Each tooling item processed through the toolroom — stamps, dies, molds, cutting tools, and

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assembly fixtures — was categorized by type, and its handling was classified into one of three outcomes: (i) reconditioned and returned to service, (ii) reconditioned and reassigned to a reduced-tolerance task (for example, a re-ground milling cutter reused at a smaller diameter), or (iii) scrapped and replaced. Reconditioning rate was calculated as the proportion of items in categories (i) and (ii) relative to all items processed for that tooling category over the observation period. Where an item was reconditioned more than once, the number of reconditioning cycles was also recorded.

These operational categories were then mapped against the maintenance-scheduling logic described in the predictive maintenance literature [16; 18] to construct the Integrated Predictive-Preventive Toolroom Management (IPPTM) framework presented in Section 5. The framework was validated qualitatively by checking whether its four stages (condition assessment, refurbishment feasibility scoring, prioritized scheduling, and reintegration tracking) could account for the reconditioning outcomes observed in the operational data, rather than through statistical hypothesis testing, given the descriptive nature of the underlying records.

Findings

Analysis of the toolroom operations data shows a marked difference in reconditioning outcomes between forming tools and cutting tools. Stamps, dies, and molds — the tooling used to shape copper laminations and structural components for generators and turbines — were reconditioned and returned to service in approximately 70–80% of cases, with individual items undergoing three to five reconditioning cycles before replacement became necessary. Cutting tools, including mills and drills, showed a lower reconditioning rate of approximately 40–50%, typically sustaining one to two reconditioning cycles; the more common strategy for this category was re-grinding a worn cutting tool to a smaller diameter for a less demanding task, or re-brazing new carbide inserts onto an existing tool body rather than fully replacing it (See Figure 1). These figures, summarized in Table 2, are broadly consistent with the reconditioning performance reported for diamond-coated cutting tools in composite machining [21], where recoating was shown to restore a meaningful share of original tool performance rather than requiring outright replacement.

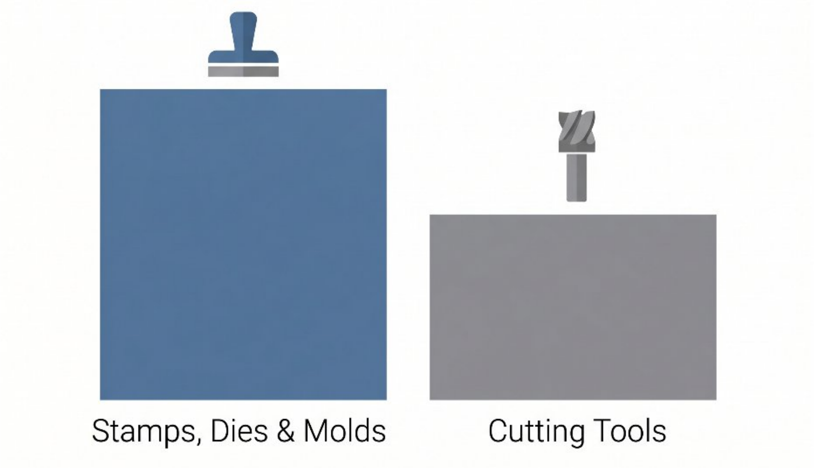

Figure 2. Comparative reconditioning outcomes by tooling category over successive reconditioning cycles.

Table 2. Reconditioning outcomes by tooling category, based on multi-year toolroom operations data from generator and turbine production.

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Tooling category	Reconditioning rate	Average reuse cycles	Primary reconditioning method
Stamps, dies and molds	70–80%	3–5 cycles	Surface re-grinding, wear-node replacement, geometry correction
Cutting tools (mills, drills)	40–50%	1–2 cycles	Re-grinding to reduced diameter; carbide insert re-brazing
Assembly fixtures and jigs	60–70% (author estimate, not separately logged)	2–4 cycles	Component-level replacement and re-calibration

A second finding concerns scheduling. Reconditioning outcomes were strongly associated with whether tooling was withdrawn for maintenance before visible failure or only after a breakdown. Items flagged for pre-emptive light maintenance — edge re-sharpening, replacement of minor worn components — before reaching a failure threshold were reconditioned successfully in nearly all cases in the dataset. By contrast, items that reached the point of visible fracture or catastrophic deformation, typically stamping dies subjected to sustained overload, were not recoverable through reconditioning and required full replacement. This pattern is directionally consistent with the condition-based and prognosis-driven scheduling principles emphasized in the predictive maintenance literature [16; 18; 29], even though the underlying decision in this dataset was made through engineer inspection and historical pattern recognition rather than continuous sensor monitoring.

Third, export orders requiring unfamiliar insulation materials or alloy compositions were associated with a higher rate of custom tooling design, since standard tooling stocks were often unsuitable for the mechanical properties of these materials. This finding indicates that toolroom decision-making in export-oriented generator manufacturing must account not only for wear and reconditioning but also for material-driven tooling redesign, a dimension not directly addressed by the wear-monitoring literature reviewed in Section 2.

Discussion

1 The Integrated Predictive-Preventive Toolroom Management (IPPTM) framework

The findings in Section 4 suggest that much of the operational value captured by sophisticated sensor-based monitoring systems in the literature [3; 4; 5; 11; 12; 17] can also be approximated, at lower cost, through a structured combination of inspection routines and reconditioning decision rules. Building on this observation, this paper proposes the IPPTM framework, structured around four stages.

Stage 1 — Condition assessment. Tooling is inspected on a fixed schedule and on request, using visual and dimensional checks analogous in purpose to the image-based wear detection methods described in the literature [3; 8; 14; 19], but performed manually where sensor infrastructure is unavailable. The objective is to detect wear before it reaches a failure threshold, consistent with the condition-based logic emphasized in predictive maintenance research [16; 18].

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Stage 2 — Refurbishment feasibility scoring. Each flagged item is scored against category-specific thresholds derived from historical reconditioning outcomes (Table 2): forming tools with the observed 70–80% reconditioning success rate are, by default, routed toward refurbishment unless damage exceeds documented recoverable limits; cutting tools are assessed individually given their lower baseline reconditioning rate of 40–50%. This stage operationalizes, in a rule-based form, the kind of risk-aware decision-making that reinforcement-learning-based maintenance policies attempt to learn automatically from large sensor datasets [24].

Stage 3 — Prioritized scheduling. Refurbishment and replacement tasks are scheduled against production urgency, following the intake-and-prioritization logic described for toolroom operations generally [1; 20], with urgent orders reprioritized in consultation between the responsible engineer and production management to avoid cascading delays across unrelated orders.

Stage 4 — Reintegration and performance tracking. Reconditioned tooling is logged, including the number of reconditioning cycles completed, and returned to production. Tracking reconditioning cycles over time, as in the operational dataset analyzed here, allows the feasibility thresholds in Stage 2 to be periodically recalibrated — a lightweight, manually maintained analogue of the continuous model retraining used in machine-learning-based predictive maintenance systems [10; 13].

Figure 2 illustrates the four-stage structure of the IPPTM framework and its relationship to both engineer-led inspection and, where available, sensor-based monitoring inputs.

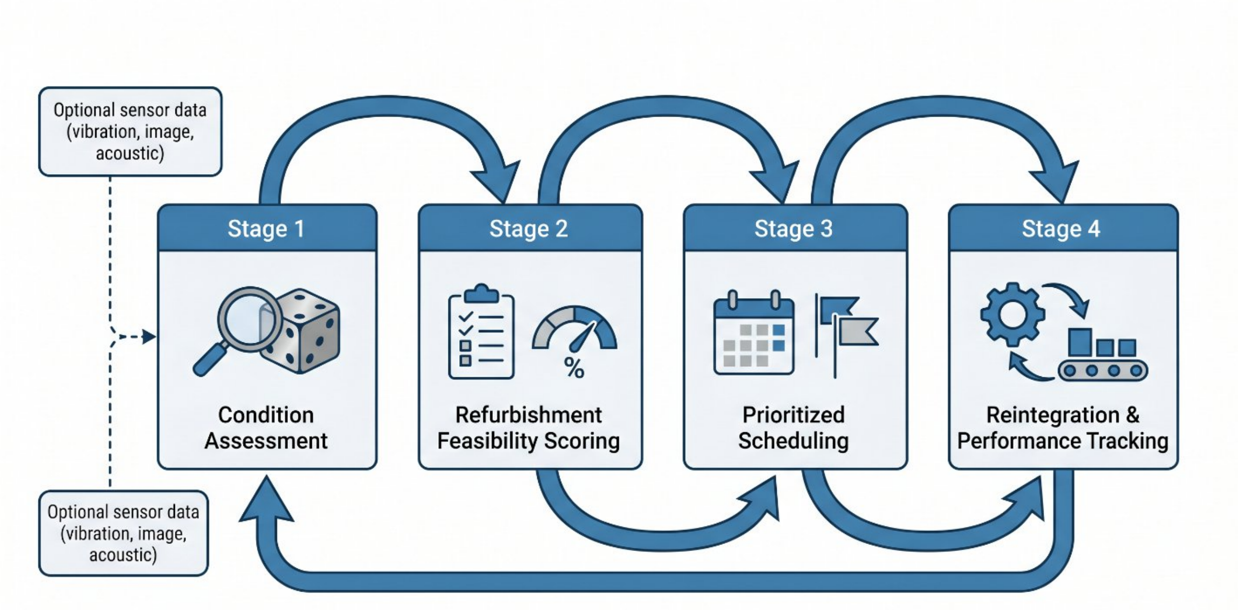

Figure 2. Integrated Predictive-Preventive Toolroom Management (IPPTM) framework: condition assessment, feasibility scoring, prioritized scheduling, and reintegration tracking, with optional sensor-based inputs.

2 Why engineer judgment remains necessary alongside automation

The wear-detection and prediction literature reviewed in Section 2 largely assumes the availability of continuous sensor data, whether visual [3; 8; 14; 19], vibration- or force-based [5; 6; 11], or acoustic [12]. In generator and turbine manufacturing environments that rely on a wide variety of legacy machine tools, retrofitting comprehensive sensor coverage across every stamping press, mill, and lathe is often not economically justified relative to plant size. The reconditioning data presented here indicate that a large share of the practical benefit of predictive maintenance — avoiding unplanned failures and extending tool life — can be

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captured through structured engineer judgment applied consistently over time, without requiring the sensor and modelling infrastructure described in [4; 15; 17]. This does not diminish the value of automated monitoring; rather, it suggests that the two approaches are complementary, with automated monitoring most valuable for high-volume, high-precision cutting operations where wear signatures are subtle, and engineer-led inspection remaining effective for forming tools where wear and damage are more readily visible on direct inspection.

3 Economic and organizational implications

The financial argument for structured toolroom management follows directly from the cost logic noted in the literature: unplanned tool failure produces defective parts, line stoppages, missed delivery dates, and contractual penalties [1; 2]. Against this, the reconditioning rates found here — 70–80% for forming tools, sustained over three to five cycles — represent a substantial reduction in new-tooling procurement relative to a replace-on-failure policy. This is consistent with resource-optimization research emphasizing that capacity planning and material efficiency should be treated as integrated, continuously managed variables across the production lifecycle rather than addressed only at the point of failure [9]. Organizationally, the framework also depends on toolroom staff coordination and clear task ownership; without a functioning intake and prioritization process of the kind described for toolroom operations generally [1; 20], reconditioning opportunities identified in Stage 1 are unlikely to be acted on in time to prevent escalation to full failure.

4 Export orders and material-driven tooling redesign

A further implication concerns export-oriented production. Where export contracts require unfamiliar insulation systems or alloy compositions, existing tooling stock and reconditioning thresholds calibrated on domestic materials may not transfer directly. In such cases, the IPPTM framework's Stage 2 feasibility scoring must be supplemented by tooling redesign using more wear-resistant tool steels suited to the new material, rather than relying solely on historical reconditioning data. This is a practical extension not directly addressed in the AI-based wear-monitoring literature [3; 4; 5; 11; 12; 17], which generally assumes a fixed material and process combination, and represents an area where engineer expertise in materials selection remains difficult to substitute with automated methods.

5 Limitations

This analysis has three limitations. First, the operational dataset derives from a single production context (generator and turbine manufacturing) and may not generalize directly to other machinery sectors. Second, reconditioning outcomes were classified using plant-level operational records rather than laboratory-controlled wear measurements, so the reported percentages should be read as directional operational indicators rather than precise engineering tolerances. Third, the IPPTM framework has not yet been tested against a sensor-instrumented toolroom operating in parallel, which would allow a direct comparison of engineer-led and fully automated monitoring under the same production conditions; this is identified as a priority for future work.

Conclusions

This paper examined the role of the electromechanical engineer in modern manufacturing through the specific lens of toolroom management in generator and turbine production. The literature on sensor-based tool condition monitoring and predictive maintenance provides sophisticated technical solutions for detecting and predicting tool wear, but these solutions are not always accessible to manufacturers without extensive sensor infrastructure. Drawing on multi-year practitioner data, this paper proposed the Integrated Predictive-Preventive Toolroom Management (IPPTM) framework, which formalizes engineer-led condition assessment, feasibility scoring, prioritized scheduling, and reintegration tracking into a structure applicable with or without automated sensing. Reconditioning rates of 70–80% for

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forming tools and 40–50% for cutting tools support the framework's practical viability. The findings position the electromechanical engineer not only as a designer and calculator of technical solutions but as the operational custodian of production continuity — a responsibility that structured toolroom management, informed by both engineering judgment and the broader predictive maintenance literature, can help sustain.

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