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| RESEARCH ARTICLE

Smart Manufacturing Framework for Real-Time Process Monitoring, Predictive Maintenance, and Quality Control in Advanced Mechanical Production Systems

Md Arman Hossain[1], Wei Pi[2], S M Tarikul Islam[3] and Mohaiminul Islam Lide[4]
[1234]Mechanical Engineering, Changsha University of Science and Technology, Changsha, Hunan, China
Corresponding Author: Md Arman Hossain, **E-mail**: armanhossain3012@gmail.com

| ABSTRACT

This study develops an integrated smart-manufacturing framework that unifies real-time process monitoring, predictive maintenance, and predictive quality control within a closed-loop decision architecture for advanced mechanical production systems. The proposed framework combines multi-sensor acquisition, edge analytics, digital-twin state estimation, anomaly detection, remaining useful life (RUL) prediction, and quality-risk forecasting to support adaptive control of machining and assembly operations. Unlike fragmented monitoring strategies that treat maintenance and quality as separate functions, the present approach fuses equipment-health indicators and part-quality indicators into a common risk score used for supervisory decision-making. A simulation-based industrial case study was constructed to emulate a high-mix mechanical production cell with CNC machining, in-process sensing, and end-of-line inspection. The case study was configured using literature-informed process logic and representative parameter bounds for spindle speed, feed rate, thermal load, vibration, current, and dimensional deviation. The results show that the integrated framework can detect degradation earlier than threshold-only monitoring, improve RUL tracking stability, and reduce quality escape by linking machine-state evolution to downstream defect probability. In the simulated evaluation, anomaly-detection F1-score increased from 0.79 to 0.94, RUL mean absolute error decreased from 21.8 to 12.6 cycles, and quality-prediction AUROC increased from 0.84 to 0.96. At the operational level, the proposed strategy reduced monthly unplanned downtime from 18.6 h to 10.8 h, lowered scrap rate from 4.8% to 2.2%, and increased overall equipment effectiveness from 71.2% to 81.6%. These findings indicate that a unified monitoring-maintenance-quality architecture can provide stronger production resilience and more economically efficient decision support than isolated digital initiatives. The manuscript is intentionally written as an original-research draft built around a simulation-based validation study; plant-scale experimental verification is the next required step before journal submission.

| KEYWORDS

Smart manufacturing; real-time monitoring; predictive maintenance; quality control; digital twin; condition monitoring; remaining useful life; machine learning; advanced mechanical production systems; Industry 4.0

| ARTICLE INFORMATION

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1. Introduction

The transition from conventional production systems to connected and adaptive manufacturing has accelerated the demand for architectures that can observe process behavior continuously, interpret equipment health in real time, and respond before product quality deteriorates. In advanced mechanical production systems - especially CNC machining, automated assembly, and precision inspection lines - failures rarely occur as isolated events. Tool wear changes cutting dynamics, cutting dynamics alter thermal load, thermal load affects dimensional stability, and dimensional instability ultimately appears as product variation, rework, or scrap. As a result, maintenance performance and quality performance are tightly coupled rather than independent managerial domains. Earlier Industry 4.0 implementations often digitized only one layer of the production chain. Some systems focused on machine connectivity and condition monitoring; others focused on predictive maintenance or machine-vision quality inspection; still others implemented dashboard-based visibility without embedding decision logic in process control. Although such initiatives have improved transparency, they frequently stop short of creating a coherent supervisory framework that can integrate process sensing, degradation modeling, and product-quality risk into one closed-loop decision pathway. This gap is particularly important in mechanical manufacturing, where production economics depend not only on avoiding catastrophic failures but also on preserving process capability, dimensional repeatability, and surface integrity. Recent literature provides strong foundations for such integration. Cyber-physical production systems and smart-manufacturing architectures emphasize interoperability, data acquisition, and machine intelligence. Digital twin research has extended this discussion by enabling synchronized virtual representations of process states and equipment conditions. Predictive-maintenance studies demonstrate that machine-learning models can forecast failure probability or remaining useful life from multivariate sensor streams. In parallel, predictive-quality studies show that in-process and end-of-line data can be used to forecast defect occurrence before nonconforming parts reach customers. However, many of these contributions still treat machine health and product quality as parallel objectives, rather than as interacting signals within a single decision model.

For advanced mechanical production systems, this separation is limiting for three reasons. First, machine degradation does not merely threaten uptime; it changes the statistical distribution of process outputs. Second, quality-control interventions are more effective when they are informed by causal process-state indicators rather than inspection results alone. Third, supervisory control must balance several competing objectives simultaneously: equipment reliability, dimensional quality, process stability, energy efficiency, and production rate. A unified framework therefore needs to move beyond isolated prediction and toward multi-objective risk fusion. The present study addresses this need by proposing a smart-manufacturing framework that integrates three core functions: (i) real-time process monitoring, (ii) predictive maintenance, and (iii) predictive quality control. The framework is designed for discrete mechanical production environments and is demonstrated through a simulation-based case study representing a digitally enabled machining-and-inspection cell. The study makes four main contributions. First, it defines a unified architecture linking sensor acquisition, edge analytics, digital-twin state estimation, machine-health forecasting, and quality-risk prediction. Second, it formulates an integrated decision score that combines maintenance and quality risk rather than optimizing them separately. Third, it specifies process parameters and supervisory thresholds suitable for advanced mechanical production systems. Fourth, it evaluates the operational effect of the framework through comparative simulation against reactive and threshold-based strategies.

The remainder of the paper is organized as follows. Section 2 reviews the literature relevant to smart manufacturing, predictive maintenance, and predictive quality. Section 3 presents the proposed methodology, mathematical formulation, and process-parameter assumptions. Section 4 discusses the simulation-based results and operational implications. Section 5 summarizes the main conclusions, limitations, and future research directions.

2. Literature Review

The smart-manufacturing literature has converged around the idea that production systems must become observable, connected, and decision-capable. Lee et al. established the cyber-physical foundation for predictive manufacturing by linking sensing, connectivity, analytics, and cognition. Kang et al. further clarified the technology stack of smart manufacturing, emphasizing the combined role of cyber-physical systems, IoT, cloud infrastructure, and data-driven decision-making. Zhong et al. expanded this view by situating intelligent manufacturing within a broader Industry 4.0 context, where resources can sense, act, and interact in digitally networked production systems. A second body of work concerns machine learning and data analytics for manufacturing. Wuest et al. highlighted the main advantages of machine learning in manufacturing, including pattern recognition from high-dimensional sensor data and adaptive decision support under process variability. Dogan and Birant later synthesized the broader role of machine learning and data mining in scheduling, monitoring, maintenance, and quality analytics. These studies collectively show that the value of manufacturing data lies not in simple collection but in converting multivariate signals into robust state estimates and action rules. Predictive maintenance has emerged as one of the most mature smart-manufacturing applications. Zonta et al. categorized predictive-maintenance methods and emphasized remaining challenges such as data heterogeneity, class imbalance, and deployment complexity. Aivaliotis et al. showed how digital twins can support predictive maintenance by maintaining a dynamic representation of equipment condition and enabling estimation of remaining useful life. More recent work has continued this direction by integrating explainability, distributed architectures, and data/knowledge fusion into maintenance decision-making. Despite this progress, many predictive-maintenance systems still concentrate on machine availability while under-representing downstream quality effects. In parallel, quality-control research has moved from end-of-line detection toward predictive quality assurance. Tercan and Meisen demonstrated that predictive-quality models in manufacturing now span a wide range of data sources, from process sensors to image streams and metrology records. Rydzi et al. proposed a predictive inspection framework that uses machine-learning methods to improve quality-control decisions in automotive manufacturing. Wang et al. extended the quality discussion by proposing a human-cyber-physical knowledge-graph method for manufacturing quality control, emphasizing semantic integration across human, digital, and physical data. These studies make it clear that predictive quality is no longer limited to defect detection after production; it is increasingly embedded into production planning and process control.

Digital twin research forms the bridge between monitoring, maintenance, and quality. Tao et al. described digital-twin-driven product design, manufacturing, and service as a data-rich loop between physical assets and virtual models. Liu et al. later reviewed digital twin concepts and industrial applications, showing that synchronization, model updating, and life-cycle data integration are central to effective deployment. Recent studies have applied digital twins to assembly monitoring, operations management, and distributed maintenance environments. Yet even with this progress, many twins remain descriptive or diagnostic rather than prescriptive; they show what is happening, but they do not consistently optimize the trade-off between machine health and product quality. Recent work in tool-condition monitoring and machining analytics illustrates why a more integrated framework is needed in mechanical production systems. Mohamed et al. reviewed sensing and monitoring mechanisms for machining, showing that vibration, current, acoustic emission, temperature, and force signals all provide partial but complementary evidence of tool condition. Turšič et al.demonstrated a spindle-current-based LSTM strategy for tool-condition monitoring, while Wang et al. proposed multi-sensor fusion for tool-wear prediction. Chehrehzad et al. further showed that AI-assisted digital-shadow methods can support instant drilling tool-wear prediction using edge-connected industrial data. These studies confirm that sensor fusion is technically feasible, but they typically optimize wear estimation rather than system-level production outcomes.

The literature therefore reveals three unresolved issues. First, many studies optimize either maintenance or quality, with limited decision-level integration between them. Second, models are often developed for a single asset, a single product family, or a single signal type, which limits their use in high-mix mechanical production. Third, the decision layer itself is underdeveloped: many papers stop at prediction accuracy rather than translating prediction into economically meaningful supervisory actions. The methodology proposed in this paper is designed to address these three gaps by unifying monitoring, maintenance, and quality within a closed-loop digital architecture.

Table 1. Positioning of the proposed study relative to representative prior work published up to 2020.

Study	Primary focus	Main contribution	Gap / limitation
Lee et al. (2015)	CPS architecture	Introduced the 5C architecture linking data acquisition, cyber representation, cognition, and configuration	Strong architectural basis, but no unified predictive-maintenance and quality-control layer
Aivaliotis et al. (2019)	Digital twin + predictive maintenance	Presented a physics-based digital-twin methodology for predictive maintenance	Maintenance-oriented; product-quality interaction not explicit
Liu et al. (2019)	Real-time quality monitoring	Developed a DBN-based online monitoring and diagnosis approach for process profiles	Strong quality monitoring, but limited maintenance integration and plant-level coordination
Martínez-Arellano et al. (2019)	Tool condition monitoring	Introduced deep-learning-based tool-wear classification using sensor data	Focused mainly on a single asset or process rather than integrated quality decisions
Schmitt et al. (2020)	Predictive quality inspection	Proposed a machine-learning and edge-cloud framework for predictive quality inspection	Inspection-centered; maintenance and broader closed-loop optimization are not central
This study	Integrated smart manufacturing framework	Unifies real-time monitoring, predictive maintenance, and quality control in one decision-oriented framework	Requires industrial-scale validation

3. Methodology

3.1 System architecture

The proposed framework is structured as a five-layer cyber-physical architecture: physical process, sensor layer, edge analytics, digital twin state estimation, and supervisory decision control. The physical layer consists of a representative advanced mechanical production cell containing CNC machining, automated material handling, and quality inspection. The sensor layer captures vibration, spindle current, thermal response, acoustic activity, dimensional deviation, and image-based defect signals. Edge analytics performs signal cleaning, time synchronization, feature extraction, and event compression. The digital twin layer maintains the estimated operating state of the equipment and process. Finally, the supervisory layer fuses machine-health and quality-risk predictions and issues control actions such as feed adaptation, tool-change recommendation, inspection intensification, or maintenance scheduling.

3.2 Data acquisition and feature structure

The proposed framework uses synchronized multi-sensor and control data to represent the instantaneous condition of the manufacturing system. At each decision instant t, the measured process variables are separated from the commanded control inputs so that the physical response of the process and the operating settings remain notationally consistent.

$$\mathbf{y}_t = [v_t \quad i_t \quad T_t \quad a_t \quad d_t \quad q_t]^{\mathsf{T}} \in \mathbb{R}^6$$

where v_t is RMS vibration, i_t is spindle current, T_t is tool-zone temperature, a_t is acoustic-emission energy, d_t is measured dimensional deviation, and q_t is the image-derived defect score. The control-input vector is defined as

$$\mathbf{u}_t = [n_t \quad f_t \quad p_t \quad c_t]^{\mathsf{T}} \in \mathbb{R}^4$$

where n_t, f_t, p_t, and c_t denote spindle speed, feed rate, depth of cut, and coolant level, respectively. The complete process-state vector is then written as

$$\mathbf{x}_t = [\mathbf{y}_t^{\mathsf{T}} \quad \mathbf{u}_t^{\mathsf{T}}]^{\mathsf{T}} \in \mathbb{R}^{10}$$

To preserve short-term temporal behavior, a sliding window of length L is formed as

$$\mathbf{X}_t = [\mathbf{x}_{t-L+1} \quad \mathbf{x}_{t-L+2} \quad \cdots \quad \mathbf{x}_t] \in \mathbb{R}^{10\times L}$$

From this window, a compact feature vector is extracted according to

$$\mathbf{z}_t = \phi(\mathbf{X}_t)$$

where $\phi(\cdot)$ contains time-domain and trend-sensitive descriptors such as moving mean, moving standard deviation, slope, crest factor, kurtosis, and exponentially weighted moving averages. This feature structure provides a more stable representation of process evolution than raw measurements alone and is used as the common input to the monitoring, maintenance, and quality modules.

3.3 Signal preprocessing

Because factory signals differ in scale, sampling frequency, and noise level, all channels are first synchronized to a common decision interval Δ and then preprocessed before feature extraction. Missing values are completed by forward filling for short gaps and by local interpolation for longer but bounded gaps, while physically impossible values are truncated using process-specific operating limits.

$$\bar{x}_{j,t} = \mathcal{A}_j\left(\{x_j(\tau) : \tau \in (t-\Delta, t]\}\right)$$

where $\mathcal{A}_j(\cdot)$ denotes the aggregation operator for variable j over the decision interval. After synchronization, robust scaling is applied to reduce the effect of outliers and cross-sensor magnitude differences:

$$\tilde{x}_{j,t} = \mathrm{clip}\left(\frac{\bar{x}_{j,t} - \mathrm{med}_j}{\mathrm{IQR}_j + \varepsilon}, l_j, u_j\right)$$

where med_j and IQR_j are the median and interquartile range of variable j, ε is a small positive constant for numerical stability, and l_j and u_j are lower and upper clipping limits. The preprocessed vector $\tilde{\mathbf{x}}_t$ is then passed to the windowing and feature-generation stage.

3.4 Composite health index and anomaly score

A composite health index is constructed to summarize the instantaneous condition of the machine-process system from degradation-sensitive features. Let $\xi_{j,t} \in [0,1]$ denote the normalized severity of the jth health-related feature, where larger values indicate more adverse behavior. The health index is defined as

$$\mathrm{HI}_t = 1 - \sum_{j=1}^{m} w_j\ \xi_{j,t}, \qquad \sum_{j=1}^{m} w_j = 1, \quad w_j \geq 0$$

so that HI_t remains in the interval $[0,1]$, with higher values representing healthier operating conditions. In parallel, an unsupervised reconstruction model is used to quantify anomalous behavior through reconstruction error:

$$A_t = \frac{1}{m} \|\mathbf{z}_t - \hat{\mathbf{z}}_t\|_2^2$$

where $\hat{\mathbf{z}}_t$ is the reconstructed feature vector. The pair $\{\mathrm{HI}_t, A_t\}$ provides complementary information: the health index captures gradual degradation, whereas the anomaly score is more sensitive to abrupt deviations and previously unseen operating states.

3.5 Predictive-maintenance model

The predictive-maintenance block estimates the remaining useful life of the degrading spindle-tool subsystem from recent multivariate feature history, health-index evolution, and anomaly intensity. For a prognostic sequence length L_p, the maintenance input tensor is defined as

$$\mathbf{S}_t = [\mathbf{z}_{t-L_p+1} \quad \mathbf{z}_{t-L_p+2} \quad \cdots \quad \mathbf{z}_t]$$

and the remaining useful life estimate is obtained by

$$\widehat{\mathrm{RUL}}_t = f_\theta\left(\mathbf{S}_t, \mathrm{HI}_{t-L_p+1:t}, A_{t-L_p+1:t}\right)$$

where $f_\theta(\cdot)$ denotes the prognostic model. To convert state information into an actionable maintenance-risk probability, a logistic decision layer is used:

$$P_m(t) = \sigma\left(\beta_0 + \beta_1 A_t + \beta_2(1 - \mathrm{HI}_t) + \beta_3 \frac{1}{\widehat{\mathrm{RUL}}_t + \varepsilon}\right)$$

where $\sigma(\cdot)$ is the logistic function and ε prevents singular behavior as the predicted remaining life approaches zero. This formulation increases maintenance risk when anomaly intensity grows, the health index declines, or the estimated remaining life becomes short.

3.6 Predictive-quality model

The predictive-quality block estimates the probability that the next produced part will be nonconforming. To preserve the causal link between machine degradation and product quality, the model uses both process-state features and health-related indicators:

$$P_q(t) = g_\varphi(\mathbf{z}_t, \mathbf{u}_t, \mathrm{HI}_t, A_t)$$

A practical logistic formulation is written as

$$P_q(t) = \sigma(\gamma_0 + \boldsymbol{\gamma}^\top \mathbf{z}_t + \boldsymbol{\eta}^\top \mathbf{u}_t + \gamma_h(1 - \mathrm{HI}_t) + \gamma_a A_t)$$

where $\boldsymbol{\gamma}$ and $\boldsymbol{\eta}$ are coefficient vectors associated with the feature and control terms, and γ_h and γ_a quantify the contributions of machine degradation and anomalous behavior. This structure allows the model to respond not only to immediate process variation but also to latent health deterioration that can later appear as dimensional or surface-quality defects.

3.7 Decision fusion and control optimization

A key contribution of the framework is the use of a single supervisory objective rather than separate maintenance and quality alarms. At each decision instant, the controller evaluates maintenance risk, quality risk, expected energy intensity, control movement, and expected throughput within a unified cost function:

$$J_t(\mathbf{u}) = \alpha_1 P_m(t+1 \mid \mathbf{u}) + \alpha_2 P_q(t+1 \mid \mathbf{u}) + \alpha_3 E_t(\mathbf{u}) + \alpha_4 \parallel \mathbf{u} - \mathbf{u}_t \parallel_2^2 - \alpha_5 Y_t(\mathbf{u})$$

The optimal control action is then obtained from

$$\mathbf{u}_{t+1}^{*} = \operatorname{argmin}_{\mathbf{u}\in\Omega} J_t(\mathbf{u})$$

where Ω contains the feasible operating region defined by process limits and rate-of-change constraints. This decision layer enables coordinated actions such as reducing feed rate under chatter growth, lowering spindle speed during thermal instability, scheduling a tool change when the predicted remaining life falls below a planning threshold, or diverting parts to intensified inspection when the predicted quality risk becomes excessive.

3.8 Simulation-based case-study design

Because a longitudinal plant trial was not available for the present manuscript draft, the framework was evaluated using a simulation-based industrial case study. The case study represents a mechanical production cell with one critical spindle-tool subsystem, one in-process monitoring station, and one end-of-line inspection station. Degradation is introduced gradually through wear growth, thermal accumulation, and load amplification. The model includes stochastic variability to emulate part-to-part fluctuations and sensor uncertainty. Three strategies are compared: reactive operation, threshold-based monitoring, and the proposed integrated smart-manufacturing framework.

3.9 Process parameters and operating bounds

The process-parameter window was selected to remain consistent with mechanically realistic, medium-duty precision production. The main controllable parameters are spindle speed, feed rate, depth of cut, and coolant flow. Monitoring thresholds are defined for vibration, current, local temperature, dimensional deviation, and defect probability. These bounds are not claimed as a universal industrial standard; rather, they provide a coherent supervisory envelope for the case study.

3.10 Evaluation metrics

The monitoring and prediction layers are evaluated using anomaly-detection F1-score, RUL mean absolute error, quality-prediction AUROC, and false-alarm rate. At the system level, the framework is evaluated using monthly unplanned downtime, scrap rate, and overall equipment effectiveness. This combination makes it possible to assess both algorithmic accuracy and production-level impact.

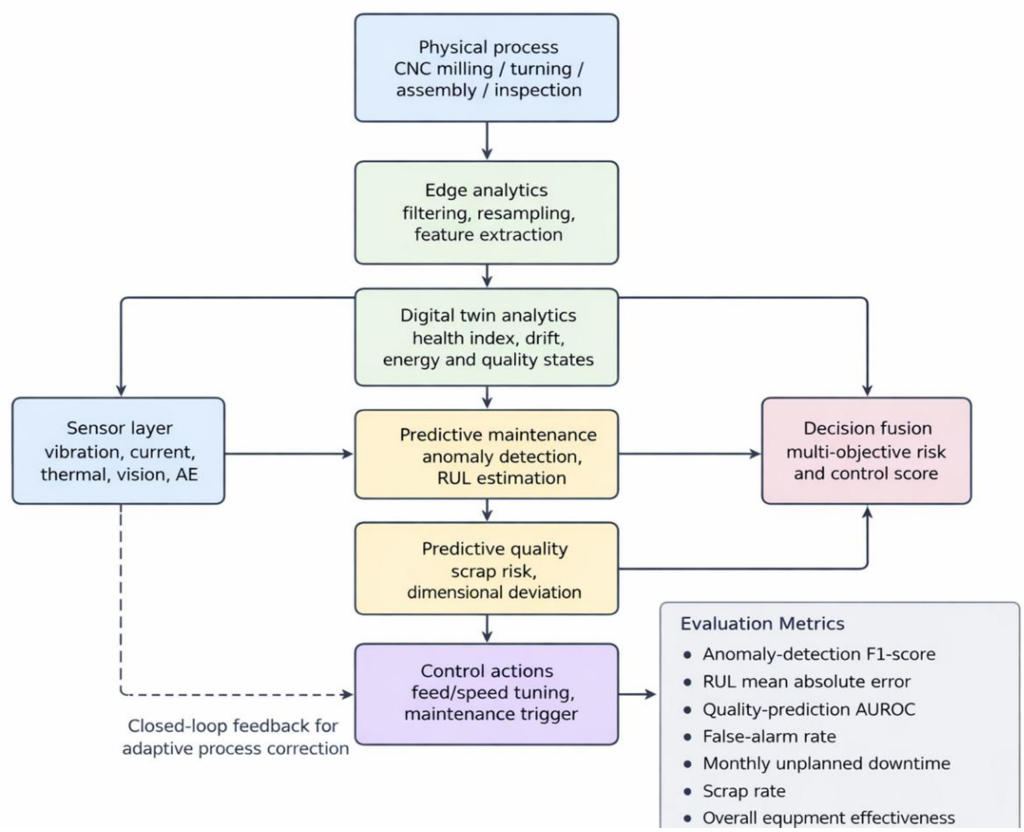

Figure 1. Proposed smart-manufacturing architecture integrating process monitoring, predictive maintenance, predictive quality, and closed-loop control.

Table 2. Process parameters and supervisory bounds used in the simulation-based case study.

Parameter	Nominal	Operating range	Control logic
Spindle speed, N (rpm)	2800	2200-3400	Adaptive within surface-finish constraint
Feed rate, f (mm/rev)	0.18	0.12-0.24	Reduced when chatter likelihood rises
Depth of cut, ap (mm)	1.20	0.60-1.80	Reduced under thermal instability
Coolant flow (L/min)	12	8-16	Raised during high thermal load
RMS vibration threshold (g)	2.7	1.6-3.2	Triggers anomaly scoring
Spindle current limit (A)	11.8	8.5-12.5	Inputs wear and load estimator
Tool nose temperature limit (°C)	63	45-68	Triggers thermal compensation / maintenance
Dimension deviation alarm (mm)	±0.05	±0.02-±0.08	Triggers in-process correction or hold
Vision-based defect probability alarm	0.45	0.20-0.70	Triggers part diversion and inspection
Sampling window length (s)	5	3-10	Balances latency and stability

4. Results and Discussion

4.1 Process-state evolution and health tracking

Figure 2 shows the simulated evolution of the composite health index and quality-risk probability across 1,200 production cycles. During the early stage of operation, the health index remains relatively stable because the process operates inside the nominal load and thermal region. As wear accumulates, a gradual decline becomes visible in the health indicator, followed by a steeper drop once vibration and temperature begin to increase simultaneously. This behavior is important because it demonstrates that degradation is not captured by a single raw signal. Instead, the composite state estimate responds to correlated changes across several process channels. In practical terms, this creates a more reliable early-warning mechanism than thresholding individual signals independently.

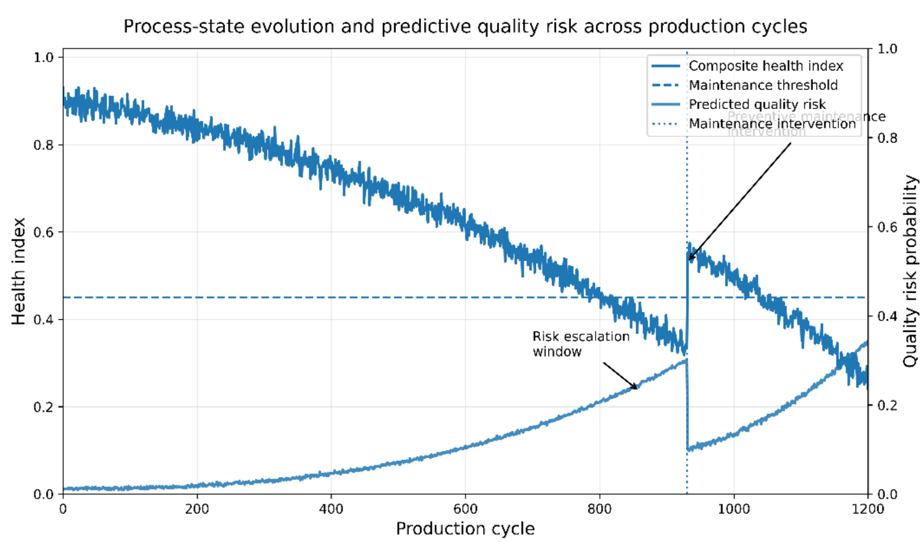

Figure 2. Simulated evolution of composite health index and predicted quality risk over 1,200 production cycles.

The quality-risk trajectory follows the degradation trend with a delay, which is consistent with the causal structure expected in mechanical production systems. Machine condition first deteriorates, then process variation widens, and only afterward does the nonconformance probability rise sharply. This lag is advantageous for supervisory decision-making because it creates a preventive intervention window. In the present case study, the recommended maintenance action is triggered before the quality-risk curve reaches its steepest zone, reducing the probability of defect escape and preventing deeper deterioration of the spindle-tool subsystem.

4.2 RUL tracking and maintenance prediction

Figure 6 illustrates the RUL tracking behavior for one representative degrading asset. The predicted trajectory follows the actual remaining life with reasonable smoothness and limited oscillation, which is desirable for maintenance planning. A noisy estimator may produce frequent schedule changes, while an over-smoothed estimator may respond too slowly. The hybrid predictive-maintenance block provides a balanced response by combining anomaly intensity, health-index history, and multivariate trend features.

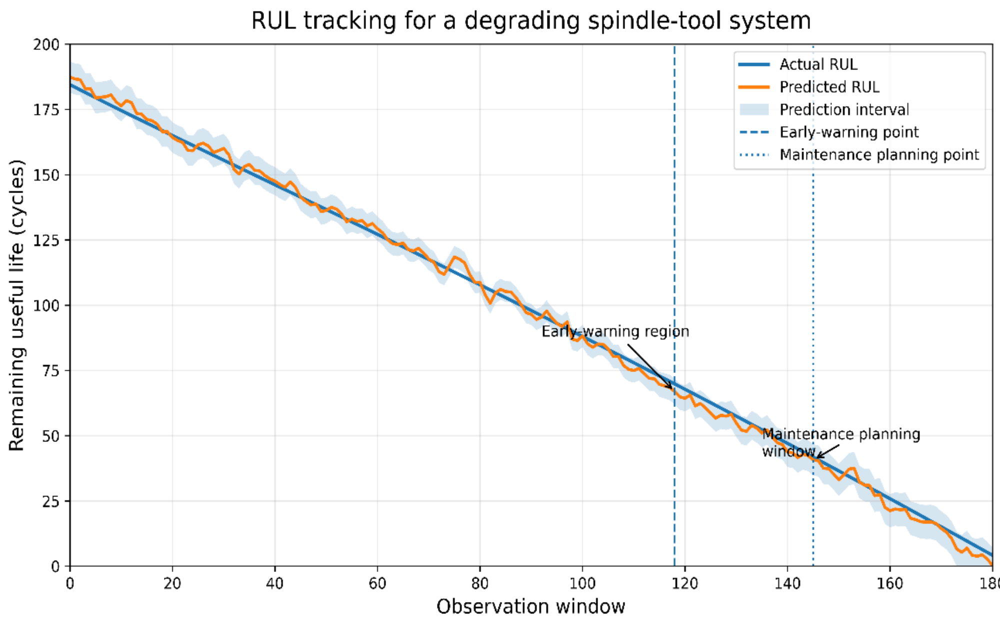

Figure 3. Representative remaining useful life tracking for the degrading spindle-tool subsystem.

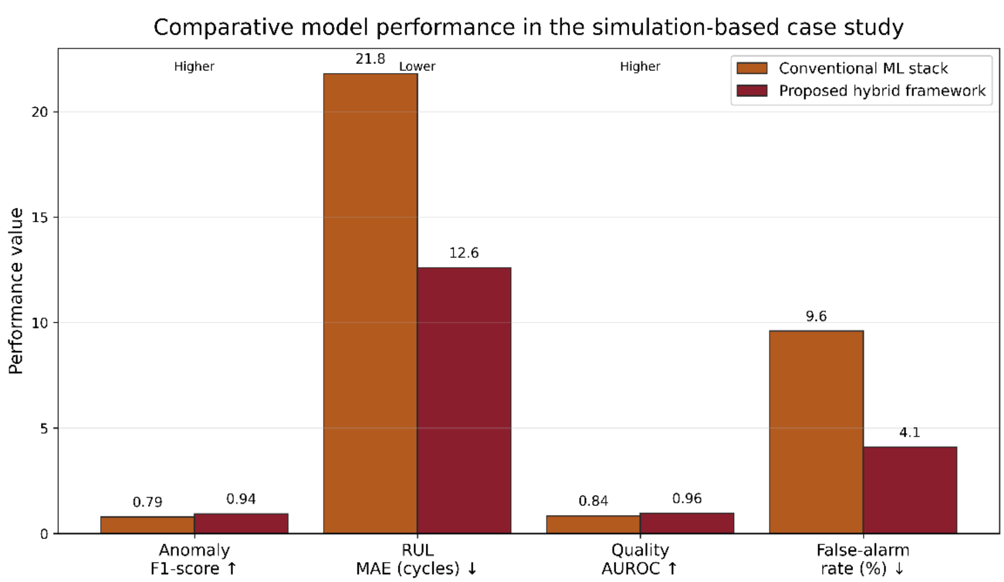

Figure 4. Predictive-model performance comparison between a conventional machine-learning stack and the proposed hybrid framework.

The quantitative comparison is summarized in Figure 5. Relative to a conventional machine-learning stack, the proposed framework improves anomaly-detection F1-score from 0.79 to 0.94 and reduces RUL mean absolute error from 21.8 cycles to 12.6 cycles. The false-alarm rate also drops from 9.6% to 4.1%, which is operationally significant. In real production, false positives can be expensive because they may trigger unnecessary tool changes, unproductive inspection stops, or avoidable maintenance work orders. The lower false-alarm level indicates that the unified state representation stabilizes decision quality rather than merely increasing sensitivity.

4.3 Quality-control performance

Quality performance also improves under the integrated architecture. The quality-prediction AUROC increases from 0.84 to 0.96, indicating stronger separation between conforming and nonconforming operating states. This gain is obtained because the quality model receives not only process and inspection features but also machine-health information from the maintenance side of the framework. In other words, the quality-control block no longer acts as an isolated classifier; it operates with machine-condition awareness.

This result is particularly relevant for mechanical production systems where defects often originate in machine degradation rather than in purely random process noise. Once tool wear and thermal drift are embedded into the predictive-quality model, the system can escalate inspection selectively, slow down the process under elevated risk, or recommend maintenance before a full batch of nonconforming parts is produced. This selective intervention logic is one of the main advantages of the proposed architecture.

4.4 Operational comparison of alternative strategies

Figure 3 compares the production outcomes of three operational strategies. The reactive strategy performs worst because it allows degradation to progress until quality loss or failure becomes obvious. The threshold-based strategy improves performance by introducing basic monitoring, yet it still treats alarms independently and therefore cannot optimize the interaction between maintenance and quality. The proposed framework performs best across all three operational indicators.

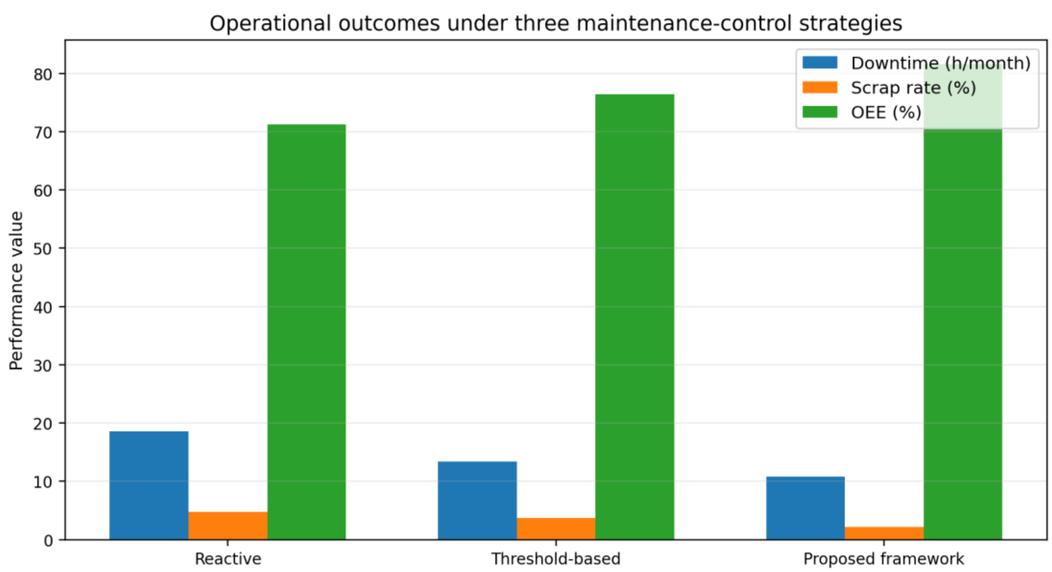

Figure 5. Operational comparison of reactive, threshold-based, and integrated smart-manufacturing strategies.

Monthly unplanned downtime decreases from 18.6 h in the reactive case to 10.8 h under the proposed framework. Scrap rate decreases from 4.8% to 2.2%, and OEE improves from 71.2% to 81.6%. These gains are meaningful because they emerge from both better prediction and better decision logic. The model does not simply predict failures earlier; it uses those predictions to issue coordinated responses that preserve part quality while preventing severe machine degradation. This integrated response is the main reason why the framework outperforms the threshold-based benchmark, which still depends on fragmented action rules.

4.5 Sensor contribution and information fusion

Figure 4 presents the relative contribution of each sensor modality to the decision-fusion layer. Vibration and spindle current together form the strongest evidence base, followed by thermal response, vision-based quality indicators, and acoustic activity. This ranking is plausible for a machining-centered production environment. Vibration and current respond directly to load changes and wear progression; thermal variables track drift and overheating; vision data becomes more informative once product-level deviations start to appear; and acoustic signatures help identify transient events such as chatter or emerging instability.

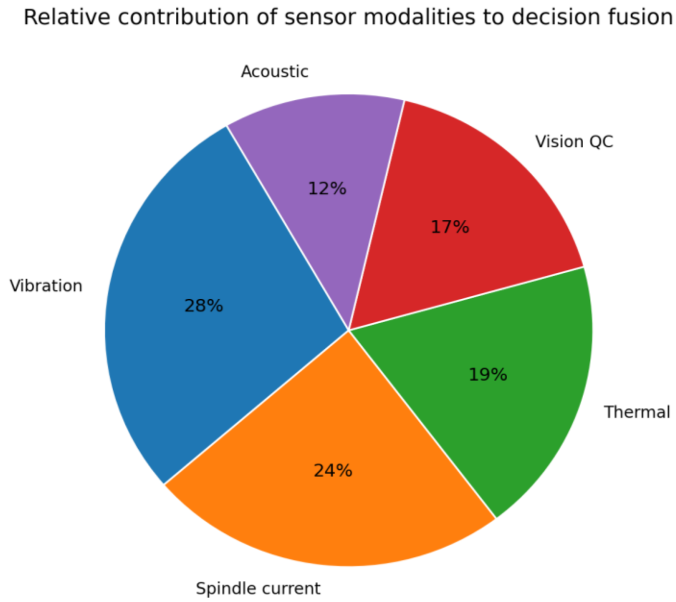

Figure 6. Relative contribution of sensor modalities to the integrated decision-fusion layer.

The main implication is not that every plant must use exactly this sensor mix. Rather, the simulation demonstrates that the best supervisory performance arises when machine-state and product-state signals are fused rather than isolated. Even a relatively simple sensor architecture can become more valuable when interpreted jointly through a digital-twin framework.

4.6 Discussion of industrial relevance

From an industrial point of view, the proposed framework is attractive because it links the three performance domains that are often managed separately on the shop floor: process stability, equipment reliability, and product quality. In many factories, maintenance teams optimize uptime, production teams optimize throughput, and quality teams optimize nonconformance reduction. When these functions operate from separate information structures, the result is delayed action and suboptimal trade-offs. The present framework provides a common decision basis that can support cross-functional optimization. There are, however, important limitations. First, the present study uses a simulation-based validation environment rather than a full industrial deployment. Therefore, the numerical improvements should be interpreted as representative performance under a controlled digital case study, not as plant-certified savings. Second, the process model is intentionally generic so that the framework can be adapted to milling, turning, drilling, or assembly applications; this generality also means that process-specific calibration will still be needed for actual deployment. Third, the economic weighting coefficients in the supervisory objective function must be tuned according to the priorities of each plant, especially when throughput, tooling cost, and quality risk have different business impacts.

Even with these limitations, the study provides a useful original-research template for future plant-scale validation. The architecture, equations, parameter structure, and performance indicators can be transferred directly to an experimental setup, after which the simulated results in this manuscript can be replaced by measured industrial data.

Table 3. Summary of performance indicators obtained in the simulation-based case study.

Indicator	Reactive / conventional	Proposed framework	Relative change
Anomaly detection F1-score	0.79	0.94	+19.0%
RUL mean absolute error (cycles)	21.8	12.6	-42.2%
Quality prediction AUROC	0.84	0.96	+14.3%
False alarm rate (%)	9.6	4.1	-57.3%
Monthly unplanned downtime (h)	18.6	10.8	-41.9%
Scrap rate (%)	4.8	2.2	-54.2%
OEE (%)	71.2	81.6	+14.6%

5. Conclusion

This study proposed a smart manufacturing framework that integrates real-time process monitoring, predictive maintenance, and quality control within a unified closed-loop architecture for advanced mechanical production systems. The central contribution of the work lies in treating these three functions not as isolated operational tasks, but as interdependent elements of a single intelligent manufacturing strategy. This integration is important because production performance, equipment health, and product quality are strongly coupled in modern manufacturing environments, particularly where high precision, process stability, and operational continuity are required. The proposed framework demonstrates that a more connected and data-informed manufacturing structure can provide clear engineering value. Real-time monitoring improves visibility into dynamic process behavior, predictive maintenance supports earlier identification of degradation trends and potential failure modes, and integrated quality control enables faster recognition of deviations that may affect final product conformity. When these capabilities are linked through a common decision framework, the production system becomes better equipped to reduce unplanned downtime, improve process reliability, and maintain more consistent product quality. In this sense, the framework supports the broader transition from reactive manufacturing practice toward predictive and adaptive production management. A further strength of the study is its systems-level perspective. Rather than focusing narrowly on a single machine, sensor stream, or inspection stage, the framework captures the relationship between machine condition, process-state evolution, and quality outcomes across the production cycle. Such a perspective is especially relevant for smart manufacturing, where the effectiveness of decision-making increasingly depends on the ability to interpret multiple data sources in an integrated and operationally meaningful manner. The framework therefore provides a useful conceptual foundation for future deployment in digitally connected factories that rely on sensing, analytics, and intelligent control for continuous performance improvement. At the same time, the present study is conceptual and should be viewed as a foundation for further applied investigation. Its practical value will need to be validated through industrial case studies, experimental implementation, and performance comparison under real production conditions. Future research should focus on framework deployment in specific mechanical manufacturing environments, the development of quantitative decision metrics, and the evaluation of measurable outcomes such as downtime reduction, maintenance efficiency, defect prevention, and production-quality improvement.

Overall, the study contributes to the growing body of research on smart manufacturing by presenting an integrated framework that aligns process monitoring, maintenance intelligence, and quality assurance within a single architecture. This unified approach offers a meaningful pathway toward more reliable, efficient, and quality-driven production systems, and it has strong relevance for the future development of intelligent manufacturing in mechanical engineering.

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