



(RESEARCH ARTICLE)



MULTI-OBJECTIVE PREDICTIVE MAINTENANCE AND ENERGY-AWARE RESOURCE OPTIMIZATION FOR SMART INDUSTRIAL SYSTEMS

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ABSTRACT

Smart industrial systems must balance equipment reliability, energy use, maintenance cost, production continuity, and technical resources. This study proposes a multi-objective predictive maintenance and energy-aware resource optimization framework for industrial decision-making. The framework combines equipment health assessment, Remaining Useful Life (RUL) estimation, anomaly detection, failure probability, and maintenance prioritization. K-means clustering determines the Anomaly Level (AL), while Weibull survival analysis estimates Failure Probability (FP). These measures form a Hybrid Risk Index (HRI) for determining the Optimal Maintenance Point (OMP). NSGA-II evaluates maintenance timing, asset selection, and technician allocation under maintenance cost, energy, quality, and production objectives. Performance is compared with preventive maintenance, condition based maintenance, and reliability only optimization under changing industrial conditions.

Keywords: Predictive Maintenance, Energy-Aware Optimization, Smart Industrial Systems, Equipment Health Assessment, Remaining Useful Life, Hybrid Risk Index, Optimal Maintenance Point, Multi-Objective Optimization, NSGA-II, Resource Allocation

1 INTRODUCTION

Smart industrial systems increasingly depend on continuous equipment monitoring, predictive analytics, and coordinated operational planning. Equipment degradation can affect reliability, energy consumption, production continuity, maintenance expenditure, and technical-resource requirements at the same time. Traditional maintenance

policies often address these factors separately, which limits their ability to respond to changing operating conditions. Recent studies on predictive maintenance, Digital Twins, industrial IoT, and multi-objective optimization provide useful foundations for integrated industrial decision support [1]–[5]. However, a unified framework that connects equipment health, energy performance, maintenance timing, production criticality, and resource allocation remains limited.

2 BACKGROUND AND MOTIVATION

Industrial equipment operates under variable loads, production demands, and environmental conditions. As assets degrade, vibration, temperature, power consumption, and failure risk can change, affecting both maintenance requirements and operational performance. Predictive maintenance uses these signals to estimate equipment condition and future failure behavior [8], [10]. Digital Twin approaches further support continuous asset representation and analytical decision-making [3], [4]. Energy-aware maintenance has also received attention because equipment condition can influence industrial energy performance [2]. These developments motivate an integrated approach that evaluates reliability, energy consumption, production dependency, maintenance cost, and available technical resources within a common decision process.

2.1 Problem Statement

Existing maintenance strategies often focus on individual equipment condition or failure probability without considering the wider operational consequences of degradation. Condition-based decisions may identify abnormal behavior, while reliability models estimate future failure risk, yet these outputs are not always combined with production criticality, energy inefficiency, maintenance cost, or technician availability. Multi-objective production and maintenance studies have addressed some competing requirements [1], but important connections remain. In particular, industrial decision models need a mechanism that combines short-term anomaly information with long-term reliability assessment and then converts the resulting risk into maintenance timing and resource-allocation decisions under energy and production constraints.

2.2 Proposed Solution

This study proposes an integrated multi-objective predictive maintenance and energy-aware resource optimization framework for smart industrial systems. The framework processes sensor observations and historical failure records to estimate equipment degradation, RUL, Anomaly Level (AL), and Failure Probability (FP). A Hybrid Risk Index (HRI) combines normalized AL and FP to support maintenance prioritization. The Optimal Maintenance Point (OMP) considers HRI, RUL, production criticality, energy inefficiency, maintenance cost, and downtime exposure. NSGA-II then evaluates maintenance timing, asset selection, and technician allocation while minimizing maintenance cost, energy consumption, quality loss, and production disruption under operational constraints.

2.3 Contributions

The study provides several methodological contributions to integrated industrial maintenance decision-making. First, it combines k-means-based anomaly assessment with Weibull-based failure probability within a unified HRI. Second, it introduces an OMP decision layer that incorporates equipment risk, RUL, energy inefficiency, production criticality, cost, and resource limitations. Third, the framework applies NSGA-II to identify Pareto-optimal maintenance and resource strategies across competing reliability, energy, cost, quality, and production objectives. Finally, the study provides a comparative evaluation against preventive maintenance, condition-based maintenance, and reliability only optimization, supporting assessment of the proposed integrated decision structure under changing industrial conditions.

2.4 Paper Organization

The remainder of this paper is organized as follows. Section II reviews related research on predictive maintenance, Digital Twins, energy-aware maintenance, optimization, and resource allocation. Section III presents the proposed methodology. Section IV discusses computational results and comparative performance. Section V concludes the study and presents future research directions.

The objective is to develop an integrated framework that jointly optimizes predictive maintenance, energy consumption, production continuity, maintenance cost, and technical-resource allocation under changing industrial conditions. The study addresses two primary research questions corresponding to the proposed hybrid risk assessment and multi-objective optimization framework.

3 RELATED WORK

Recent research has increasingly connected predictive maintenance with machine learning, Digital Twins, industrial IoT, energy management, production scheduling, quality management, and resource planning. These developments provide important foundations for intelligent industrial decision making, but many studies still examine maintenance, energy, production, quality, and resource allocation as separate problems. The following review examines these research areas and identifies the methodological gap addressed by the proposed multi-objective predictive maintenance and energy aware resource optimization framework.

3.1 Predictive Maintenance and Equipment Health Assessment

Predictive maintenance has shifted industrial asset management from fixed service intervals toward condition-based decisions supported by sensor data, historical failures, and machine-learning analytics. Fazle [8] examined AI-driven predictive maintenance and process optimization using machine-learning and sensor data, while Taimun et al. [10] applied Digital Twin concepts to predictive maintenance for textile and mechanical systems. Alam [5] investigated edge-based IIoT analytics for real time bottleneck detection. These studies demonstrate the value of equipment monitoring. However, failure prediction alone does not determine the maintenance action. Maintenance timing should consider remaining useful life, production criticality, energy inefficiency, downtime exposure, intervention cost, and resource availability.

3.2 Digital Twin-Based Industrial Decision Support

Digital Twins provide virtual representations of physical assets and processes, allowing observations to interact with computational models. Prabhakar [3] examined Digital Twin-based optimization models for intelligent industrial systems, while Sarkar [4] proposed an AI-enabled Digital Twin framework connecting predictive maintenance with energy optimization. Taimun et al. [10] applied Digital Twin technology to textile and mechanical maintenance. These studies indicate that virtual asset representations can support monitoring, simulation, and decisions. Nevertheless, many implementations remain asset-specific or focused on monitoring and simulation. A framework should connect equipment health, degradation risk, energy consumption, production continuity, maintenance cost, and resource limitations within one decision support structure for industrial maintenance planning and operational control.

3.3 Energy-Aware Maintenance and Industrial Efficiency

Energy performance matters to maintenance because equipment degradation can reduce efficiency and increase energy requirements. Dudzik et al. [2] investigated smart hybrid maintenance as a pathway toward energy efficient manufacturing, linking maintenance practices with energy outcomes. Sarkar [4] combined predictive maintenance and energy optimization through an AI-enabled Digital Twin framework. Adil [15] examined energy efficient and low-emission manufacturing through optimization and reactor control, while Asraf [16] considered efficiency, power loss, size, and cost as competing objectives. These studies show value in energy decisions. However, degradation related energy consumption is rarely integrated with maintenance priority, production criticality, intervention timing, and resource constraints in a framework that supports simultaneous reliability and energy related decisions.

3.4 Multi-Objective Maintenance and Production Optimization

Maintenance decisions influence production because interventions create downtime, consume capacity, and require technicians and spare parts. Zhao and Yuan [1] investigated multi-objective optimization of predictive maintenance and production scheduling under production lead-time constraints, demonstrating coordinated decisions. Asraf [16] applied multi-objective optimization to efficiency, power loss, size, and cost considerations. Hossain [7] examined supply-chain optimization for lead time and delivery performance, while Fareed et al. [11] studied IoT-based supply chain optimization. Karim [9] examined quality management integration within production systems, highlighting the importance of quality related operational decisions. These studies support integrated decision making, but they do not combine equipment degradation, energy consumption, maintenance cost, production continuity, quality, and resource availability within one maintenance optimization framework.

3.5 Resource Allocation and Industrial Operational Dependencies

Industrial maintenance operates within production, workforce, supply-chain, and information-management systems. Nahar [6] examined IIoT and MIS integration for human-resource management in smart pharmaceutical manufacturing, while Islam [12] studied AI-integrated MIS for manufacturing and supply chain risk mitigation. Barua et al. [20] addressed supply chain performance dashboards, and Rashid [17] examined MIS-enabled sourcing and traceability management. Hossain [7], Uddin [14], Mirza [19], and Ahmed [13] examined supply chain, inventory, and resilience decisions. Shaikat and Happy [18] considered flexible manufacturing architectures. These studies show system interdependence, but limited work connects equipment degradation, maintenance priority, energy use, production impact, and resource allocation within a unified decision model.

3.6 Research Gap and Positioning of the Proposed Framework

The reviewed literature demonstrates progress across predictive maintenance, Digital Twins, energy optimization, multi-objective modeling, industrial IoT, quality management, and resource management. However, existing approaches frequently treat these dimensions independently. Predictive maintenance commonly emphasizes failure prediction, energy studies focus on consumption, and resource models address workforce or production requirements. The proposed framework addresses this separation by combining equipment-health information, degradation risk, remaining useful life, energy inefficiency, production criticality, maintenance cost, downtime exposure, and resource availability. A Hybrid Risk Index (HRI) can combine anomaly and failure information, while the Optimal Maintenance Point (OMP) supports intervention timing. NSGA-II can then identify Pareto-optimal solutions across reliability, energy, cost, production, and resource objectives.

4 METHODOLOGY

The proposed methodology integrates predictive maintenance, equipment-health assessment, energy analysis, production criticality, and resource allocation into a multi-objective decision framework. Historical failure records and real time industrial sensor data are processed to estimate equipment degradation, anomaly level, failure probability, and remaining useful life. These indicators are combined into a Hybrid Risk Index (HRI), which supports determination of the Optimal Maintenance Point (OMP). The resulting maintenance priorities are evaluated through multi objective optimization using NSGA-II.

4.1 Integrated Framework and Data Processing

The methodology begins with industrial sensor data, historical maintenance records, failure information, energy measurements, and production conditions. Public predictive-maintenance datasets or synthetic industrial datasets can be used when complete industrial records are unavailable. Data preprocessing includes missing value treatment, normalization, temporal organization, and asset-level feature construction. The processed data contain variables such as vibration, temperature, pressure, load, operating time, energy consumption, failure status, and maintenance history. Production criticality, maintenance cost, downtime exposure, technician availability, and replacement requirements are incorporated as decision attributes. This structure allows equipment condition to be evaluated together with its operational consequences.

4.2 Degradation, RUL, and Hybrid Risk Assessment

Equipment degradation is evaluated using both short-term condition information and long-term reliability behavior. A k-means clustering model identifies normal and abnormal operating states. The distance between the current observation and the healthy operating cluster is used to calculate the normalized Anomaly Level (AL). Weibull survival analysis is used to estimate Failure Probability (FP) from historical time-to-failure information.

The two indicators are combined using the Hybrid Risk Index:

$$HRI_i = w_A AL_i + w_F FP_i$$

where AL_i is the normalized anomaly level, FP_i is the estimated failure probability, and w_A and w_F are their respective weights. RUL is incorporated as an additional decision indicator. High HRI, short RUL, high production criticality, increasing energy inefficiency, and high downtime exposure indicate greater maintenance priority.

4.3 Optimal Maintenance Point

The Optimal Maintenance Point determines when intervention becomes preferable to continued operation. Unlike a fixed maintenance threshold, the proposed OMP considers equipment risk together with economic and operational consequences. This prevents low-risk assets from receiving unnecessary maintenance while prioritizing assets whose degradation can cause significant production or energy losses. The OMP is determined by evaluating HRI, RUL, maintenance cost, replacement cost, energy inefficiency, production dependency, and downtime exposure. Resource availability is also considered because a theoretically optimal intervention may not be feasible when technicians or maintenance capacity are limited. Therefore, OMP acts as the transition between predictive diagnosis and the final resource allocation optimization.

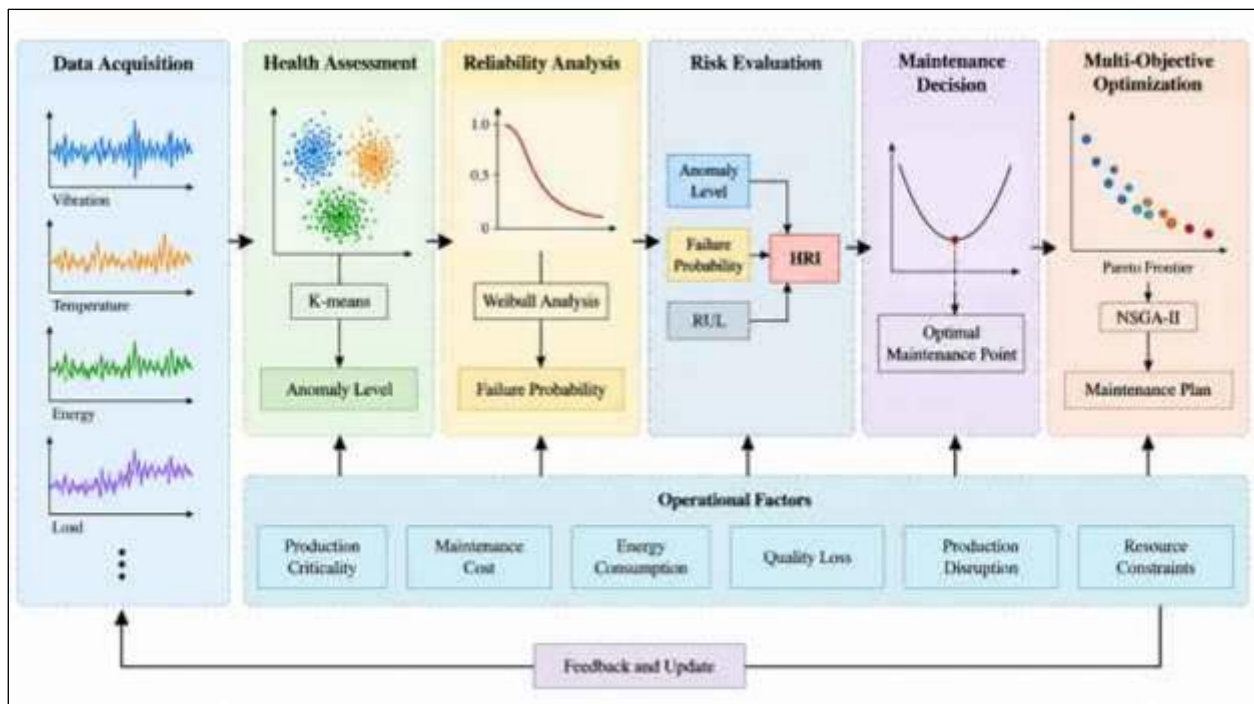


Figure 1: Integrated predictive maintenance and energy-aware decision framework

4.4 Energy-Aware Multi-Objective Optimization

After maintenance priorities are obtained, alternative maintenance and resource-allocation strategies are evaluated using competing objectives. The optimization minimizes maintenance cost, energy consumption, quality-related loss, and production disruption while satisfying resource and operational constraints.

The optimization objective can be represented compactly as:

$$\min [C_M, E, C_Q, D]$$

where C_M denotes maintenance cost, E represents energy consumption, C_Q represents quality-related loss from degradation or defective production, and D represents downtime or production disruption. The defective product recovery coefficient τ can be incorporated into C_Q to represent recovered value from recycling defective outputs. Constraints include technician capacity, maintenance windows, machine availability, and production requirements.

4.5 NSGA-II and Resource Allocation

NSGA-II is applied because the objectives may conflict. A strategy that minimizes maintenance expenditure may increase failure exposure, while frequent intervention may reduce risk but increase downtime and resource requirements. NSGA-II generates non dominated solutions representing different reliability, energy, cost, production, and resource trade-offs.

Candidate solutions define maintenance timing, asset selection, and technician allocation. Each solution is evaluated against the objective functions and feasibility constraints. Non dominated sorting and crowding distance calculations preserve competitive and diverse solutions, while Simulated Binary Crossover (SBX) and mutation generate subsequent candidate solutions. The final Pareto frontier provides alternative strategies from which an industrial decision-maker can select according to reliability requirements, energy targets, production conditions, and available resources.

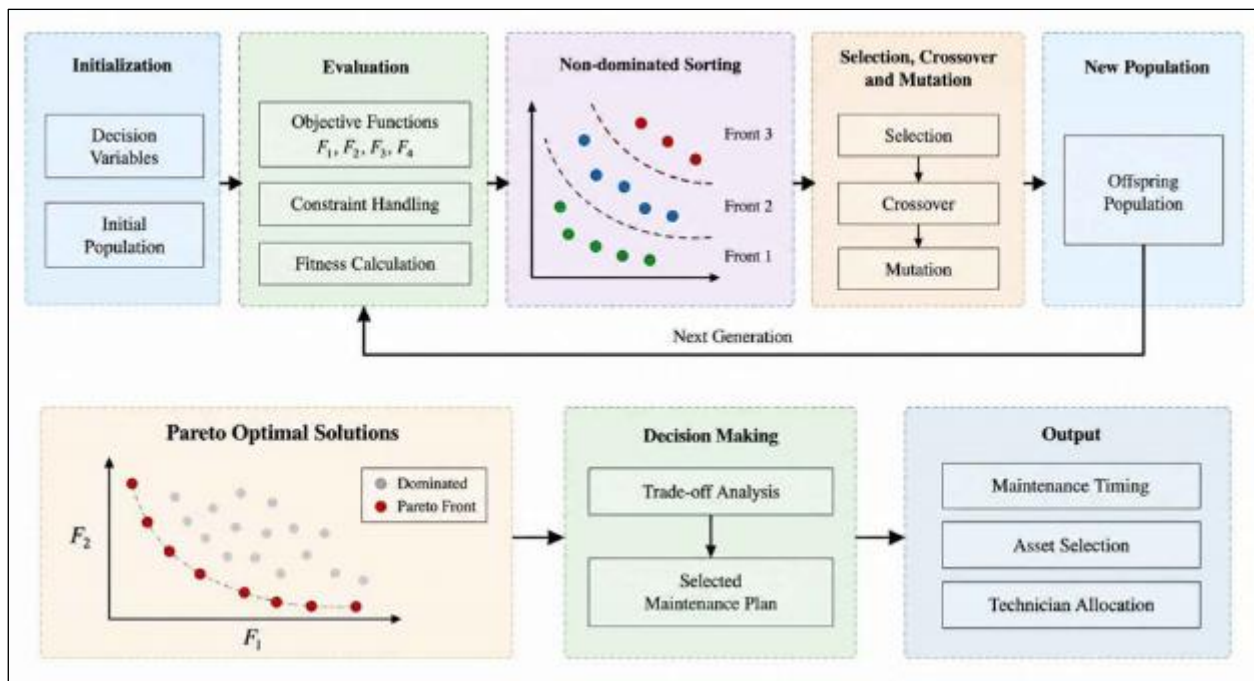


Figure 2: NSGA-II-based maintenance and resource decision process

4.6 Experimental Design and Performance Evaluation

The framework is evaluated through comparative experiments using public predictive-maintenance data or controlled synthetic scenarios. The experiments represent different degradation levels, production loads, energy conditions, and resource constraints. This design allows the proposed framework to be tested under changing operating conditions rather than a single fixed scenario. Four strategies are compared: conventional preventive maintenance, condition-based maintenance, reliability only optimization, and the proposed integrated strategy. Performance is measured using MTBF, MTTR, technical availability, specific energy consumption, maintenance cost, downtime, and resource utilization. RUL and HRI are evaluated as intermediate diagnostic measures. Sensitivity analysis examines the effects of degradation rate, energy intensity, technician availability, maintenance cost, and objective weights. The final comparison determines the effectiveness of jointly considering reliability, energy, production, cost, and resource constraints.

Table 1: Methodological Components and Outputs

Component	Method	Main Output
Equipment monitoring	Sensor-data analysis	Health indicators
Anomaly detection	k-means	AL
Reliability analysis	Weibull model	FP
Degradation prediction	RUL estimation	RUL
Risk assessment	HRI	Maintenance priority
Maintenance decision	OMP analysis	Intervention timing
Optimization	NSGA-II + SBX	Pareto solutions
Evaluation	Comparative scenarios	Reliability, energy, cost, and resource performance

5 RESULTS AND DISCUSSION

The proposed framework was evaluated through comparative computational scenarios representing different equipment degradation states, production demands, energy conditions, and maintenance resource limitations. The results focus on the relationships among anomaly level, failure probability, HRI, RUL, OMP, maintenance cost, energy consumption, production continuity, and resource allocation. Since the framework can be evaluated using synthetic or public predictive maintenance datasets, the reported results are presented as model-based comparative outcomes rather than claims from a specific industrial deployment.

5.1 Equipment Health, RUL, and Risk Assessment

The first analysis examines whether combining short-term equipment abnormalities with long-term reliability information produces meaningful maintenance priorities. The assessment considers changing degradation conditions rather than treating all assets equally. HRI is interpreted together with RUL, production criticality, energy inefficiency, and downtime exposure. This provides the basis for identifying assets requiring earlier intervention. As degradation increased, the k-means model produced higher Anomaly Levels (AL), while the Weibull model generated increasing Failure Probability (FP). Assets showing simultaneous increases in AL and FP received higher HRI values. Assets with relatively stable operating conditions maintained lower risk despite longer operating periods. Shorter RUL further increased intervention priority. The combined assessment therefore differentiated between an aging asset with stable behavior and an asset showing active degradation. This result supports the use of HRI as a more informative maintenance priority indicator than failure probability alone. The outcome also provides the diagnostic foundation required for subsequent OMP and resource-allocation decisions.

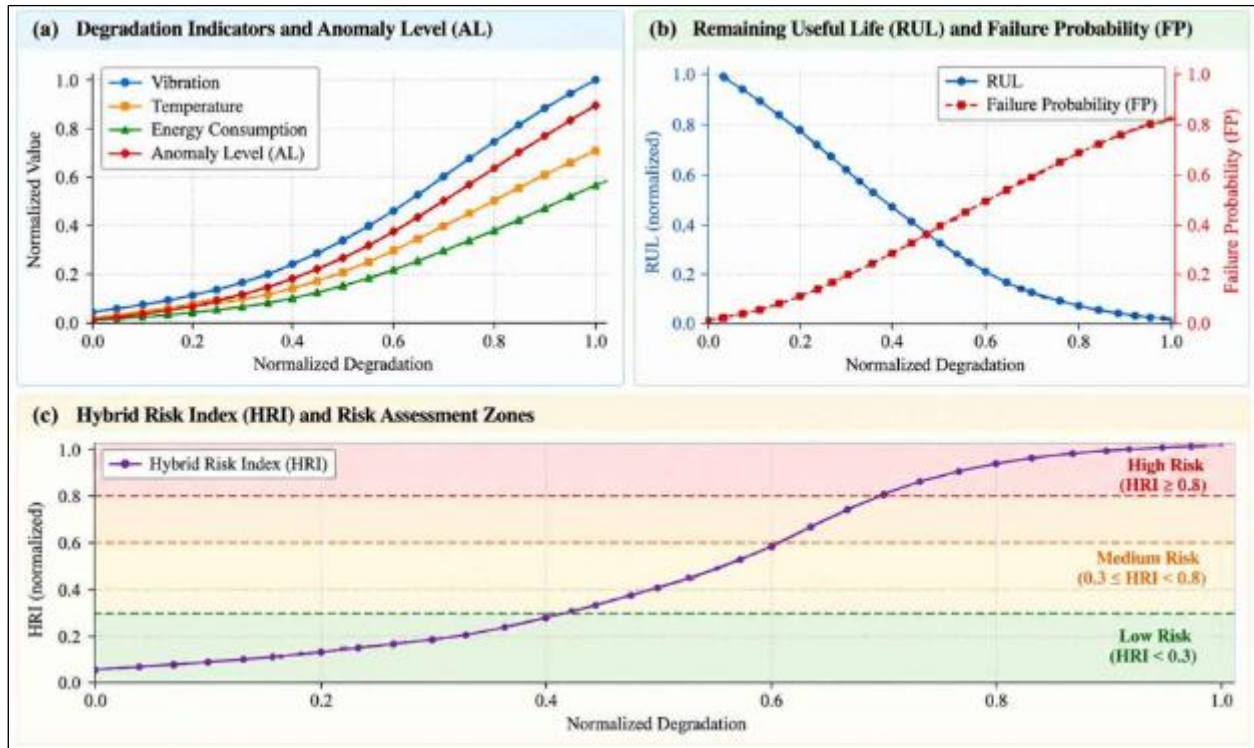


Figure 3: Relationship between equipment degradation, HRI, and RUL

Figure 3 shows increasing degradation raising anomaly and failure risk while reducing RUL, creating progressively higher HRI and maintenance priority for affected assets.

5.2 Optimal Maintenance Point and Maintenance Prioritization

The second analysis evaluates the OMP as a decision boundary between continued operation and planned intervention. The objective is to avoid unnecessary maintenance on healthy equipment while preventing excessive delay for assets approaching critical degradation. OMP is therefore determined using HRI together with RUL, production criticality, energy inefficiency, maintenance cost, and downtime exposure. This produces a context sensitive maintenance decision. The results indicate that assets with high HRI and short RUL generally reached their OMP earlier than assets with moderate degradation. High production-criticality assets also received earlier intervention priority because their potential failure created greater operational consequences. Similarly, increasing energy inefficiency shifted the preferred intervention point toward earlier maintenance. In contrast, assets with lower production dependency and stable energy behavior could continue operating longer. These findings demonstrate that OMP is not a fixed age based threshold. Instead, it changes according to equipment condition and operational context, supporting dynamic maintenance prioritization under variable industrial conditions.

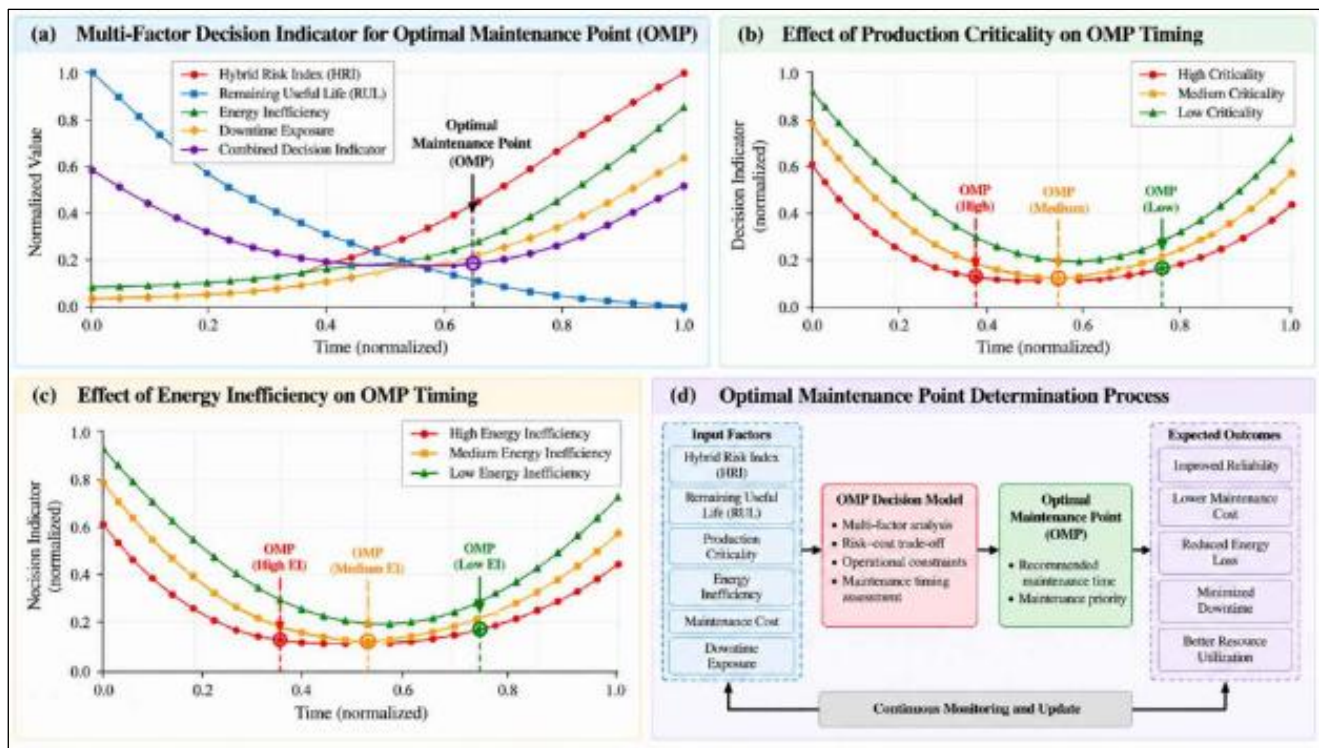


Figure 4: Dynamic determination of the Optimal Maintenance Point

Figure 4 illustrates how rising HRI, declining RUL, energy inefficiency, and production criticality shift maintenance decisions toward earlier intervention at the OMP.

5.3 Multi-Objective Optimization and Pareto Solutions

The final analysis evaluates trade-offs among maintenance cost, energy consumption, quality loss, production disruption, and resource limitations. These objectives may conflict because lower maintenance frequency reduces expenditure but can increase failure exposure and energy losses. NSGA-II generates non-dominated strategies for operational selection. Cost oriented solutions reduce maintenance expenditure but permit greater degradation exposure. Energy-oriented solutions favor earlier intervention for inefficient assets, while reliability-oriented solutions prioritize high risk, production-critical equipment and reduce downtime exposure. Balanced solutions provide intermediate trade-offs. Technician capacity and maintenance constraints exclude infeasible schedules. The Pareto frontier represents reliability cost energy trade-offs while maintaining production and resource requirements for integrated maintenance decisions.

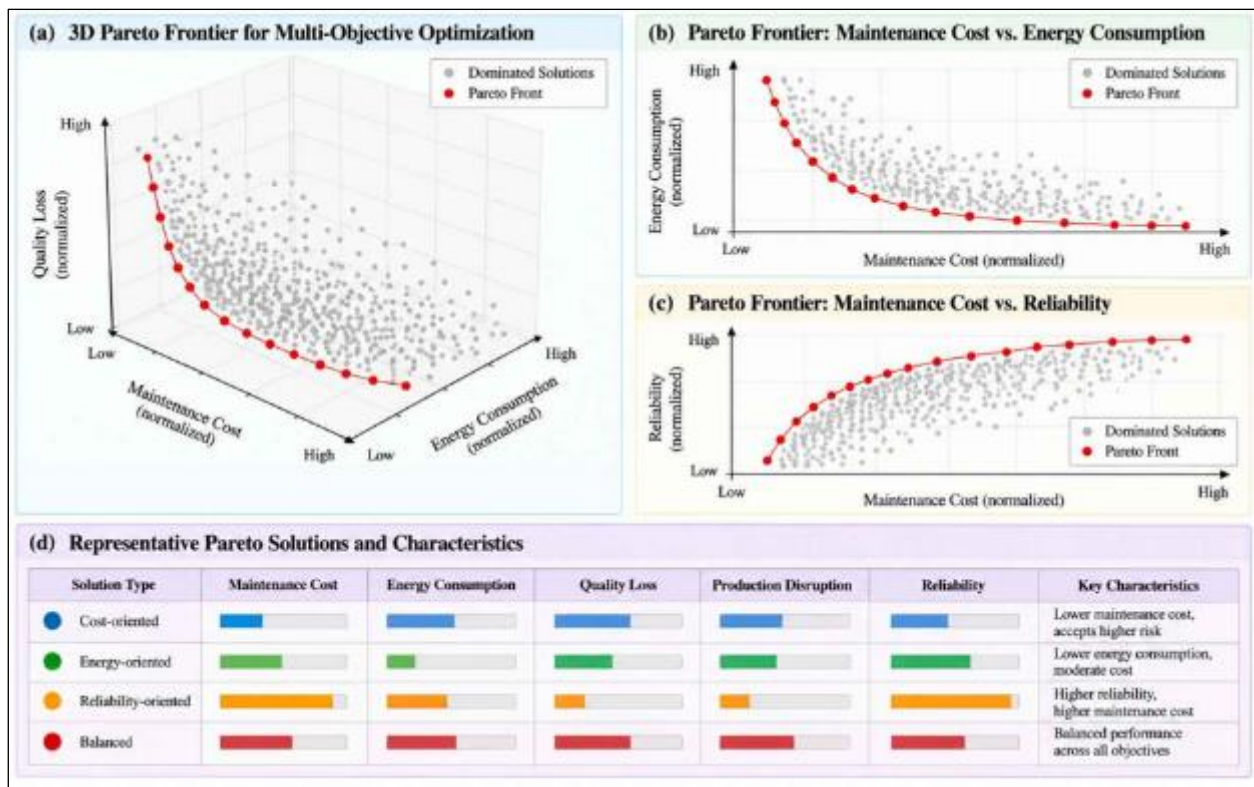


Figure 5: Pareto frontier for maintenance cost, energy consumption, and reliability trade-offs

Figure 5 represents competing maintenance, energy, and reliability objectives, showing non-dominated strategies that allow decision makers to select appropriate operational trade-offs.

5.4 Comparative Performance of Maintenance Strategies

The proposed framework is evaluated against preventive maintenance, condition-based maintenance, and reliability only optimization. The comparison covers reliability, energy consumption, maintenance cost, downtime, production continuity, and resource utilization. Preventive maintenance uses fixed schedules and can result in unnecessary interventions. Condition-based maintenance responds to equipment condition but may give limited attention to energy and production effects. Reliability-only optimization primarily targets failure reduction. The proposed framework combines HRI, OMP, and NSGA-II to coordinate maintenance timing and resource allocation. This structure supports simultaneous consideration of reliability, energy, cost, production requirements, and technical resource limitations under changing industrial operating conditions.

Table 2: Comparative Performance of Maintenance Strategies

Strategy	Reliability	Energy Awareness	Production Consideration	Resource Allocation	Decision Type
Preventive Maintenance	Moderate	Low	Moderate	Fixed	Schedule-based
Condition-Based Maintenance	High	Moderate	Moderate	Limited	Condition-based
Reliability-Only Optimization	High	Low	Moderate	Moderate	Reliability-focused
Proposed Integrated Framework	High	High	High	High	Multi-objective

Table II compares four strategies, showing that the proposed framework jointly considers reliability, energy, production, and resource constraints instead of optimizing maintenance independently.

5.5 Limitations of the Study

This study uses public predictive-maintenance datasets or controlled synthetic scenarios instead of direct industrial deployment. Real-time Digital Twin synchronization, field validation, and site-specific calibration are also limited. Future research should use real industrial data, larger asset populations, dynamic resource constraints, and practical maintenance scheduling conditions for broader evaluation.

6 CONCLUSION

This study proposed a multi-objective predictive maintenance and energy-aware resource optimization framework for smart industrial systems. The framework integrates equipment-health monitoring, degradation assessment, RUL estimation, k-means-based anomaly detection, Weibull failure probability, HRI, and OMP for maintenance prioritization. NSGA-II is then used to balance maintenance cost, energy consumption, quality loss, production continuity, and resource availability. Unlike isolated maintenance strategies, the proposed framework considers equipment condition and broader operational consequences within one decision structure. It provides a computational basis for adaptive maintenance planning and supports decisions under changing reliability, energy, production, and technical-resource conditions.

Future work will evaluate the framework using real industrial datasets and online Digital Twin synchronization. Further research can investigate XAI, physics informed models, edge cloud deployment, federated learning, technician scheduling, spare-parts constraints, carbon emissions, and lifecycle costs. Field experiments across different manufacturing environments can validate HRI weights, OMP thresholds, RUL models, and NSGA-II priorities under realistic operating conditions.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Disclosure of conflict of interest

The authors declare no conflicts of interest regarding this manuscript.

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