



Multi-Objective Optimization of Energy Cost, Production Quality, and Equipment Degradation Using AI-Based Dynamic Models

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Received: 27 September 2026 | Revised: 10 October 2026 | Revised: 20 October 2026 | Published: 4 November 2026

Abstract

Purpose: This study aims to develop a transparent AI-assisted dynamic optimization framework that simultaneously addresses energy and operating costs, production quality, and equipment degradation in industrial manufacturing systems.

Research Methodology: The study employs a mathematical modeling and illustrative simulation approach integrating AI-based prediction, coupled dynamic state models, uncertainty-aware feasibility constraints, and Pareto-based multi-objective optimization. A reproducible simulation design is specified for a 24-hour horizon comprising 96 fifteen-minute decision intervals, supported by objective normalization and a staged validation framework.

Results: The proposed framework illustrates how energy costs, quality deviations, and equipment degradation can be evaluated simultaneously while maintaining operational feasibility. The illustrative simulations demonstrate the conceptual trade-offs among competing objectives and highlight the roles of uncertainty margins, Pareto-optimal policy selection, and dynamic feasibility assessment. All numerical examples are synthetic and do not represent experimentally validated industrial performance.

Conclusions: Integrating AI-based prediction with dynamic modeling and Pareto optimization provides a structured approach to balancing operational efficiency, product quality, and equipment reliability. The framework emphasizes transparent decision-making, operational constraints, and systematic validation before industrial implementation.

Limitations: The study relies on synthetic scenarios without empirical factory data. Its simplified dynamic models, uncertainty assumptions, and optimization procedures require calibration and validation under actual industrial operating conditions.

Contributions: This study advances AI-assisted industrial optimization by integrating multi-objective decision modeling, uncertainty-aware feasibility assessment, and Pareto-based policy selection into an auditable framework. It also proposes a staged validation protocol to support responsible and reproducible industrial deployment.

Keywords: *Digital Twin, Energy Efficiency, Industrial AI, Model Predictive Control, Multi-Objective Optimization*

How to Cite: Shah, A., Nayak, P. K., & Sahani, S. K. (2026). Multi-Objective Optimization of Energy Cost, Production Quality, and Equipment Degradation Using AI-Based Dynamic Models. *Jurnal Teknik dan Informatika (JTI)*, 6(2), 73-101.

1. Introduction

Industrial manufacturing systems face increasing pressure to improve energy efficiency, maintain product quality, and preserve equipment reliability while meeting production requirements. These objectives are closely interconnected because operational decisions that improve one aspect of performance may adversely affect others. Increasing production speed, operating temperature, pressure, or equipment utilization can improve throughput and reduce immediate unit costs, but may simultaneously increase energy consumption, accelerate equipment degradation, and raise the risk of product defects. Conversely, conservative operating strategies may extend equipment life while limiting production capacity and increasing operational costs. These competing requirements highlight the importance of developing integrated optimization approaches capable of balancing multiple performance objectives within a unified decision-making framework.

Recent advances in artificial intelligence (AI), machine learning, and industrial digitalization have created opportunities to improve manufacturing decision-making through predictive modeling and dynamic optimization. AI-based models can identify nonlinear relationships among operating conditions, energy consumption, product quality, and equipment health, while dynamic models describe how current operational decisions influence future system performance. Digital twin technologies and predictive maintenance systems further support the continuous assessment of production processes by integrating sensor measurements, historical operating records, and equipment condition indicators. Nevertheless, predictive accuracy alone does not guarantee effective operational decisions because recommendations must also satisfy physical constraints, production requirements, and equipment safety limits.

Existing research has explored AI-based energy forecasting, production scheduling, predictive maintenance, quality control, and industrial process optimization ([Abadi et al., 2025](#); [Ma et al., 2024](#); [Wei et al., 2025](#)). These approaches have contributed to improvements in individual dimensions of manufacturing performance, particularly energy efficiency, equipment reliability, and process stability. Research on multi-objective optimization has also demonstrated the importance of Pareto-based approaches for identifying trade-offs among competing objectives ([Deb et al., 2002](#)). Despite these developments, integrating energy costs, product quality, and equipment degradation within a single dynamic optimization framework remains challenging. Energy-focused strategies may overlook long-term equipment deterioration, while maintenance-oriented approaches may insufficiently consider production requirements and quality-related costs. Furthermore, optimization models that rely exclusively on weighted objective functions may obscure trade-offs and provide limited transparency regarding the feasibility of recommended operating policies.

The research gap addressed in this study concerns the need for a transparent and integrated decision framework that evaluates energy costs, quality loss, and equipment degradation along the same operational trajectory while explicitly incorporating prediction uncertainty and operational feasibility. Although previous studies have investigated these objectives individually or in selected combinations, their integration into a modular, uncertainty-aware dynamic optimization process requires further methodological development. In particular, a decision architecture should distinguish predictive modeling from operational control, reject infeasible solutions before evaluating managerial preferences, and provide a systematic procedure for validating recommended policies. Such considerations are essential for ensuring that AI-assisted optimization supports reliable industrial decision-making without compromising production requirements or equipment safety.

The novelty of this study lies in developing an integrated AI-assisted multi-objective optimization framework that combines learned quality and degradation predictors, coupled dynamic state models, uncertainty-aware feasibility constraints, and Pareto-based policy selection within a unified architecture. Unlike approaches that prioritize a single performance objective or directly combine competing objectives through predetermined weights, the proposed framework first identifies feasible, non-dominated operating policies and subsequently applies transparent decision criteria to support

policy selection. The framework also incorporates objective normalization, uncertainty margins, and dynamic feasibility assessment to improve the interpretability and auditability of optimization decisions. A staged validation procedure is proposed to facilitate future calibration and evaluation using synchronized industrial operating data.

Accordingly, this study aims to formulate a dynamic optimization framework that simultaneously considers energy and operating costs, production quality, and equipment degradation. Specifically, the study examines how these objectives can be represented within a unified mathematical model, how predicted operating states can be evaluated against physical and operational constraints, how Pareto-optimal alternatives can support transparent decision-making, and how validation and governance procedures can guide responsible industrial implementation. An illustrative simulation framework with a 24-hour planning horizon and 96 fifteen-minute decision intervals is used to demonstrate the proposed modeling and decision-making procedures. The numerical examples are synthetic and are intended to explain the framework rather than establish empirical performance improvements or quantified industrial savings.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and identifies the research gap. Section 3 describes the research methodology, including the system definition, the mathematical and dynamic optimization models, the AI-assisted decision workflow, and the illustrative simulation, evaluation, and validation design. Section 4 presents and discusses the illustrative results and their implications for industrial decision-making, deployment governance, threats to validity, limitations, and opportunities for future research. Section 5 concludes the study.

2. Literature Review and Hypothesis/es Development

2.1 Artificial Intelligence in Energy-Efficient Manufacturing

Artificial intelligence (AI) plays an increasingly important role in manufacturing by improving energy efficiency, production scheduling, process monitoring, and operational decision-making. Machine learning enables the identification of nonlinear relationships between operating conditions and energy consumption, supporting predictive modeling and resource optimization ([Kapp et al., 2023](#); [Narciso & Martins, 2020](#); [Abadi et al., 2025](#)). Digital twin technology further enhances these capabilities through real-time monitoring and predictive analysis ([Billey & Wuest, 2023](#); [Kerrouchi et al., 2024](#); [Risling et al., 2024](#)). However, effective implementation requires reliable data integration, manageable computational complexity, and adaptive modeling to accommodate changing industrial conditions ([Aghazadeh Ardebili et al., 2024](#); [Hafeez et al., 2024](#)).

Energy optimization must also consider equipment reliability, production quality, and operational constraints. Previous studies have integrated energy-saving opportunities into preventive maintenance planning ([Zhou et al., 2020](#)), jointly optimized maintenance, energy efficiency, and quality costs ([Yang et al., 2022](#)), and explored machine learning and knowledge graphs for energy-based maintenance strategies ([Orošnjak, 2025](#)). These findings highlight the importance of integrating energy management with equipment health and production requirements rather than minimizing electricity consumption independently, consistent with ISO 50001 energy-management principles ([International, 2018](#)).

2.2 Predictive Maintenance and Production Quality Control

Predictive maintenance enhances equipment reliability and reduces unplanned downtime by using operational data to anticipate deterioration and optimize maintenance interventions. Digital twin technologies further support predictive maintenance through integrated monitoring, data standardization, and production–maintenance coordination ([Ma et al., 2024](#); [Abd Wahab et al., 2024](#); [Fede et al., 2024](#)). Equipment degradation also affects production quality by influencing process stability and product conformity. [Wei et al. \(2025\)](#) emphasized the importance of integrating production, maintenance, and quality-control decisions to improve manufacturing performance.

Recent studies have examined the joint optimization of condition-based maintenance and product quality under uncertain operating conditions ([Zhang et al., 2026](#)), quality control and maintenance in systems with quality-dependent failures ([J. Wang et al., 2025](#)), and dynamic quality monitoring alongside equipment degradation ([Li et al., 2026](#)). Although these approaches demonstrate the interdependence of equipment reliability and production quality, integrating these factors with energy-related objectives remains challenging. This highlights the need for dynamic multi-objective models that simultaneously capture energy consumption, quality performance, and equipment degradation over time.

2.3 Multi-Objective Optimization and Dynamic Decision-Making

Industrial optimization involves competing objectives, including energy efficiency, production quality, and equipment degradation. Multi-objective optimization addresses these trade-offs by identifying feasible operating strategies through Pareto-based approaches. [Deb, Pratap, Agarwal, and Meyarivan \(2002\)](#) introduced NSGA-II, a widely used algorithm for identifying non-dominated solutions, while [Wang, Li, and Zhao \(2024\)](#) applied multi-objective optimization to predictive maintenance scheduling. Dynamic optimization further supports sequential decision-making by incorporating updated system observations and future operational constraints, as demonstrated through model predictive control ([Rawlings, Mayne, & Diehl, 2017](#)).

Mathematical modeling and numerical optimization have also been applied to industrial engineering, including heat exchanger design ([Sahani, 2022](#); [Sahani, & Sah, 2023a](#)), industrial plant performance assessment ([Sahani, 2022](#); [Sahani, & Sah, 2023b](#)), steel production analysis ([Sahani, Oruganti, Kumar, & Karna, 2025](#); [Sahani, Oruganti, & Kumar, 2025b](#)), and machine learning-based numerical error prediction ([Sahani, 2022](#); [Sahani, Oruganti, & Kumar, 2025c](#)). Collectively, these studies highlight the potential of integrating predictive models, dynamic system representations, and multi-objective optimization. However, ensuring simultaneous compliance with production, quality, and equipment constraints while maintaining transparent trade-off evaluation remains an important methodological challenge.

2.4 Equipment Degradation, Reliability, and Industrial System Modeling

Equipment degradation is an important factor in manufacturing optimization because operating intensity, mechanical stress, thermal exposure, and maintenance practices influence long-term equipment reliability. Previous studies have examined maintenance optimization and operational performance in cement manufacturing ([Sahani et al., 2025c, 2025d](#)), reliability-centered maintenance and statistical reliability modeling ([Sahani et al., 2023a, 2023b](#)), and industrial plant reliability using the Chapman–Kolmogorov differential equation ([Sahani & Sah, 2023a](#)). These approaches emphasize the importance of integrating equipment health and maintenance planning into operational decisions, consistent with ISO 55001 asset management principles ([International, 2024](#)).

Mathematical and numerical methods further support the analysis of complex industrial systems, including woolen knitting dynamics ([Sahani et al., 2025](#)), plastic pipe performance ([Sahani, 2022](#)), AI-enhanced structural analysis ([Sahani et al., 2025](#)), and IoT-based structural health monitoring ([Sahani, 2023a](#)). Additional applications include mechanical vibration analysis ([Sahani et al., 2025](#)), heat conduction modeling ([Sahani, 2023b](#)), and reliability assessment in plywood manufacturing ([Sahani et al., 2025](#)). Collectively, these studies demonstrate the relevance of numerical modeling for representing equipment behavior, assessing reliability, and supporting industrial optimization decisions.

2.5 Research Gap and Theoretical Integration

Previous studies have advanced AI-assisted energy management ([Abadi et al., 2025](#)), digital twin-based predictive maintenance ([Ma et al., 2024](#); [Abd Wahab et al., 2024](#)), and integrated maintenance and quality optimization ([Wei et al., 2025](#); [J. Wang et al., 2025](#); [Zhang et al., 2026](#)). Multi-objective optimization and dynamic decision-making are further supported by the methodological foundations of

[Deb et al. \(2002\)](#), and [Rawlings et al. \(2017\)](#). However, integrating energy costs, production quality, and equipment degradation within a unified dynamic optimization framework remains challenging, particularly in accounting for prediction uncertainty, operational constraints, and transparent policy selection.

This study addresses these challenges by proposing an AI-assisted multi-objective optimization framework that integrates energy-cost prediction, quality assessment, and equipment-degradation modeling through coupled dynamic state equations. The framework incorporates uncertainty-aware feasibility constraints, objective normalization, and Pareto-based policy selection. Its principal novelty lies in explicitly separating predictive modeling, hard-constraint verification, and managerial preference evaluation within an auditable decision-support architecture. A staged validation procedure further supports future empirical implementation, providing a methodological foundation for transparent, reliable, and responsible AI-assisted manufacturing optimization.

3. Research Methodology

This study adopts a mathematical modeling and illustrative simulation approach. The methodology begins with defining the production system and its underlying assumptions, followed by formulating the energy-cost, quality-loss, and degradation objectives alongside coupled state dynamics, AI predictors, uncertainty margins, and operational constraints. The multi-objective optimization model and its uncertainty-aware feasibility conditions are then specified, followed by the development of an AI-assisted receding-horizon workflow and its computational procedure. The methodology also incorporates model identification, calibration, and data-quality requirements, together with illustrative simulation, evaluation, and staged validation procedures. All numerical values used in this study are synthetic and serve to demonstrate the proposed framework rather than represent actual field measurements.

3.1 System Definition and Assumptions

Consider a production asset controlled over intervals $k = 0, 1, \dots, N-1$. The main decision u_k is normalized operating intensity, bounded by $u_{\min}$ and $u_{\max}$. The state includes quality deviation q_k and degradation d_k . Exogenous inputs w_k include electricity price, demand, ambient conditions, material variation, and product mix. A state estimate is updated from sensor and historian data at each decision epoch. Table 1 summarizes the main system variables, their definitions, and the illustrative specifications adopted in this study.

Table 1. Main system variables and illustrative specifications

Symbol	Meaning	Illustrative specification
u_k	Normalized operating intensity	$0.45 \leq u_k \leq 1.00$
q_k	Deviation from target quality	$-0.12 \leq q_k \leq 0.12$
d_k	Normalized degradation / health loss	$0 \leq d_k \leq 0.85$
P_k	Electrical power demand	Nonlinear function of u_k
y_k	Production output during interval k	Must meet cumulative demand
c_k	Electricity price in interval k	Scenario input
m^q_k, m^d_k	Prediction uncertainty margins	Non-negative buffers
N	Number of control intervals	96 for a 24 h, 15 min case

The state variables are normalized for clarity and consistency in the mathematical formulation. In practical applications, the corresponding physical units must be defined, model parameters calibrated, and relationships between normalized values and actual measurements documented. The scalar degradation state represents an aggregate indicator of equipment health rather than a comprehensive model of physical failure mechanisms. Table 2 presents the principal mathematical symbols used in the proposed framework,

together with their definitions, to facilitate interpretation and implementation of the optimization model.

Table 2. Summary of symbols and implementation notes

Symbol	Definition
U	Control sequence $[u_0, \dots, u_{n-1}]$
J_E, J_Q, J_D	Energy/operating cost, quality-loss, and degradation objectives
q_k, d_k	Quality deviation and normalized degradation state
F_Q, F_D	AI state-prediction functions
m_k^q, m_k^d	Uncertainty margins for quality and degradation
Y_{req}	Required cumulative production
w_E, w_Q, w_D	Non-negative preference weights summing to one
r_{max}	Maximum allowed change in operating intensity per interval
$\varepsilon_k^q, \varepsilon_k^d$	Process disturbance / model error terms

3.2 Mathematical Formulation

3.2.1 Power and Energy Cost

Electrical power demand is modeled using a convex nonlinear function that captures increasing energy requirements at higher operating intensities. The mathematical formulation is presented in Formula 1.

$$P_k = P_0 + \alpha u_k + \beta u_k^2 + P_{aux}, \quad \alpha \geq 0, \quad \beta \geq 0 \quad (1)$$

In Formula 1, P_k represents electrical power demand, P_0 denotes baseline power consumption, α and β describe the linear and quadratic effects of operating intensity u_k , and P_{aux} represents auxiliary power demand. The quadratic term reflects the accelerated increase in energy requirements at higher operating intensities.

Total energy and operating costs are calculated by combining electricity expenditure with additional production-related variable costs, as shown in Formula 2.

$$J_E(U) = \sum_{k=0}^{N-1} c_k P_k \Delta t + \sum_{k=0}^{N-1} C_{var}(y_k) \quad (2)$$

In Formula 2, $J_E(U)$ represents total operating costs, c_k denotes the electricity tariff, Δt represents the interval duration, and $C_{var}(y_k)$ accounts for variable costs associated with production output y_k . Electricity costs are calculated by multiplying power demand, interval duration, and the applicable tariff. Additional variable costs should be included only when reliable data are available. Time-varying tariffs may support load shifting, provided that production and equipment constraints remain satisfied.

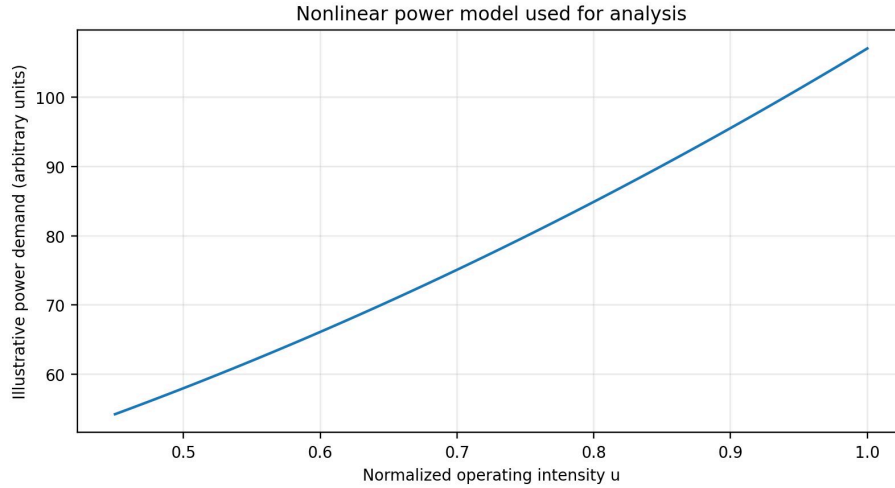


Figure 1. Illustrative nonlinear power curve; values are synthetic and not calibrated to a specific plant

Figure 1 illustrates the nonlinear relationship between normalized operating intensity and electrical power demand. The curve shows that power consumption increases progressively as operating intensity rises, with a steeper increase at higher operating levels. This pattern reflects the quadratic component of the proposed power model, indicating that higher production intensity may lead to disproportionately greater energy requirements.

3.2.2 Quality-Loss Objective

Product quality is evaluated using a quadratic loss function that penalizes deviations from the target quality state ($q^*=0$) and nonconforming production outcomes. The quality-loss objective is formulated in Formula 3.

$$J_Q(U) = \sum_{k=0}^{N-1} w_Q (q_k - q^*)^2 + \rho_Q N_{\text{bad}} \quad (3)$$

In Formula 3, $J_Q(U)$ represents total quality loss, q_k denotes the predicted quality state, w_Q is the quality-deviation weight, N_{bad} represents the number of nonconforming units or intervals, and ρ_Q is the corresponding penalty coefficient. The quadratic term assigns greater penalties to larger deviations, while the nonconformance term accounts for quality failures. This objective should be evaluated alongside defect rates and other relevant quality indicators to ensure comprehensive quality assessment.

3.2.3 Degradation Objective

Equipment degradation is modeled as a cumulative process influenced by operating conditions and equipment health. The degradation objective accounts for progressive wear, deterioration near operational limits, and potential equipment failures, as expressed in Formula 4.

$$J_D(U) = \sum_{k=0}^{N-1} [w_D d_k + r_D \phi(d_k) + C_{\text{fail}} p_{\text{fail}}(d_k, u_k)] \quad (4)$$

In Formula 4, $J_D(U)$ represents the degradation objective, d_k denotes the degradation state, and w_D determines the weight assigned to accumulated wear. The coefficient r_D controls the nonlinear penalty

$\varphi(d_k)$, while C_{fail} and $p_{fail}(d_k, u_k)$ represent the estimated failure cost and probability, respectively. This formulation balances short-term production requirements with long-term equipment reliability. All degradation parameters and failure estimates must be supported by operational data or explicitly identified as scenario assumptions.

3.2.4 Coupled State Dynamics

The relationships among operating intensity, product quality, and equipment degradation are represented using coupled dynamic state equations. These simplified models describe how current operating conditions influence subsequent system states. The quality state transition is formulated in Formula 5.

$$q_{k+1} = q_k - \lambda(q_k - q^*) + \beta_q(d_k - d_0) + \gamma(u_k - u^*)^2 + \varepsilon_k^q \quad (5)$$

In Formula 5, q_{k+1} and q_k represent the subsequent and current quality states, respectively. The parameter λ determines the recovery rate toward the target quality q^* , while β_q describes the influence of degradation relative to the initial state d_0 . The coefficient γ captures deviations from the preferred operating intensity u^* , and ε_k^q represents unmodeled quality disturbances.

Equipment degradation accumulates through operating intensity, electrical power demand, and excessive quality deviations, as expressed in Formula 6.

$$d_{k+1} = d_k + \Delta t \left[au_k^p + bP_k^r + c \max(0, |q_k - q^*| - q_0)^2 \right] + \varepsilon_k^d \quad (6)$$

In Formula 6, d_{k+1} and d_k denote the subsequent and current degradation states. The coefficients a , b , and c represent the effects of operating intensity, power demand, and quality deviations, while p and r determine their nonlinear responses. The parameter q_0 defines the tolerated quality-deviation threshold, Δt represents the interval duration, and ε_k^d captures unmodeled degradation effects.

These coupled equations illustrate how equipment deterioration and unstable operating conditions may influence product quality and accelerate degradation. All model parameters must be calibrated using equipment-specific operational data, while disturbance terms account for uncertainties affecting predicted system states.

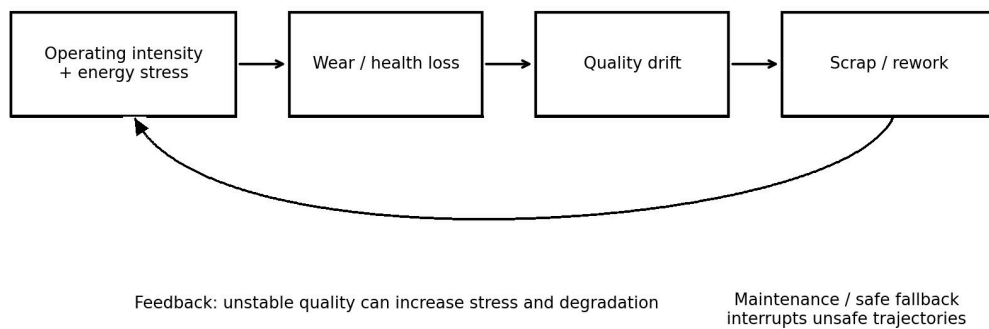


Figure 2. Conceptual feedback path linking operating stress, degradation, quality drift, and rework. The diagram is explanatory.

Figure 2 illustrates the conceptual feedback mechanism linking operating intensity, equipment degradation, product quality deviation, and production losses. Increased operating intensity and energy-related stress contribute to equipment wear, which may lead to quality deterioration and higher scrap or rework requirements. The feedback mechanism further indicates that unstable product quality

can increase operational stress and accelerate degradation, while maintenance interventions and safe fallback strategies can interrupt potentially unsafe operating conditions.

3.2.5 AI Predictors and Uncertainty Margins

Artificial intelligence (AI) predictors estimate future product quality and equipment degradation using operational data, including sensor measurements, operating conditions, maintenance history, and previous state estimates. The prediction functions are formulated in Formula 7.

$$\hat{q}_{k+1} = F_Q(z_k, u_k, \hat{d}_k), \quad \hat{d}_{k+1} = F_D(z_k, u_k, \hat{d}_k) \quad (7)$$

In Formula 7, F_Q and F_D represent the quality and degradation prediction functions, respectively. These models may employ gradient-boosted trees, temporal neural networks, Gaussian processes, or calibrated ensembles (Goodfellow et al., 2016). Model selection should consider predictive accuracy, interpretability, computational efficiency, and time-ordered validation.

To account for prediction uncertainty, conservative margins are incorporated into operational feasibility constraints, as expressed in Formula 8.

$$|\hat{q}_k - q^*| + m_k^q \leq q_{\max}, \quad \hat{d}_k + m_k^d \leq d_{\max} \quad (8)$$

In Formula 8, m_k^q and m_k^d represent uncertainty margins for quality deviation and equipment degradation, while $q_{\max}$ and $d_{\max}$ define their permissible limits. Larger margins produce more conservative operating policies. These margins should be calibrated using independent validation data and updated when operating conditions, sensor performance, or model accuracy change.

3.2.6 Hard Constraints and Production Feasibility

Operational constraints ensure that optimization strategies satisfy production, quality, and equipment safety requirements independently of objective preference weights. The operating intensity, degradation, and quality constraints are formulated in Formula 9.

$$u_{\min} \leq u_k \leq u_{\max}, \quad d_k \leq d_{\max}, \quad |q_k - q^*| \leq q_{\max} \quad (9)$$

In Formula 9, $u_{\min}$ and $u_{\max}$ define the permissible operating intensity range, while $d_{\max}$ and $q_{\max}$ represent the maximum allowable degradation and quality deviation, respectively.

Production requirements and operating stability are maintained through additional constraints, as expressed in Formula 10.

$$\sum_{k=0}^{N-1} y_k \geq Y_{\text{req}}, \quad |u_k - u_{k-1}| \leq r_{\max} \quad (10)$$

In Formula 10, Y_{req} represents minimum cumulative production demand, while $r_{\max}$ limits changes in operating intensity between consecutive intervals. Production output is modeled as $y_k = G(u_k, w_k)$, which requires calibration using operational data. Candidate policies that violate these constraints are excluded from optimization. Independent safety interlocks and equipment

protection systems remain mandatory and cannot be overridden by the proposed decision-support framework.

3.2.7 Multi-Objective Problem and Pareto Dominance

The proposed optimization framework integrates energy and operating costs, product quality loss, and equipment degradation into a unified multi-objective model. The optimization problem is formulated in Formula 11.

$$\min_U \mathbf{J}(U) = [J_E(U), J_Q(U), J_D(U)] \quad (11)$$

In Formula 11, $U = (u_0, u_1, \dots, u_{n-1})$ represents the sequence of operating decisions, while $J_E(U)$, $J_Q(U)$, and $J_D(U)$ denote the energy-cost, quality-loss, and degradation objectives, respectively.

The optimization seeks feasible policies that minimize these competing objectives while satisfying dynamic state equations, operational constraints, and production requirements. Pareto dominance is used to identify non-dominated solutions, where no objective can be improved without worsening at least one other objective. The resulting Pareto front illustrates the trade-offs among energy efficiency, product quality, and equipment reliability, supporting transparent policy selection based on managerial priorities.

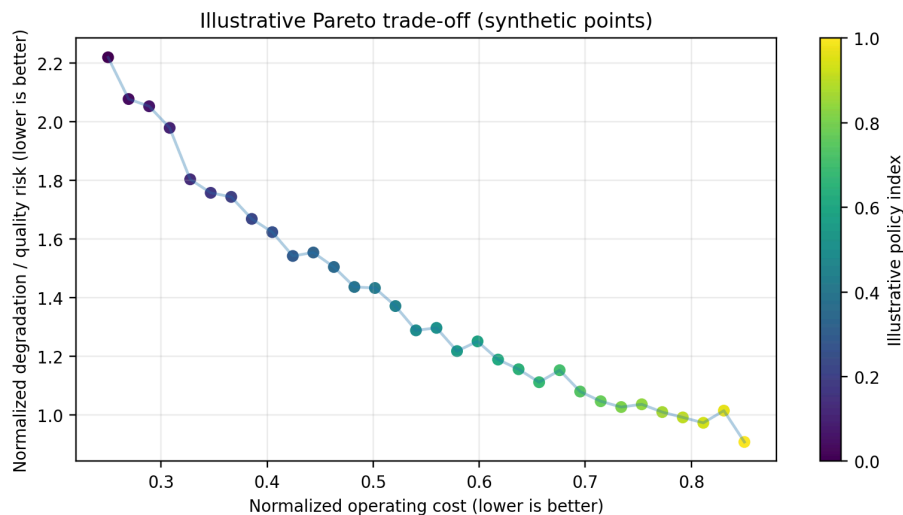


Figure 3. Illustrative Pareto trade-off using synthetic points. It is not an empirical result or the output of a calibrated factory model.

Figure 3 illustrates the Pareto trade-offs between normalized operating costs and equipment degradation or quality-related risks using synthetic data points. The downward trend indicates that lower operating costs are generally associated with higher degradation or quality risks, while reducing these risks may require increased operating expenditure. The distribution of non-dominated solutions highlights the competing nature of the optimization objectives and demonstrates how Pareto-based analysis can support the selection of operating policies that balance economic efficiency, product quality, and equipment reliability. These results are illustrative and do not represent empirical industrial measurements.

3.2.8 Normalization and Final Policy Selection

The optimization objectives have different units and scales, requiring normalization before calculating an aggregate decision score. Each objective is transformed into a dimensionless value using its minimum and maximum reference values, as shown in Formula 12.

$$J_i^N = \frac{J_i - J_i^{\min}}{J_i^{\max} - J_i^{\min}}, \quad i \in \{E, Q, D\} \quad (12)$$

In Formula 12, J_i represents the objective value, $J_i^{\min}$ and $J_i^{\max}$ denote its reference limits, and J_i^N is the normalized value. Numerical safeguards are required when the reference range approaches zero.

The normalized objectives are combined using a weighted scoring function to select a preferred policy from the feasible Pareto-optimal alternatives, as expressed in Formula 13.

$$S(U) = w_E J_E^N + w_Q J_Q^N + w_D J_D^N, \quad w_E + w_Q + w_D = 1 \quad (13)$$

In Formula 13, $S(U)$ represents the aggregate decision score, while w_E , w_Q , and w_D denote nonnegative preference weights for energy costs, quality loss, and equipment degradation, respectively. These weights reflect managerial priorities rather than monetary conversion factors.

Final policy selection involves excluding infeasible alternatives, identifying the Pareto-optimal set, and applying a documented decision rule, such as knee-point selection or stakeholder-approved weights. This approach ensures transparent trade-offs while maintaining operational and safety constraints.

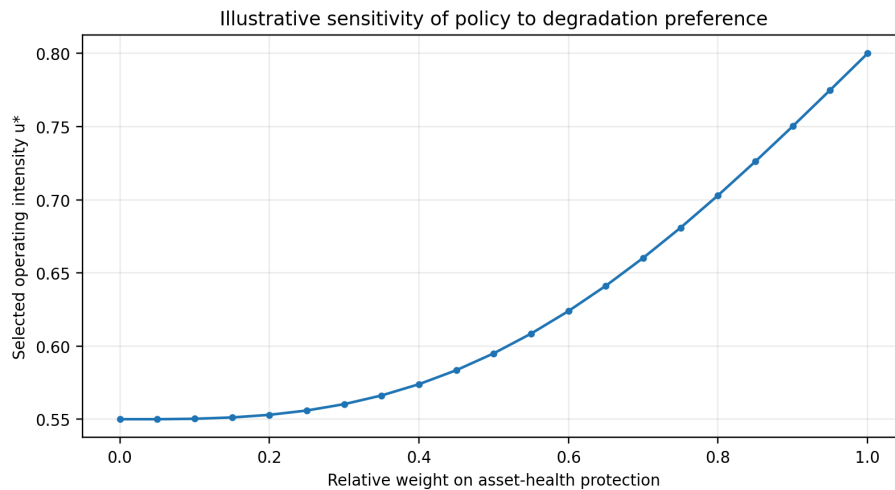


Figure 4. Illustrative sensitivity of the selected intensity to asset-health preference. The curve is schematic.

Figure 4 illustrates the sensitivity of the selected operating intensity to changes in the relative weight assigned to equipment degradation protection. The curve shows that operating intensity increases gradually as the preference for asset-health protection becomes stronger, rising from approximately 0.55 to 0.80. This nonlinear relationship demonstrates how changes in managerial preferences can influence the selection of operating policies within the proposed multi-objective optimization framework. The results are illustrative and based on synthetic data rather than empirical industrial measurements.

3.3 Formal Optimization Model and Mathematical Properties

The optimization problem is formulated over N intervals, indexed by $k = 0, \dots, N-1$. The decision vector $x_k = [u_k, y_k, m_k]^T$ represents operating intensity, production quantity, and maintenance decisions, while the state vector $s_k = [q_k, d_k, r_k]^T$ describes quality deviation, equipment degradation, and production backlog. The complete decision sequence is denoted by $X = \{x_0, \dots, x_{N-1}\}$.

The dynamic model accounts for how current operating decisions affect future energy costs, product quality, equipment condition, and production requirements. The corresponding state transition is presented in Formula 14.

$$s_{k+1} = f(s_k, x_k, z_k; \theta) + w_k, \quad k = 0, \dots, N - 1 \quad (14)$$

In Formula 14, z_k represents contextual operating conditions, θ denotes calibrated model parameters, and w_k captures process disturbances and model mismatch. The transition function f integrates physical relationships and AI-based predictions to represent system dynamics. Practical implementation requires equipment-specific calibration, uncertainty assessment, and continuous operational monitoring.

3.3.1 Energy Objective Derived from Power and Tariff

Electrical energy consumption is calculated by multiplying power demand by the sampling interval, expressed as $E_k \approx P_k \Delta t$. When power is measured in kilowatts and time in hours, electricity costs are determined using the applicable tariff. The relationship between power demand and operating intensity is formulated in Formula 15.

$$P_k = P_0 + \alpha u_k + \beta u_k^2 + \gamma^T z_k, \quad \beta \geq 0 \quad (15)$$

In Formula 15, P_k represents electrical power demand, P_0 denotes baseline power, α and β describe the linear and quadratic effects of operating intensity u_k , and $\gamma^T z_k$ captures contextual operating loads.

Total energy and operating costs, including applicable start-up and idle-state costs, are calculated using Formula 16.

$$J_E(X) = \sum_{k=0}^{N-1} [c_k P_k \Delta t + C_{\text{start}} a_k + C_{\text{idle}} i_k] \quad (16)$$

In Formula 16, $J_E(X)$ represents total operating costs, c_k denotes the electricity tariff, and C_{start} and C_{idle} represent start-up and idle-state costs. The binary variables a_k and i_k indicate the corresponding operating states. These costs should be included only when supported by operational data, using the applicable tariff for each interval.

Specific energy consumption (SEC) measures energy use per expected accepted production unit, as expressed in Formula 17.

$$SEC = \frac{\sum_k P_k \Delta t}{\max(\varepsilon, \sum_k y_k (1 - p_k^{\text{def}}))} \quad (17)$$

In Formula 17, y_k represents production output, p_k^{def} denotes the estimated defect probability, and ε prevents division by zero. SEC supports comparisons across operating strategies, although accurate assessments should also consider first-pass yield, rework energy, and scrap-related costs.

3.3.2 Expected Quality Loss and Asymmetric Penalties

Product quality is evaluated by considering deviations from target specifications and the economic consequences of defective products. The model incorporates expected losses associated with scrap, rework, and warranty claims, as expressed in Formula 18.

$$L_{Q,k} = w_e e_k^2 + C_{\text{scrap}} p_k^{\text{def}} + C_{\text{rework}} p_k^{\text{rw}} + C_{\text{warranty}} p_k^w \quad (18)$$

In Formula 18, $L_{Q,k}$ represents the expected quality loss per unit, while w_e and e_k denote the deviation weight and predicted quality deviation. The parameters C_{scrap} , C_{rework} , and C_{warranty} represent the corresponding costs, while p_k^{def} , p_k^{rw} , and p_k^w indicate their estimated probabilities.

Total expected quality loss is calculated by multiplying unit-level losses by production output across the planning horizon, as shown in Formula 19.

$$J_Q(X) = \sum_{k=0}^{N-1} y_k L_{Q,k} \quad (19)$$

The variable $J_Q(X)$ represents total expected quality loss, while y_k denotes production quantity during interval k . Probability estimates should be calibrated using inspection data, considering class imbalance and evaluating precision, recall, calibration error, and false-negative costs. For continuous quality measurements, prediction errors and the probability of exceeding specification limits should also be assessed.

3.3.3 Degradation, Reliability, and Maintenance Cost

Equipment degradation is represented by a normalized state d_k ranging from 0 to 1, where higher values indicate poorer equipment health. The model considers operating intensity, temperature, vibration, and quality deviations to estimate future degradation, as formulated in Formula 20.

$$d_{k+1} = \text{clip} [d_k + \Delta t (a_0 + a_1 u_k^p + a_2 T_k + a_3 v_k + a_4 |e_k|), 0, 1] \quad (20)$$

In Formula 20, a_0 – a_4 represent degradation coefficients, p denotes the nonlinear operating-intensity exponent, and Δt represents the interval duration. The clipping function maintains the normalized degradation range, while model parameters require calibration using operational data. Partial maintenance recovery may also be incorporated based on maintenance effectiveness.

Equipment reliability is assessed using Weibull survival and hazard functions, as expressed in Formula 21.

$$R(t) = \exp \left[- \left(\frac{t}{\eta_W} \right)^\kappa \right], \quad h(t) = \frac{\kappa}{\eta_W} \left(\frac{t}{\eta_W} \right)^{\kappa-1} \quad (21)$$

In Formula 21, $R(t)$ represents equipment reliability, $h(t)$ denotes the failure hazard rate, η_W is the scale parameter, and κ is the shape parameter. The Weibull model should be validated against historical failure data before application.

The degradation objective integrates equipment wear, preventive maintenance costs, and expected failure consequences, as presented in Formula 22.

$$J_D(X) = \sum_{k=0}^{N-1} [C_{\text{wear}} \Delta d_k + C_{\text{pm}} m_k + C_{\text{fail}} p_k^{\text{fail}} C_{\text{conseq}}] \quad (22)$$

In Formula 22, $J_D(X)$ represents total degradation-related costs, C_{wear} denotes the wear-cost coefficient, Δd_k represents incremental degradation, C_{pm} is the preventive maintenance cost, and m_k indicates maintenance decisions. The term $C_{\text{fail}} p_k^{\text{fail}} C_{\text{conseq}}$ represents the modeled failure-related cost contribution. Cost components must be consistently defined to prevent double counting and ensure reliable economic evaluation.

3.3.4 Constraints, Feasibility, and Safety Hierarchy

The feasible set consists of operating trajectories that satisfy physical, quality, maintenance, and production requirements. Hard constraints must be enforced independently of optimization preferences to prevent cost reductions from compromising operational safety or product quality.

$$u_{\min} \leq u_k \leq u_{\max}, \quad |u_k - u_{k-1}| \leq r_{\max} \quad (23)$$

In Formula 23, $u_{\min}$ and $u_{\max}$ define the permissible operating intensity range, while $r_{\max}$ limits changes between consecutive intervals to prevent operational instability.

$$d_k \leq d_{\max}, \quad |e_k| \leq e_{\max}, \quad \sum_k y_k \geq Y_{\text{req}} \quad (24)$$

In Formula 24, $d_{\max}$ and $e_{\max}$ represent the maximum allowable degradation and quality deviation, respectively, while Y_{req} denotes minimum cumulative production demand.

$$g_j(s_k, x_k, z_k) \leq 0, \quad j = 1, \dots, M \quad (25)$$

In Formula 25, g_j represents the j -th operational constraint, while s_k , x_k , and z_k denote system states, decision variables, and contextual inputs, respectively. These constraints may include equipment temperature, pressure, electrical limits, staffing, and maintenance availability. All constraints must use consistent measurement units and sampling intervals, and infeasible operating strategies must be excluded from further optimization.

3.3.5 Pareto Optimality and Preference Selection

The three optimization objectives, comprising energy costs, quality loss, and equipment degradation, are evaluated as a vector to preserve their competing characteristics. The multi-objective optimization problem is formulated in Formula 26.

$$\min_X \mathbf{F}(X) = [J_E(X), J_Q(X), J_D(X)]^T, \quad \text{subject to } X \in \Omega \quad (26)$$

$$X \prec X' \iff J_i(X) \leq J_i(X') \quad \forall i, \quad \text{and} \quad J_j(X) < J_j(X') \quad \text{for some } j \quad (27)$$

Formula 27 indicates that policy X dominates X' when it performs no worse across all objectives and strictly better in at least one. Non-dominated policies form the Pareto set, providing alternative trade-offs for decision-making.

$$J_i^N = \frac{J_i - J_i^{\text{ref},\min}}{J_i^{\text{ref},\max} - J_i^{\text{ref},\min} + \varepsilon} \quad (28)$$

In Formula 28, J_i^N represents the normalized objective value, $J_i^{\text{ref},\min}$ and $J_i^{\text{ref},\max}$ denote reference limits, and ε prevents division by zero.

$$S(X) = w_E J_E^N + w_Q J_Q^N + w_D J_D^N, \quad w_E + w_Q + w_D = 1 \quad (29)$$

In Formula 29, $S(X)$ represents the aggregate decision score, while w_E , w_Q , and w_D are nonnegative weights reflecting managerial priorities. Weight sensitivity should be assessed, and alternative methods, such as ε -constraint or evolutionary optimization, may be applied to explore non-convex Pareto solutions.

3.4 Uncertainty-Aware Prediction and Robust Feasibility

Industrial measurements are affected by sensor noise, missing data, model drift, and operational disturbances. AI-based predictions must therefore incorporate uncertainty estimates to prevent operating decisions from violating quality and equipment safety limits. The probabilistic feasibility constraints are formulated in Formula 30.

$$|\mu_k| + z_{1-\delta/2} \sigma_k \leq e_{\max}, \quad \mu_{d,k} + z_{1-\delta} \sigma_{d,k} \leq d_{\max} \quad (30)$$

In Formula 30, μ_k and $\mu_{d,k}$ represent predicted quality deviation and degradation, while σ_k and $\sigma_{d,k}$ denote their uncertainties. The parameter δ determines the confidence level, and $e_{\max}$ and $d_{\max}$ represent permissible limits. These constraints assume calibrated predictive distributions, with empirical alternatives required when normality assumptions are unsuitable.

Robust feasibility can also be evaluated by requiring operational constraints to remain satisfied under all disturbances within a predefined uncertainty set, as expressed in Formula 31.

$$g_j(s_k, x_k, z_k, w) \leq 0, \quad \text{for all } w \in W_k \quad (31)$$

In Formula 31, g_j represents an operational constraint, while W_k denotes the uncertainty set. Its boundaries must be calibrated to balance operational safety and excessive conservatism.

Risk-sensitive policy selection may additionally incorporate conditional value at risk (CVaR) to account for severe potential losses, as formulated in Formula 32.

$$\text{CVaR}_\alpha(L) = \min_{\zeta} \left\{ \zeta + \frac{1}{1-\alpha} \mathbb{E} [(L - \zeta)^+] \right\} \quad (32)$$

In Formula 32, $\text{CVaR}_\alpha(L)$ represents the expected loss in the worst $(1-\alpha)$ proportion of outcomes, α denotes the confidence level, and ζ is an optimization threshold. The uncertainty-management process requires continuous calibration, drift monitoring, and periodic model updates. When uncertainty exceeds acceptable limits or sensor reliability deteriorates, the system should adopt a validated conservative operating policy rather than rely on uncertain predictions.

3.5 AI-Assisted Optimization Workflow

The architecture separates data quality, prediction, dynamic feasibility, optimization, and execution. Candidate controls are simulated over a rolling horizon. Only the first action of the selected feasible policy is proposed; after new measurements arrive, the state is re-estimated and the horizon is solved again. This receding-horizon procedure limits reliance on a long-range forecast.

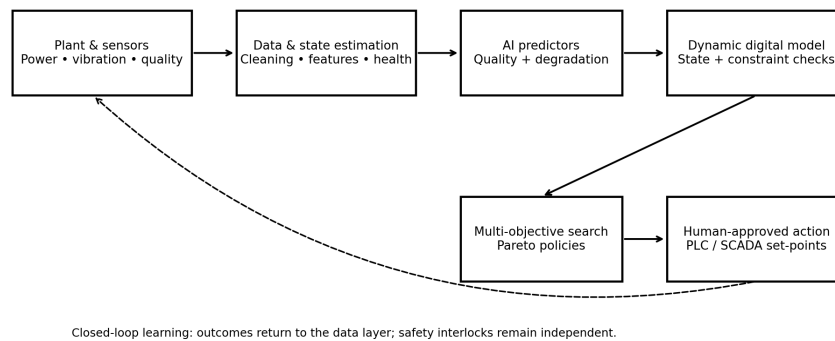


Figure 5. Proposed architecture connecting sensors, learned predictions, dynamic validation, Pareto search, and supervised execution.

Figure 5 illustrates the proposed AI-assisted optimization framework, integrating sensor data, state estimation, AI-based predictions, dynamic feasibility assessment, and Pareto-based policy selection. The framework incorporates human-approved control decisions and closed-loop feedback while maintaining independent safety mechanisms.

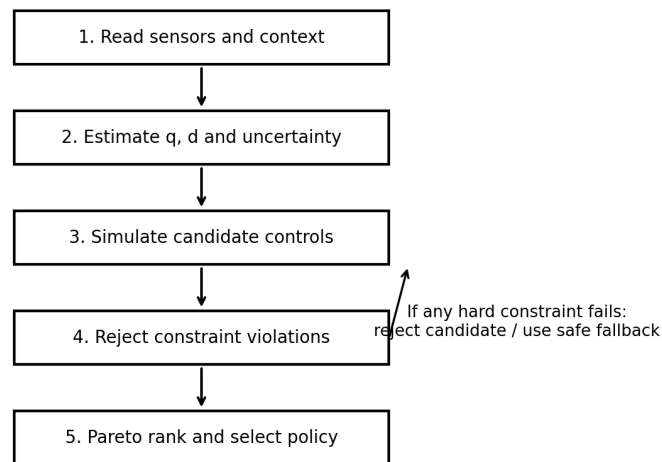


Figure 6. Operational workflow. Any candidate violating a hard constraint is rejected before preference-based ranking.

Figure 6 illustrates the AI-assisted optimization workflow, which includes sensor data acquisition, state and uncertainty estimation, candidate control simulation, constraint verification, and Pareto-based policy selection. Candidate policies that violate hard constraints are rejected or replaced with a validated safe fallback strategy.

3.5.1 Receding-Horizon Procedure

Table 3. Receding-horizon procedure and required safeguards

Step	Operation	Required output / safeguard
1	Acquire and validate sensor, price, demand, and quality data	Timestamp checks, missingness and sensor-range flags
2	Estimate current quality and degradation states	State estimate plus confidence / uncertainty margins
3	Generate candidate control sequences	Bounded operating intensity and ramp-rate feasibility
4	Predict and propagate each candidate	Quality, degradation, power, and production trajectories
5	Reject infeasible candidates	Hard constraints checked before objective ranking
6	Generate non-dominated feasible policies	Pareto set with objective values and active constraints
7	Select and review one policy	Knee point or documented weights; human approval where required
8	Apply first action and observe outcome	Log action, model versions, override, and realized result

Table 3 summarizes the eight stages of the receding-horizon optimization procedure, including data acquisition, state estimation, candidate control generation, feasibility assessment, Pareto-based policy selection, and implementation. Each stage incorporates specific safeguards to ensure operational reliability, constraint compliance, and transparent decision-making.

3.5.2 Optimization Algorithm Choices

NSGA-II is one possible evolutionary search method for nonlinear, non-convex objectives (Deb, Pratap, Agarwal, & Meyarivan, 2002). For a small continuous system, a constrained nonlinear solver

may be more efficient; for discrete maintenance and scheduling decisions, mixed-integer or hierarchical formulations may be needed. Algorithm choice should be based on feasibility rate, runtime, Pareto diversity, and repeatability not novelty alone.

3.6 Computational Procedure and Implementation Detail

The proposed framework applies receding-horizon control, continuously updating operating decisions using sensor data, production requirements, and system-state estimates. Candidate control sequences are evaluated against operational constraints, while feasible alternatives are optimized using deterministic methods or NSGA-II (Deb, Pratap, Agarwal, & Meyarivan, 2002). Only the first action is implemented before optimization is repeated with updated observations.

The procedure includes data validation, state and uncertainty estimation, candidate evaluation, feasibility screening, and Pareto-based policy selection. Selected actions undergo independent safety verification and operator approval when required. A validated fallback policy is activated when data or model reliability is insufficient, while operational decisions and outcomes are recorded for reproducibility.

Computational complexity depends on population size (M), generations (G), planning horizon (N), and model evaluation cost (C_f), with an approximate prediction complexity of $O(MGNC_f)$. Real-time implementation requires total computation time to remain within the control deadline, as formulated in Formula 33.

$$T_{\text{solve}} \approx T_{\text{state}} + T_{\text{predict}} + T_{\text{search}} + T_{\text{verify}} < T_{\text{deadline}} \quad (33)$$

In Equation (20), T_{solve} represents total computation time, including state estimation, prediction, optimization, and verification, while T_{deadline} denotes the maximum allowable processing time. If the deadline is exceeded, the system must apply a previously validated action or activate a safe fallback policy. Such events should be documented to evaluate operational reliability.

3.7 Model Identification, Calibration, and Data Quality

The reliability of the proposed framework depends on data quality, accurate calibration, and consistent monitoring. Data from energy meters, process sensors, quality inspections, production records, and maintenance logs must be synchronized and validated to identify missing values, sensor drift, and measurement inconsistencies.

State estimation is essential because equipment degradation cannot always be measured directly. Equipment health may be estimated using vibration, temperature, maintenance history, and remaining-useful-life indicators, with validation against independent inspection records to prevent data leakage.

Model calibration should use representative operational data, with separate datasets for parameter estimation and validation. Energy, quality, and degradation models must be calibrated within their intended operating ranges, while changes in production conditions, equipment characteristics, and sensor performance should trigger model reassessment.

Table 4. Data provenance and quality-control plan for implementation

Data Stream	Example Fields	Quality Checks	How it Enters the Model
Energy meter	kW, kWh, timestamp, meter ID	Units, gaps, impossible spikes, calibration date	Power curve and energy-cost objective
Process telemetry	speed, pressure, temperature, vibration	Range checks, sensor drift, synchronization	State transition and degradation predictors

Data Stream	Example Fields	Quality Checks	How it Enters the Model
Quality inspection	measured dimension, pass/fail, defect code	Inspection bias, missing labels, class imbalance	Quality-loss objective and constraint
Production record	SKU, batch, accepted units, scrap, rework	Duplicate records, yield reconciliation	Demand feasibility and unit-cost calculations
Maintenance log	work order, failure mode, duration, parts	Event coding, right-censoring, intervention timing	Reliability, maintenance cost, health reset

Table 4 summarizes the required data sources, key quality-control procedures, and their roles in developing and validating the proposed optimization framework. Continuous monitoring, version-controlled datasets, and documented recalibration procedures are necessary to maintain prediction reliability and ensure safe industrial implementation.

3.8 Illustrative Simulation Design

The example design uses a 24-hour horizon with 15-minute intervals ($N=96$). Operating intensity is bounded between 0.45 and 1.00. The initial degradation state is $d_0=0.18$, the illustrative maximum is $d_{\max}=0.85$, and quality must remain within ± 0.12 normalized units. Electricity price and demand vary by interval. These values are modelling assumptions for demonstration and must not be interpreted as factory measurements.

Table 5. Illustrative simulation design and evidence status

Item	Specification	Evidence status
Horizon	24 h; 96 intervals of 15 min	Design assumption
Initial degradation	$d_0 = 0.18$	Synthetic starting state
Quality target / band	$q^* = 0; q \leq 0.12$	Normalized assumption
Operating intensity	0.45–1.00	Decision bounds
Power function	$P_o + \alpha u + \beta u^2 + P_{aux}$	Parameterized surrogate
AI uncertainty	Margins m^p and m^d	Robustness mechanism
Production	$\sum y_k \geq Y_{req}$	Same target across strategies
Evaluation	Cost, quality loss, degradation, feasibility, output	Simulation metrics

Table 5 summarizes the illustrative simulation design, including the planning horizon, operating intensity limits, initial degradation state, quality constraints, and production requirements. The table also identifies the evidence status of each parameter, emphasizing that the specified values are synthetic assumptions used to demonstrate the proposed optimization framework rather than actual industrial measurements.

3.9 Evaluation Design and Results Reporting

A reliable comparison of operating strategies requires consistent external conditions, planning horizons, and production targets. The evaluation considers cost-only optimization (S1), cost and quality optimization (S2), cost and degradation optimization (S3), and integrated multi-objective optimization (S4), using actual operating practices as the reference baseline. Each strategy is assessed based on its simulated outcomes rather than predicted objective values alone. Table 6 summarizes the evaluation metrics, calculation methods, and interpretation criteria used to compare these strategies.

Table 6. Evaluation metrics for comparing operating strategies

Metric	Definition/Calculation	Interpretation
Operating cost	$\sum c_k P_k \Delta t$ plus explicitly modelled variable costs	Lower is preferred, if output is comparable

Metric	Definition/Calculation	Interpretation
Quality loss	$\Sigma(q_k - q^*)^2$ and observed / simulated defect count	Lower loss and fewer violations preferred
Final degradation	d_N ; also report maximum d_k	Lower is preferred, subject to output
Constraint violations	Count of quality, health, and control-limit breaches	Target is zero for hard constraints
Production attainment	$\Sigma y_k / Y_{\text{req}}$	Must be ≥ 1.0
Decision regret	$J(\text{realized action}) - J(\text{perfect-information benchmark})$	Lower indicates less cost from imperfect decisions
Runtime	Wall-clock solve time per decision epoch	Must meet control-cycle deadline

The illustrative comparison in this study should not be interpreted as measured savings. In particular, a comparison table is valid only if the units, normalization, production index, and constraint-violation counts are defined consistently. If a strategy reports lower cost but also lower production than the requirement, it is infeasible and must not be ranked as a successful saving. This revised framework therefore prioritizes feasibility and matched-output comparison before reporting economic differences.

3.9.1 Reporting Numerical Findings Responsibly

For a simulation-only paper, report the parameter values, equations, random seeds, optimization settings, and whether plotted points are generated by the same code used for the table. For a field study, additionally report sample period, plant type, measurement units, missing-data treatment, calibration/test separation, uncertainty intervals, and a defensible baseline. Do not describe illustrative curves as experimental validation.

3.9.2 Sensitivity and Stress Testing

Vary the relative penalty on quality and degradation, energy-price profiles, demand peaks, degradation-rate coefficients, and uncertainty margins. Stress scenarios should include high demand, elevated initial wear, sudden quality drift, missing sensors, and model residual shifts. A robust policy should fail gracefully, preserve hard constraints, and switch to a safe fallback when confidence is insufficient.

3.10 Experimental Design, Baselines, and Statistical Evaluation

The proposed framework should be evaluated against five strategies, including a fixed-rule policy, energy-only optimization, optimization without a learned quality predictor, optimization without degradation feedback, and the complete multi-objective framework. To ensure fair comparisons, all strategies should use identical demand profiles, electricity tariffs, initial equipment conditions, disturbances, and operational constraints.

Model validation should employ chronological data splitting to prevent temporal leakage, with earlier observations used for training, subsequent data for validation, and a final hold-out period for testing. When multiple machines or production lines are available, additional asset-level validation should be conducted to assess model generalizability and transferability.

Table 7. Recommended evaluation metrics for prediction, optimization, and operations

Evaluation Dimension	Metric	Definition/Interpretation	Reporting Caution
Energy prediction	MAE	Mean absolute error between measured and predicted energy	Report in engineering units and by operating regime

Evaluation Dimension	Metric	Definition/Interpretation	Reporting Caution
Energy prediction	RMSE	Square root of mean squared prediction error	Highlights large errors; sensitive to outliers
Quality prediction	Precision / recall	Correct defect detections among predicted/actual defects	Use for imbalanced defect labels
Probability calibration	Brier score	Mean squared error of predicted event probabilities	Lower is better; check reliability plots
Optimization quality	Hypervolume	Volume dominated by an approximation to the Pareto front	Use a fixed reference point for fair comparison
Constraint safety	Violation rate	Fraction of intervals or trajectories violating hard limits	Report severity as well as frequency
Operational value	Accepted output / energy	Accepted units per unit energy consumed	Also report total accepted output and downtime
Maintenance value	Unplanned downtime	Time lost to unplanned failure or repair	Normalize by observation duration and exposure

Table 7 summarizes the recommended evaluation metrics for assessing prediction accuracy, optimization performance, operational efficiency, and equipment reliability. These metrics provide a comprehensive basis for evaluating the proposed framework while emphasizing consistent measurement, constraint compliance, and transparent reporting.

Prediction accuracy is evaluated using mean absolute error (MAE) and root mean squared error (RMSE), which measure average prediction errors and sensitivity to larger deviations, respectively. Both metrics are formulated in Formula 34.

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|, \quad \text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (34)$$

In Formula 34, y_i represents the observed value, $\hat{y}_i$ denotes the predicted value, and n is the number of observations. Lower values indicate better prediction accuracy.

For defect classification, precision and recall are calculated using Formula 35.

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN} \quad (35)$$

In Equation (35), TP , FP , and FN represent true positives, false positives, and false negatives, respectively. Precision measures the proportion of correct defect alerts, while recall indicates the proportion of actual defects successfully identified. Both metrics should be complemented by probability calibration and cost-sensitive evaluation.

Multi-objective optimization performance is assessed using hypervolume, inverted generational distance, constraint feasibility, solution diversity, and computational efficiency. When the true Pareto front is unavailable, an approximate reference front should be explicitly identified. Stochastic optimization methods should be evaluated across repeated runs, reporting median performance, interquartile ranges, and paired comparisons using identical scenario seeds. Confidence intervals should account for temporal or asset-level dependencies to ensure statistically reliable comparisons.

3.10.1 Ablation Study and Falsifiable Hypotheses

An ablation study removes one component at a time while holding the remaining design fixed. Removing the degradation predictor tests whether health feedback changes decisions; removing uncertainty margins tests whether nominal optimization increases constraint violations; removing the Pareto stage tests whether scalarization hides useful alternatives; and removing the dynamic state model tests whether static predictions miss delayed consequences. A strong paper should state the expected direction of each effect before looking at the results and report null or adverse findings honestly.

Table 8. Falsifiable hypotheses and corresponding evaluation evidence

Hypothesis	Comparison	Primary Outcome	Evidence that Would Weaken the Hypothesis
H_1 : Joint optimization improves trade-off quality	Full framework vs energy-only baseline	Quality/health at comparable accepted output	No improvement in either quality or health at matched output
H_2 : State feedback improves long-horizon decisions	Dynamic vs static optimization	Cumulative cost and terminal degradation	Similar or worse outcomes under repeated scenarios
H_3 : Uncertainty margins reduce unsafe actions	Robust vs nominal constraints	Hard-constraint violation rate	No reduction after calibration, or excessive infeasibility
H_4 : Pareto selection improves transparency	Pareto set vs single weighted run	Decision stability under weight changes	No meaningful alternative trade-offs or unstable front

Table 8 presents four falsifiable hypotheses used to evaluate the contributions of joint optimization, dynamic state feedback, uncertainty margins, and Pareto-based policy selection. Each hypothesis is linked to a specific comparison, primary evaluation outcome, and evidence that could challenge its validity, providing a systematic basis for assessing the proposed framework.

3.11 Validation Roadmap and Reproducibility

Table 9. Staged validation roadmap and exit criteria

Phase	Method	Exit Criteria
1. Historical replay	Run decisions against time-ordered archived data without plant control	Baseline reproduced; no data leakage; constraints evaluated
2. Shadow mode	Generate live recommendations while existing control remains active	Recommendations logged; drift and feasibility monitored
3. Constrained pilot	Use a bounded asset and human approval	Quality, safety, output, and runtime requirements met
4. Scale-up	Expand after independent review	Governance, cybersecurity, and maintenance integration approved

Based on Table 9, the proposed framework follows a four-stage validation roadmap comprising historical replay, shadow-mode testing, constrained pilot implementation, and operational scale-up. Each phase establishes specific exit criteria to ensure data integrity, model reliability, operational safety, and implementation readiness. Reproducibility is supported through documented model parameters, preprocessing procedures, optimization settings, and evaluation results.

The reproducibility package should include state equations, parameter ranges and units, data dictionary, preprocessing steps, training/test time windows, random seeds, optimizer version and settings, objective normalization ranges, constraint definitions, and scripts used to create all figures and tables. If data are confidential, anonymized aggregate results and a synthetic benchmark can still support methodological scrutiny.

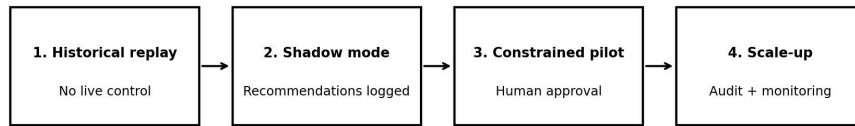


Figure 7. Staged validation from historical replay to controlled pilot and scale-up

Figure 7 illustrates the four-stage validation roadmap for implementing the proposed AI-assisted optimization framework, comprising historical replay, shadow-mode testing, constrained pilot implementation, and operational scale-up. This sequential approach emphasizes controlled testing, human oversight, and continuous monitoring to ensure system reliability, operational safety, and deployment readiness.

4. Results and Discussions

4.1 Illustrative Simulation Results

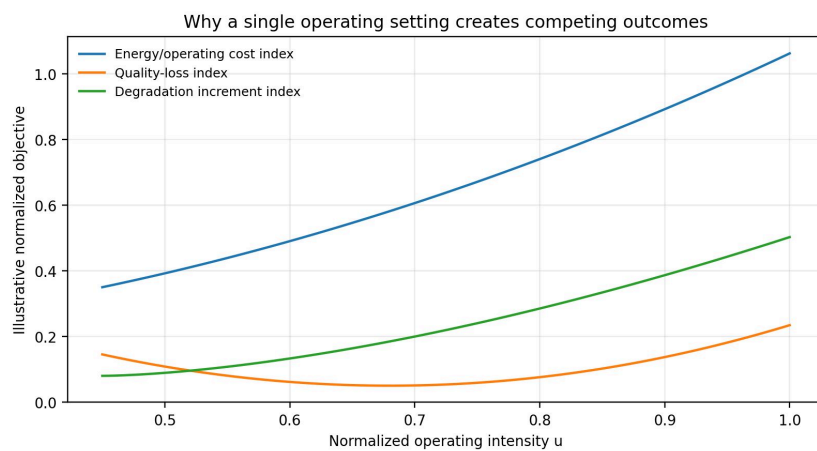


Figure 8. Illustrative competing objective trends as operating intensity rises

Figure 8 illustrates the competing effects of operating intensity on energy costs, quality loss, and equipment degradation. As operating intensity increases, energy costs and degradation rise, while quality loss initially decreases before increasing at higher operating levels. These conceptual trends highlight the trade-offs among optimization objectives and the need for a balanced multi-objective operating strategy.

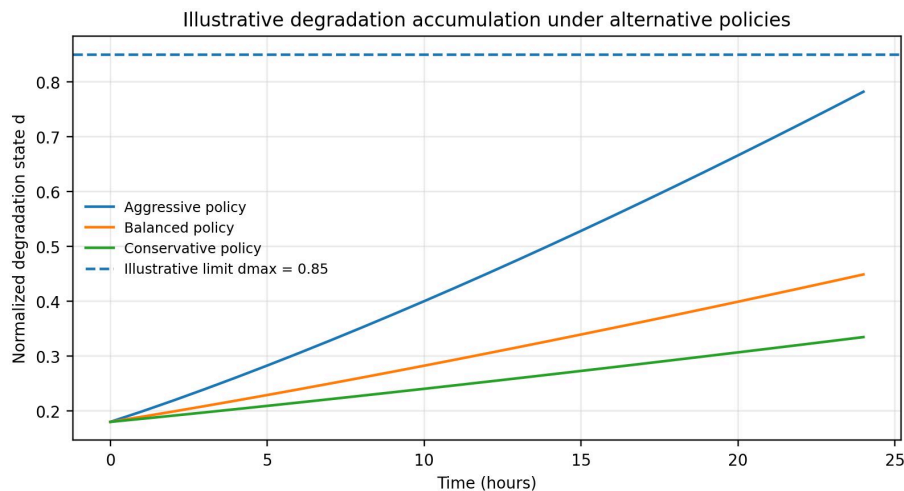


Figure 9. Synthetic degradation trajectories under aggressive, balanced, and conservative policies

Figure 9 illustrates the cumulative effects of aggressive, balanced, and conservative operating policies on equipment degradation over a 24-hour period. The aggressive policy produces the highest degradation, while the balanced and conservative policies result in progressively lower equipment wear. All three illustrative trajectories remain below the maximum degradation limit of 0.85, highlighting the importance of operating policy selection for long-term equipment reliability.

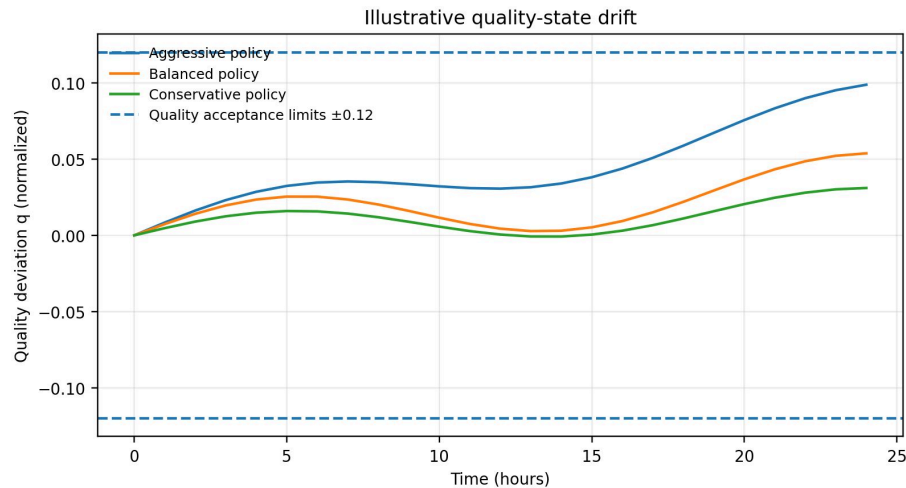


Figure 10. Synthetic quality-state trajectories with illustrative ± 0.12 acceptance limits

Figure 10 illustrates the simulated quality-state deviations under aggressive, balanced, and conservative operating policies over a 24-hour period. The aggressive policy exhibits the greatest quality drift, while the balanced and conservative policies maintain smaller deviations. All three trajectories remain within the acceptance limits of ± 0.12 , highlighting the importance of operating policy selection in maintaining product quality.

4.2 Worked Numerical Example and Interpretation

This subsection presents a hypothetical numerical example to illustrate multi-objective policy selection. Three feasible operating policies are considered: aggressive (A), balanced (B), and conservative (C). Their objective values are normalized using predefined reference ranges. The resulting indices demonstrate the decision-making procedure and do not represent actual industrial measurements or experimental findings.

Table 10. Hypothetical normalized objectives for three feasible operating policies

Policy	Normalized energy J^N_E	Normalized quality loss J^N_Q	Normalized degradation J^N_D	Feasible?
A — aggressive	0.20	0.65	0.80	Yes, but near quality/health limits
B — balanced	0.42	0.28	0.35	Yes
C — conservative	0.72	0.15	0.18	Yes, higher energy cost

Table 10 presents the hypothetical normalized energy costs, quality losses, and equipment degradation levels for three feasible operating policies. The comparison illustrates the trade-offs between aggressive, balanced, and conservative strategies, providing a basis for multi-objective policy selection.

The three feasible policies are evaluated using illustrative preference weights of $w_E = 0.40$, $w_Q = 0.35$, and $w_D = 0.25$. The weighted score combines normalized energy costs, quality losses, and equipment degradation, with lower scores indicating more favorable alternatives. The

calculations for policies A, B, and C are presented in Formula 36, Formula 37, and Formula 38, respectively.

$$S_A = 0.40(0.20) + 0.35(0.65) + 0.25(0.80) = 0.5075 \quad (36)$$

$$S_B = 0.40(0.42) + 0.35(0.28) + 0.25(0.35) = 0.3535 \quad (37)$$

$$S_C = 0.40(0.72) + 0.35(0.15) + 0.25(0.18) = 0.3855 \quad (38)$$

Based on Formula 36, Formula 37, Formula 38 policy *B* achieves the lowest weighted score and is therefore preferred under the specified weights. However, this selection depends on managerial priorities and does not establish universal superiority.

Sensitivity analysis evaluates whether policy rankings change when objective weights are adjusted. When the quality weight changes, the remaining weights can be proportionally normalized using Formula 39.

$$w'_E = \frac{(1 - w'_Q)w_E}{w_E + w_D}, \quad w'_D = \frac{(1 - w'_Q)w_D}{w_E + w_D} \quad (39)$$

In Formula 39, w'_Q represents the revised quality weight, while w_E and w_D are the adjusted energy and degradation weights. This procedure maintains a total weight of one and supports policy comparisons under alternative preferences. The analysis demonstrates that policy selection depends on objective normalization, feasibility constraints, and decision-maker preferences. Consequently, weight sensitivity and reference ranges should be documented to ensure transparent and robust decision-making.

4.3 Discussion

The main implication is that prediction accuracy and decision quality are different. A predictor may have low average error but still recommend an action that violates a constraint near the edge of its training distribution. Conversely, a slightly less accurate model can be more useful if uncertainty margins and a dynamic feasibility layer prevent costly or unsafe decisions. Model evaluation should therefore include downstream objective values, feasibility rate, constraint violations, and decision regret.

The Pareto front makes managerial trade-offs visible. An energy manager may favour low cost during a low-price window, while a maintenance manager may prefer lower intensity when health is close to a threshold. A quality-critical product may justify a more conservative policy. These preferences are context-dependent and should be agreed by accountable stakeholders, not learned implicitly from historical decisions without review.

The architecture is designed as a decision-support layer above existing controls. PLCs, SCADA, safety instrumented systems, and operator procedures remain responsible for immediate control and protection. Recommendations should include the predicted quality margin, degradation trajectory, active constraints, expected cost, model confidence, and comparison with the current baseline.

4.3.1 Practical Deployment Implications

Deployment requires synchronized energy, production, quality, and maintenance data; stable asset identifiers; calibrated sensors; documented control limits; and an auditable record of recommendations and overrides. Cybersecurity measures should include least-privilege access, authenticated services, network segmentation, signed model/configuration updates, and a safe fallback state. Data integrity is part of mathematical correctness: corrupted timestamps or manipulated sensor values can make an otherwise correct optimizer act on a false state.

4.3.2 Lifecycle and Maintenance Extension

The proposed framework can be extended by incorporating maintenance decisions, intervention costs, downtime, and post-maintenance equipment recovery. The degradation state transition under maintenance intervention is formulated in Formula 40.

$$d_{k+1} = (1 - m_k)d_{k+1}^{\text{run}} + m_k d_{\text{reset}} \quad (40)$$

In Formula 40, $m_k \in \{0,1\}$ represents the maintenance decision, d_{k+1}^{run} denotes the predicted degradation state without maintenance, and d_{reset} represents the degradation level following maintenance.

The extended objective incorporates maintenance cost C_M and downtime τ_M , enabling comparisons among continued operation, preventive maintenance, and equipment replacement. Reliable cost and degradation data are required for practical implementation; otherwise, the results should be interpreted as illustrative scenarios.

4.4 Research Contribution and Practical Decision Rules

The principal contribution of this study is an integrated AI-assisted multi-objective optimization framework that simultaneously considers energy costs, production quality, and equipment degradation. By combining dynamic state modeling, uncertainty-aware prediction, hard feasibility constraints, and Pareto-based decision-making, the framework provides a transparent approach to evaluating competing industrial objectives. Practical implementation requires calibrated models, clearly defined operational constraints, and documented managerial preferences. The selected operating policy should be evaluated against feasible alternatives based on objective values, uncertainty estimates, and operational risks. Decision priorities may be adjusted in response to changing production requirements and electricity tariffs, while mandatory safety and quality constraints must remain unchanged.

4.5 Deployment Governance, Cybersecurity, and Human Oversight

Industrial deployment requires appropriate governance, cybersecurity safeguards, and human oversight. Consistent with the NIST AI Risk Management Framework (Tabassi, 2023), the proposed approach emphasizes risk identification, model monitoring, access control, and documented decision accountability. The system should incorporate secure data transmission, role-based access, model version control, independent safety verification, and operator authorization when required. Deployment should progress through historical validation, shadow-mode testing, controlled pilot implementation, and gradual operational expansion. Continuous monitoring should identify prediction drift, sensor failures, constraint violations, and optimization delays. When operational reliability cannot be assured, the system must activate a validated fallback policy rather than continue autonomous optimization.

4.6 Threats to Validity and Reproducibility

The proposed framework has several limitations affecting its validity and generalizability. Its mathematical models require calibration using representative industrial data, while the illustrative simulations cannot establish actual energy savings, quality improvements, or equipment-life extensions. Potential threats include inaccurate degradation indicators, data leakage, inconsistent baseline comparisons, model drift, limited production environments, and uncertainty in objective normalization. These factors should be addressed through independent validation, matched operating scenarios, sensitivity analysis, and repeated experiments.

Reproducibility requires transparent documentation of model equations, parameter values, data preprocessing, validation procedures, optimization settings, and evaluation metrics. Where industrial data are confidential, anonymized results and synthetic benchmarks may support methodological verification. All reported outcomes should clearly distinguish simulated results from empirical observations.

5. Conclusions

This paper presents an AI-assisted dynamic optimization framework that treats energy/operating cost, product quality, and equipment degradation as coupled objectives. Its mathematical core combines a nonlinear power function, quality and degradation state transitions, explicit production and safety constraints, uncertainty margins, and Pareto-based policy selection. The framework is designed so that AI estimates future states while the dynamic model and hard constraints determine whether a candidate action is feasible.

The central recommendation is procedural: compare policies under identical conditions and required output; reject infeasible policies before ranking; inspect the Pareto set before applying managerial preferences; and evaluate decision outcomes as well as prediction error. The simulation figures in this paper are explanatory and synthetic, not field evidence. The study therefore offers a reproducible architecture rather than a claim of universal industrial savings. Validation with synchronized real-plant data is essential before performance claims or autonomous control are justified.

Acknowledgement

The authors gratefully acknowledge the Faculty of Science, Technology, and Engineering, Rajarshi Janak University, Janakpurdham, Nepal, for the academic support provided during this study.

Author Contributions

AS contributed to the conceptualization, methodology development, formal analysis, visualization, and preparation of the original manuscript draft. PKN was responsible for investigation, validation, data curation, and manuscript review and editing. SKS contributed to conceptualization, methodology development, supervision, and manuscript review and editing. All authors have read and approved the final version of the manuscript.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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