Electronic Research Archive

ERA, 34(9): 6734–6771.
DOI: 10.3934/era.2026294
Received: 16 May 2026
Revised: 30 July 2026
Accepted: 04 August 2026
Published: 11 August 2026

https://www.aimspress.com/journal/ERA

Research article

Delay-aware predictive maintenance control for multi-equipment systems using approximate Bayesian neural reliability networks

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Abstract: This study proposes a delay-aware predictive maintenance control framework for multiequipment systems operating under dynamic and uncertain industrial environments. The proposed framework integrates a multilayer neural reliability prediction model, an approximate Bayesian reliability updating mechanism, and a rolling-horizon maintenance optimization model to support maintenance decision-making under delayed and asynchronous industrial information. Unlike conventional predictive maintenance approaches that rely primarily on instantaneous observations or static reliability estimation, the proposed framework explicitly models time-varying communication delays, degradation evolution, imperfect maintenance effects, and dynamic state propagation within a closed-loop maintenance control architecture. The proposed methodology first estimates machine failure probabilities using a multilayer neural network trained on heterogeneous operational and degradation-related variables. The predicted reliability is subsequently refined through approximate Bayesian filtering by integrating historical posterior information and delayed observations. Based on the updated reliability trajectories, a rolling-horizon genetic algorithm determines preventive maintenance schedules while considering maintenance capacity, workforce availability, and operational constraints. The optimization objective minimizes the total expected maintenance cost, including preventive maintenance, corrective maintenance, downtime, and reliability penalty costs. Experimental results demonstrate that the proposed framework provides competitive probability prediction performance while achieving superior maintenance cost reduction and improvements in reliability under delayed operating conditions.

Keywords: delay-aware predictive maintenance; approximate Bayesian reliability updating; neural reliability prediction; preventive maintenance scheduling; multiequipment systems; smart manufacturing

1. Introduction

In recent years, predictive maintenance has become an important research topic in intelligent manufacturing because unexpected equipment failures may cause production interruptions, safety risks, and significant economic losses. Traditional maintenance strategies, such as periodic and reactive maintenance, are generally unable to adapt to dynamically changing equipment conditions. Consequently, modern industrial systems increasingly use data-driven predictive maintenance approaches that integrate sensor monitoring, machine learning, reliability analysis, and maintenance optimization to improve operational efficiency and the system's reliability.

The rapid development of the Industrial Internet of Things (IIoT) and distributed sensing technologies has greatly increased the availability of real-time operational data for equipment monitoring. Although these advances have promoted the application of artificial intelligence to predictive maintenance, several practical challenges remain, including delayed sensor observations, uncertain evolution of degradation, incomplete information, and limited maintenance resources. Most existing predictive maintenance approaches implicitly assume synchronized observations and instantaneous information, which may reduce their effectiveness in industrial environments with communication latency and asynchronous monitoring.

Recent studies have demonstrated that neural-network-based models are effective for learning nonlinear degradation patterns from high-dimensional operational data. However, purely data-driven approaches often provide limited interpretability and are sensitive to delayed or incomplete observations. Bayesian reliability models offer probabilistic reasoning and uncertainty management, but they generally rely on predefined statistical assumptions and may be less effective for modeling complex nonlinear degradation behaviors. Furthermore, the integration of delay-aware reliability updating with maintenance scheduling remains relatively underexplored.

To address these challenges, this study proposes the delay-aware dynamic Bayesian neural reliability framework with preventive maintenance control (DBNR-DAPMC) for multiequipment industrial systems. The proposed framework integrates multilayer neural reliability prediction, Bayesian reliability updating, time-varying delay modeling, and rolling-horizon genetic algorithm optimization into a unified predictive maintenance architecture. By combining nonlinear learning, probabilistic reasoning, and delay-aware reliability modeling, the proposed framework aims to improve maintenance decision-making under uncertain and dynamically evolving industrial environments.

The major contributions of this study are summarized as follows. First, a delay-aware neural reliability prediction mechanism is developed to capture nonlinear degradation behavior while explicitly incorporating delayed observations into reliability estimation. Second, Bayesian reliability updating is integrated with neural prediction to improve the robustness and temporal consistency of reliability estimation under delayed information. Third, a rolling-horizon preventive maintenance optimization model is developed to jointly consider the maintenance cost, downtime, reliability, and resource constraints. Finally, the proposed framework establishes an integrated decision-support architecture that combines reliability prediction, uncertainty management, and maintenance scheduling. Extensive numerical experiments demonstrate its effectiveness in supporting predictive maintenance for modern smart manufacturing systems.

2. Literature review

2.1. Neural-network-based predictive maintenance

With the increasing availability of industrial monitoring data, neural-network-based predictive maintenance has attracted substantial attention in recent years. Deep learning models possess strong nonlinear approximation capability and can effectively capture complex degradation characteristics from high-dimensional sensor signals. Li et al. [1] proposed a particle swarm optimization–gated recurrent unit (PSO-GRU) neural-network-based preventive maintenance model for asphalt pavement systems, demonstrating that recurrent neural networks can effectively learn the deterioration dynamics in infrastructure maintenance applications. Similarly, Nasser and Al-Khazraji [2] combined convolutional neural networks and long short-term memory networks to improve the performance of predictive maintenance under sequential industrial monitoring environments.

Several studies also integrated neural-network-based prediction with maintenance optimization and industrial scheduling. Zonta et al. [3] developed a predictive maintenance framework using deep neural networks to optimize production schedules in manufacturing systems. Xia et al. [4] proposed a maintenance planning recommendation framework based on graph neural networks and knowledge graphs for complex industrial equipment. Apeiranthitis et al. [5] used convolutional neural networks for predictive maintenance of rotating machinery, while Potharaju et al. [6] proposed a two-step machine learning framework for anomaly detection and predictive maintenance in environmental sensor systems. Zhang et al. [7] developed a windowed sparse-attention Transformer tool predicting remaining useful life under time-varying processing parameters, demonstrating the effectiveness of attention-based models in capturing dynamic quality and degradation patterns. More recent studies by Seyedrezaei et al. [8] and Liu et al. [9] also demonstrated the applicability of neural-network-based maintenance prediction in industrial production systems and petrochemical equipment maintenance.

In addition to maintenance applications, neural network architectures have also been extensively investigated in broader engineering domains. Liu et al. [10] proposed the RFDNet neural network for satellite-based road extraction, showing that advanced neural architectures can effectively perform complex feature extraction tasks. Wu et al. [11] developed an interpretable hierarchical semantic convolutional neural network for melanoma diagnosis, emphasizing the importance of explainable deep learning structures in high-risk decision environments. Furthermore, Guo et al. [12] investigated synchronization analysis in delayed quaternion-valued memristor-based neural networks and demonstrated that delayed dynamics significantly influence neural networks' behavior and systems' stability.

Although existing neural-network-based predictive maintenance approaches provide strong predictive capability, several limitations remain. Most current studies focus primarily on the accuracy of predictions while lacking explicit probabilistic uncertainty representation and reliability updating mechanisms. Moreover, delayed sensor observations and time-varying delay effects are rarely considered in predictive maintenance neural network architectures. Therefore, integrating neural learning mechanisms with probabilistic reliability analysis and delay-aware structures remains an important research challenge.

2.2. Bayesian reliability analysis and predictive maintenance

Bayesian inference has become an important methodology for reliability analysis and predictive maintenance because it effectively characterizes uncertainty and dynamically updates a system's reliability using observed information. Zhao et al. [13] proposed a Bayesian-based maintenance framework for multiasset systems, while Anderson et al. [14] applied Bayesian reliability analysis to investigate the effects of scheduled maintenance on wind turbine failures.

Recent research has increasingly combined Bayesian inference with machine learning for predictive maintenance. Zhuang et al. [15] developed a Bayesian deep learning framework for prognostics with uncertainty quantification, whereas Liu et al. [16] used a non-Gaussian copula Bayesian network for safety assessments related to metro tunnel maintenance. Bayesian methods have also been integrated into models of industrial deterioration [17] and mining maintenance records for vehicle quality analysis [18]. In addition, advanced computational techniques, including data-driven compressive sensing [19] and learning-informed prior distributions using normalizing flows [20], have further improved the scalability of Bayesian inference for large-scale engineering applications.

More recently, reliability-based maintenance has been extended to systems with dependent competing failure processes. Ling et al. [21] proposed a preventive maintenance framework for humanoid robot systems, while Huang et al. [22] introduced a coupling variable model for reliability analysis under dependent competing failures. Ling et al. [23] proposed a variational Bayesian inference-assisted approach for multiobjective reliability-based design optimization, illustrating the value of approximate Bayesian inference in reliability-oriented decision problems. These studies demonstrate the importance of accurately modeling the evolution of reliability for maintenance optimization.

Despite these advances, most existing Bayesian maintenance frameworks primarily focus on modeling reliability degradation and seldom integrate delay-aware reliability updating, neural reliability prediction, and maintenance scheduling optimization within a unified decision-support framework. Consequently, there remains a need for predictive maintenance approaches capable of simultaneously addressing uncertainty, delayed observations, reliability updating, and maintenance decision optimization.

2.3. Delay-aware scheduling and time-varying delay systems

Delay-aware scheduling has been widely investigated in communication systems, computing systems, and resource optimization problems. Djukic and Valaee [24] proposed delay-aware link scheduling for multihop wireless networks, while Wang et al. [25] investigated cost-aware scheduling for delay-tolerant applications. Qu et al. [26] further studied delay-aware resource optimization within network function virtualization environments. Yuan et al. [27] proposed time-aware task scheduling for green data centers with guaranteed delay constraints, and Liu and Yang [28] investigated delay-aware scheduling in unmanned aerial vehicle (UAV)-enabled mobile edge computing systems.

More recent studies continued expanding delay-aware optimization mechanisms in cyber-physical systems. Lai et al. [29] proposed delay-aware container scheduling in Kubernetes environments. Gao et al. [30] developed deterministic delay-aware task scheduling approaches using graph embedding and deep reinforcement learning techniques. These studies collectively indicate that delay-aware optimization mechanisms have become increasingly important in modern intelligent systems.

In parallel, extensive research has investigated the stability and control of systems with time-varying delays. Michiels et al. [31] studied the stabilization of systems with controlled time-varying delays, while Park and Ko [32] investigated robust stability conditions for systems with variable delays. Kim [33] further analyzed the stability of linear systems with time-varying delay structures. Zeng et al. [34] proposed hierarchical stability conditions for systems with variable delays, and Cao et al. [35] investigated observer-based dynamic event-triggered control for multiagent systems with time-varying delays.

More recent studies have continued advancing time-varying delay theory in intelligent systems and control applications. Zhang et al. [36] proposed matrix-separation-based stability analysis methods for discrete-time systems with time-varying delays. Zhang et al. [37] developed adaptive dynamic programming-based prescribed-time control methods for nonlinear delay systems with uncertain parameters. Aslam et al. [38] further investigated self-triggered schemes for Takagi–Sugeno fuzzy systems with time-varying delay effects, while Zhu et al. [39] studied stochastic cellular neural networks with time-varying delays.

Although delay-aware scheduling and time-varying delay theories have been extensively studied in communication systems and control engineering, their integration into predictive maintenance and industrial reliability optimization remains relatively limited. Existing predictive maintenance frameworks often assume synchronized and immediately available observations, which may not accurately reflect practical industrial monitoring environments. Therefore, incorporating delay-aware reliability updating and time-varying delay mechanisms into predictive maintenance optimization constitutes an important research direction.

2.4. Research gap and motivation

In light of the literature review above, several important research gaps can be identified. First, many neural-network-based predictive maintenance models primarily emphasize the prediction of nonlinear degradation while providing limited support for probabilistic reliability updating under delayed and uncertain observations. Second, Bayesian reliability models offer uncertainty reasoning but generally have limited capability for capturing complex nonlinear degradation behaviors from high-dimensional industrial data. Third, time-varying communication delays and asynchronous monitoring are rarely incorporated into predictive maintenance and maintenance scheduling frameworks, despite their practical importance in modern industrial environments. Finally, relatively few studies have integrated neural-network-based reliability prediction, approximate Bayesian reliability updating, delay-aware degradation modeling, and rolling-horizon maintenance optimization into a unified predictive maintenance framework.

To address these research gaps, this study proposes the DBNR-DAPMC for multiequipment industrial systems. The proposed framework integrates multilayer neural-network-based reliability prediction, approximate Bayesian reliability updating, time-varying delay modeling, and rolling-horizon genetic algorithm optimization into a unified predictive maintenance architecture. By combining nonlinear learning, probabilistic reliability reasoning, and adaptive maintenance optimization, the proposed framework aims to improve the robustness of reliability estimations and maintenance decisions in delayed and dynamically evolving industrial environments.

3. Model development

3.1. Description of the research problem

Modern industrial production systems increasingly operate in dynamic and interconnected environments where the equipment's reliability is affected by operational uncertainty, heterogeneous degradation behaviors, and delayed information transmission. In smart manufacturing systems, data on machines' conditions are continuously collected through distributed cyber-physical infrastructures and IIoT platforms. However, communication latency, asynchronous data updates, sensors' instability, and network congestion may prevent the received information from accurately reflecting the equipment's actual condition, thereby reducing the effectiveness of conventional predictive maintenance approaches that rely primarily on instantaneous observations.

In addition, modern manufacturing systems typically involve multiple heterogeneous machines operating under limited maintenance resources. Consequently, preventive maintenance scheduling must jointly consider equipment degradation, maintenance capacity, workforce availability, and the equipment's criticality. These factors make maintenance-related decision-making considerably more challenging because inappropriate maintenance timing may either increase the operational risk or lead to unnecessary maintenance costs.

To address these challenges, this study proposes a delay-aware predictive maintenance control framework based on dynamic Bayesian neural reliability networks. The proposed framework integrates multilayer neural-network-based reliability prediction, Bayesian reliability updating, degradation evolution, and rolling-horizon maintenance optimization into a unified decision-support architecture. Its objective is to continuously estimate equipment's reliability within delayed observation environments while dynamically determining preventive maintenance schedules that minimize long-term operational costs.

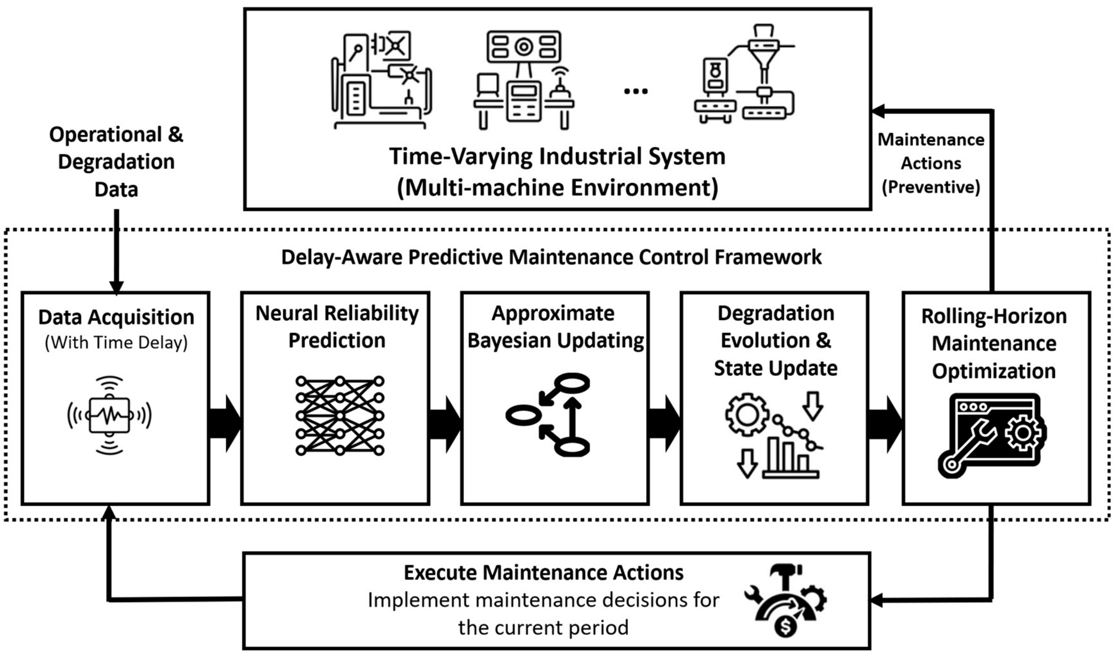

Figure 1. Overall framework of the proposed delay-aware predictive maintenance control model.

Figure 1 illustrates the overall architecture of the proposed framework. Operational and degradation-related information is first collected from the industrial monitoring system while explicitly accounting for communication delays. The neural prediction model estimates the machines' failure probabilities, which are subsequently refined through Bayesian reliability updating using historical posterior information and delayed observations. The updated reliability states are then propagated through the degradation evolution model and incorporated into the rolling-horizon maintenance optimization module to generate preventive maintenance schedules under resource constraints.

After maintenance decisions are executed, the equipment's states are updated and fed back into the monitoring system, forming a closed-loop predictive maintenance process. This recursive cycle of prediction–updating–optimization enables the proposed framework to continuously adapt maintenance decisions according to evolving conditions of the equipment and delayed industrial information.

3.2. Delay-aware degradation dynamics

The reliability evolution of industrial equipment is highly dependent on degradation accumulating over time. In practical manufacturing systems, machines' degradation is usually affected by multiple operational and environmental factors, including the production load, vibration by the machine, operating temperature, and delayed information on the machines' condition. To capture these dynamic characteristics, this study models the evolution of degradation of each machine using a delay-aware degradation process.

Let $i \in I = \{1,2,\ldots,N\}$ denote the index of machines, where N represents the total number of machines in the production system. Let $t \in T = \{1,2,\ldots,H\}$ denote the planning period index, where H is the length of the planning horizon. In this study, instantaneous degradation refers to the actual degradation state of the machine at the current decision period t, denoted $D_{i,t}$. Owing to communication latency, the maintenance decision system may instead receive a delayed degradation observation, corresponding to an earlier degradation state $D_{i,t-\tau_{i,t}}$. Unless otherwise specified, the term "degradation observation" refers to the degradation information available to the decision system, which may be delayed within the industrial monitoring environment under consideration. The evolution of degradation is formulated as

$$D_{i,t+1} = D_{i,t} + g_{i,t}, \tag{1}$$

where $g_{i,t}$ denotes the growth of degradation during period t. The growth of degradation is influenced by the operational conditions and delayed degradation effects and is defined as

$$g_{i,t} = \alpha_i + \beta_i L_{i,t} + \gamma_i \mathrm{Temp}_{i,t} + \delta_i V_i b_{i,t} + \eta_i D_{i,t-\tau_{i,t}} + \varepsilon_{i,t}. \tag{2}$$

In this formulation, α_i represents the baseline degradation rate of machine i, which reflects the natural degradation tendency of the equipment. The variable $L_{i,t}$ denotes the operational load level of machine i at period t, while β_i is the corresponding load sensitivity coefficient. Similarly, $\mathrm{Temp}_{i,t}$ and $V_i b_{i,t}$ represent the operating temperature and vibration level, respectively, and γ_i and δ_i denote their associated degradation sensitivity coefficients.

To capture the equipment's heterogeneity, each machine was assigned an independent set of degradation coefficients (α_i, β_i, γ_i, δ_i), which were generated once during initialization of the simulator according to the predefined parameter ranges described in the simulation settings. These machine-specific coefficients remained fixed throughout all experiments and were identically applied to every benchmark method. Consequently, all maintenance policies were evaluated using the same degradation characteristics, operating conditions, and delayed observation sequences, thereby ensuring a fair and reproducible comparison.

One of the most important components of the proposed model is the incorporation of delayed degradation information. The term $D_{i,t-\tau_{i,t}}$ represents the degradation level observed with the delay $\tau_{i,t}$, where $\tau_{i,t}$ denotes the time-varying delay associated with transmission of information on the machine's condition. The parameter η_i measures the influence of delayed degradation propagation on the current growth in degradation. This delayed degradation component enables the proposed framework to capture the uncertainty caused by asynchronous sensor updates, communication latency, or incomplete observation environments commonly encountered in cyber-physical production systems.

The stochastic disturbance term $\varepsilon_{i,t}$ is introduced to represent random environmental uncertainty and operational variability. In this study, the disturbance term is assumed to follow a Gaussian distribution

$$\varepsilon_{i,t} \sim N(0, \sigma_i^2), \tag{3}$$

where σ_i^2 denotes the variance of degradation uncertainty for machine i.

In addition to the evolution of degradation, the proposed framework also considers the effective aging behavior of equipment. Let $A_{i,t}$ denote the effective age of machine i at period t. Unlike chronological age, effective age reflects the actual operational deterioration accumulated through the evolution of degradation. The effective age updating process is modeled as follows:

$$A_{i,t+1} = A_{i,t} + \phi_0 + \phi_1 max\left(g_{i,t}, 0\right), \tag{4}$$

where ϕ_0 denotes the natural aging coefficient and ϕ_1 represents the degradation acceleration coefficient associated with positive growth in degradation. This formulation allows the effective age to dynamically increase according to the machine's degradation condition rather than simply following calendar time.

The proposed delay-aware degradation dynamics provide the fundamental reliability evolution mechanism for the subsequent neural-network-based reliability prediction and approximate Bayesian filtering procedures. By explicitly incorporating delayed degradation propagation and operational uncertainty, the proposed model can more realistically represent the reliability behavior of industrial equipment operating under uncertain and delayed information environments.

3.3. Neural-network-based reliability prediction model

After modeling the degradation evolution process, the next step is to estimate the failure probability of each machine based on its operational and degradation-related variables. Since equipment degradation in modern industrial systems is typically nonlinear and affected by multiple interacting operational factors, conventional linear reliability models are often insufficient to capture the complex relationships between degradation states and failure risk. To address this issue, this study adopts a multilayer perceptron (MLP) neural network to approximate the nonlinear mapping from machine condition variables to the probability of failure.

Unlike conventional logistic regression models that rely on a single linear transformation, the proposed MLP uses multiple hidden layers with nonlinear activation functions, enabling hierarchical feature extraction from degradation-related variables. Consequently, the proposed neural predictor can learn complex degradation patterns and interaction effects that are difficult to model using traditional statistical reliability approaches.

Let

$$\mathbf{x}_{i,t} = \left[D_{i,t}, Temp_{i,t}, Vib_{i,t}, \tau_{i,t}, A_{i,t}, C_i\right]^T \tag{5}$$

denote the input feature vector of machine i at period t, where $D_{i,t}$ denotes the degradation level, $\mathrm{Temp}_{i,t}$ denotes the operating temperature, $Vib_{i,t}$ denotes the vibration level, $\tau_{i,t}$ represents the delayed observation time, $A_{i,t}$ denotes the effective machine age, and C_i represents the machine criticality level.

The first hidden layer transforms the input vector into a latent representation through a nonlinear activation function

$$\mathbf{h}_{i,t}^{(1)} = \phi\left(\mathbf{W}^{(1)}\mathbf{x}_{i,t} + \mathbf{b}^{(1)}\right), \tag{6}$$

where $\mathbf{W}^{(1)}$ denotes the weight matrix of the first hidden layer, $\mathbf{b}^{(1)}$ denotes the corresponding bias vector, and $\phi(\cdot)$ denotes the nonlinear activation function.

In this study, the rectified linear unit (ReLU) is adopted owing to its computational efficiency and superior convergence performance in nonlinear regression problems

$$\phi(z) = max(0, z). \tag{7}$$

The hidden representations are then propagated through additional hidden layers according to

$$\boldsymbol{h}^{(l)} = \phi\left(\boldsymbol{W}^{(l)}\boldsymbol{h}^{(l-1)} + \boldsymbol{b}^{(l)}\right), l = 2, \dots, L, \tag{8}$$

where L denotes the total number of hidden layers, while $\mathbf{W}^{(l)}$ and $\mathbf{b}^{(l)}$ represent the weight matrix and bias vector of the l-th hidden layer, respectively.

Finally, the output layer converts the learned latent representation into a failure probability using the sigmoid activation function

$$\hat{p}_{i,t}^{NN} = \sigma\left(\boldsymbol{W}^{(o)}\boldsymbol{h}_{i,t}^{(L)} + \boldsymbol{b}^{(o)}\right), \tag{9}$$

where

$$\sigma(z) = \frac{1}{1 + e^{-z}}. \tag{10}$$

maps the network output into the interval [0, 1], thereby satisfying the probabilistic interpretation of the probability of machine failure.

The neural network parameters

$$\Theta = \left\{\boldsymbol{W}^{(1)}, \dots, \boldsymbol{W}^{(L)}, \boldsymbol{W}^{(o)}, \boldsymbol{b}^{(1)}, \dots, \boldsymbol{b}^{(L)}, \boldsymbol{b}^{(o)}\right\} \tag{11}$$

are estimated by minimizing the prediction loss over the training dataset. Let $y_{i,t}$ denote the observed failure-risk label (or target reliability value) associated with machine i at period t. The network parameters are obtained by solving

$$\min_{\Theta} \mathcal{L}(\Theta) = \frac{1}{N} \sum_{(i,t)} \left(y_{i,t} - \hat{p}_{i,t}^{NN}\right)^2, \tag{12}$$

where N denotes the total number of training samples. The optimization is performed using the adaptive moment estimation (Adam) algorithm, and an early-stopping strategy is used to prevent overfitting and improve the generalization capability of the neural predictor.

The resulting neural reliability prediction model provides a nonlinear approximation of the equipment's degradation behavior and serves as the initial reliability estimation layer of the proposed predictive maintenance framework. Compared with conventional statistical reliability models, the MLP can effectively capture high-order interactions among degradation severity, operating conditions, delayed observations, and machines' criticality, thereby providing more accurate failure risk estimations within complex industrial environments.

Nevertheless, neural-network-based predictions remain susceptible to noisy measurements and delayed observations. In practical industrial systems, communication latency and asynchronous sensor updates may introduce temporary fluctuations into the estimated failure probability. Consequently, relying solely on instantaneous neural-network-based predictions may produce unstable maintenance decisions. Therefore, the neural prediction generated in this subsection is subsequently refined through the dynamic Bayesian reliability updating mechanism described in the following subsection.

3.4. Approximate Bayesian reliability updating mechanism

The neural-network-based reliability prediction model developed in the previous subsection provides an instantaneous estimate of the machine's failure probability based on the latest operational observations. However, in practical industrial environments, sensor measurements are frequently affected by communication latency, asynchronous data transmission, and incomplete observations. Consequently, the neural network's prediction alone may not accurately represent the current reliability state of the equipment. To improve the estimation's robustness, this study incorporates a Bayesian reliability updating mechanism that sequentially combines the current neural network's prediction with historical reliability information and delayed observations.

Although Bayes' theorem provides the conceptual motivation for recursively incorporating prior information and newly observed evidence, the exact likelihood function is unavailable for heterogeneous industrial degradation processes with time-varying delays. Therefore, the proposed framework adopts an approximate Bayesian filtering formulation rather than exact Bayesian posterior inference. Accordingly, Eqs (13)–(16) are introduced only to illustrate the Bayesian motivation of the proposed updating strategy, whereas the actual implementation used throughout the numerical experiments is given by Eq (36). Unlike static reliability estimation approaches, the proposed approximate Bayesian filtering mechanism recursively estimates the posterior failure probability as new information becomes available. Let $\hat{p}_{i,t}^{B}$ denotes the posterior failure probability of machine i at period t.

For conceptual completeness, the classical Bayesian posterior is first introduced as the theoretical motivation of the proposed updating framework

$$P(F_{i,t} \mid Z_{i,1:t}) = \frac{P(Z_{i,t} \mid F_{i,t})P(F_{i,t} \mid Z_{i,1:t-1})}{P(Z_{i,t} \mid Z_{i,1:t-1})}, \tag{13}$$

where $F_{i,t}$ denotes the latent failure state of machine i at period t, and $Z_{i,t}$ denotes the newly observed degradation-related information. In this equation, $P(F_{i,t} \mid Z_{i,1:t-1})$ represents the prior distribution of failure state before incorporating the current observation, $P(Z_{i,t} \mid F_{i,t})$ denotes the likelihood of observing the current degradation information conditional on the latent failure state, and $P(F_{i,t} \mid Z_{i,1:t})$ be the posterior distribution of failure state after approximate Bayesian filtering. The denominator $P(Z_{i,t} \mid Z_{i,1:t-1})$ is the evidence term, which serves as a normalizing constant to ensure that the posterior distribution is properly normalized.

Because the exact observation likelihood is generally unavailable in practical industrial systems with heterogeneous operating conditions, this study uses the neural-network-based prediction introduced in Section 3.3 as a data-driven likelihood surrogate (i.e., a condition-dependent evidence score that summarizes how strongly the currently available degradation-related features support the latent failure state). Accordingly, the neural network's prediction is not interpreted as an analytically specified likelihood distribution, but as a computationally tractable evidence measure used in the recursive reliability-updating process. Specifically, we have

$$P(Z_{i,t} \mid F_{i,t}) \propto \hat{p}_{i,t}^{NN}, \tag{14}$$

where $\hat{p}_{i,t}^{NN}$ is the neural-network-based failure probability.

To approximate the recursive propagation of historical reliability information under delayed observations, the previous posterior estimates are linearly fused as

$$P(F_{i,t} \mid Z_{i,1:t-1}) = \alpha\hat{p}_{i,t-1}^{B} + (1-\alpha)\hat{p}_{i,t-\tau_{i,t}}^{B}, \tag{15}$$

where $\tau_{i,t}$ denotes the communication delay. The weighting parameter α is introduced here only as a conceptual coefficient to illustrate the recursive propagation of historical posterior information. In the implemented approximate Bayesian filtering rule (Eq (36)), this conceptual weighting is generalized through the implementation coefficients $\lambda_1, \ldots, \lambda_4$, which jointly combine the current neural prediction, previous posterior estimate, delayed posterior estimate, and machines' criticality.

For conceptual completeness, the contribution of machines' criticality to posterior reliability estimation is conceptually illustrated after the recursive reliability propagation process. In the implemented approximate Bayesian filtering framework, however, the criticality contribution is incorporated directly into the unified convex filtering rule in Eq (36), where it forms one component of the overall reliability fusion process rather than an independent updating stage.

$$\hat{p}_{i,t}^{B} = (1-\beta)\tilde{p}_{i,t}^{B} + \beta C_i, \tag{16}$$

where C_i denotes the normalized machine criticality score. The parameter β conceptually represents the relative contribution of machines' criticality to posterior reliability estimation. In the implemented filtering rule (Eq (36)), this contribution is incorporated through the implementation coefficient λ_4, thereby maintaining consistency between the conceptual Bayesian interpretation and the practical approximate Bayesian filtering formulation. Accordingly, Eq (16) should be regarded as a conceptual interpretation of the criticality adjustment rather than the numerical implementation adopted in this study.

3.5. Preventive maintenance decision model

On the basis of the posterior reliability estimation obtained from the dynamic Bayesian reliability updating mechanism, this study develops a preventive maintenance decision model to determine optimal maintenance schedules for multiple heterogeneous machines operating under limited maintenance resources. Unlike conventional maintenance optimization models, in which maintenance decisions only influence the optimization objective, the proposed framework explicitly models the interaction between maintenance actions and future equipment degradation. Consequently, maintenance decisions directly affect the subsequent evolution of degradation, reliability estimation, and future maintenance scheduling, thereby establishing a closed-loop predictive maintenance control mechanism.

Let the binary decision variable $x_{i,t}$ indicate whether preventive maintenance is performed on machine i during period t as follows:

$$x_{i,t} = \begin{cases} 1, & \text{if preventive maintenance is performed,} \\ 0, & \text{otherwise.} \end{cases} \tag{17}$$

When preventive maintenance is executed, the accumulated degradation is partially restored according to

$$D_{i,t+1} = D_{i,t} + \Delta D_{i,t} - \psi_i^D x_{i,t}, \tag{18}$$

where $D_{i,t}$ denotes the accumulated degradation level of machine i at period t, $\Delta D_{i,t}$ is the degradation increment obtained from Eq (2), $x_{i,t}$ is a binary decision variable indicating whether preventive maintenance is performed, and ψ_i^D denotes the physical degradation recovery coefficient associated with preventive maintenance. Because preventive maintenance is imperfect, it only partially restores the accumulated degradation rather than returning the machine to a good as new condition.

Similarly, the effective machine age is partially rejuvenated after preventive maintenance according to

$$A_{i,t+1} = A_{i,t} + \phi_0 + \phi_1 D_{i,t} - \psi_i^A x_{i,t}, \tag{19}$$

where $A_{i,t}$ denotes the effective machine age, ϕ_0 represents the natural aging increment, ϕ_1 measures the contribution of accumulated degradation to the growth of effective-age, and ψ_i^A denotes the effective age rejuvenation coefficient associated with preventive maintenance. Unlike Eq (18), which models the partial restoration of the physical degradation state, Eq (19) captures the reduction in the machine's accumulated effective age. Consequently, Eqs (18) and (19) describe two complementary maintenance effects acting on different state variables rather than duplicating the same restoration process.

The updated degradation state subsequently becomes the input of the neural reliability prediction model in the next decision epoch as follows:

$$\hat{p}_{i,t+1}^{NN} = f_{NN}\left(D_{i,t+1}, Temp_{i,t+1}, Vib_{i,t+1}, \tau_{i,t+1}, A_{i,t+1}, C_i\right), \tag{20}$$

where $f_{NN}(\cdot)$ denotes the multilayer neural reliability prediction model developed in Section 3.3. The predicted failure probability is subsequently refined through the Bayesian reliability updating mechanism described in Section 3.4 before entering the maintenance optimization module. Consequently, maintenance decisions influence not only the current operational state but also future reliability predictions and subsequent maintenance scheduling decisions.

In practical industrial environments, preventive maintenance is generally imperfect because maintenance actions cannot completely eliminate all degradation mechanisms. Let ρ_i denote the imperfect maintenance coefficient of machine i, where $0 < \rho_i < 1$.

The posterior failure probability after preventive maintenance is therefore expressed as

$$\tilde{p}_{i,t} = \hat{p}_{i,t}^{B}\left[1 - (1 - \rho_i)x_{i,t}\right], \tag{21}$$

where $\tilde{p}_{i,t}$ denotes the adjusted posterior failure probability after maintenance. When $x_{i,t} = 0$, no maintenance is performed and the posterior failure probability remains unchanged, i.e., $\tilde{p}_{i,t} = \hat{p}_{i,t}^{B}$.

When $x_{i,t} = 1$, preventive maintenance reduces the posterior failure probability to $\tilde{p}_{i,t} = \rho_i \hat{p}_{i,t}^{B}$, reflecting the imperfect maintenance assumption.

The improvement in maintenance gradually diminishes as equipment continues operating after maintenance. To capture this phenomenon, the maintenance recovery effect is modeled using an exponential decay function

$$\tilde{p}_{i,t+k} = \hat{p}_{i,t+k}^{B}[1 - (1 - \rho_i)e^{-\kappa k}], k = 0,1, \dots, K_i, \tag{22}$$

where K_i denotes the maintenance carryover duration and κ represents the maintenance effect's decay coefficient. The exponential formulation guarantees that the maintenance effect decreases gradually over time while ensuring that the adjusted failure probability remains physically meaningful and never exceeds the unrepaired failure probability.

The proposed maintenance decision model therefore establishes a dynamic interaction among the evolution of degradation, neural-network-based reliability prediction, Bayesian reliability updating, and maintenance scheduling. Preventive maintenance decisions continuously modify the equipment's state, while the updated degradation conditions recursively influence future reliability predictions over the rolling prediction horizon. Consequently, the proposed framework forms a closed-loop predictive maintenance control architecture capable of adapting maintenance decisions to dynamically evolving industrial operating environments.

The primary objective of the proposed maintenance decision model is to minimize the total expected operational cost over the planning horizon while maintaining acceptable reliability performance under delayed information conditions. The complete optimization formulation, including the preventive maintenance cost, expected corrective maintenance cost, expected downtime cost, reliability penalty cost, and maintenance interval penalty cost, is presented in the following subsection.

3.6. Objective function formulation

The proposed preventive maintenance control model aims to minimize the total expected operational cost of the multiequipment system over the planning horizon while maintaining acceptable reliability performance within delayed information environments. Since maintenance decisions influence both the current and future reliability of the system, the optimization problem must simultaneously consider preventive the maintenance cost, corrective maintenance risk, downtime loss, and the stability of reliability.

The overall objective function of the proposed model is formulated as follows:

$$min\ Z = Z^{PM} + Z^{CM} + Z^{DT} + Z^{REL} + Z^{PEN}, \tag{23}$$

where Z denotes the total expected operational cost. The objective function consists of five major components corresponding to preventive maintenance cost, expected corrective maintenance cost, expected downtime cost, reliability penalty cost, and preventive maintenance interval penalty cost.

The first component represents the preventive maintenance cost

$$Z^{PM} = \sum_{t \in T} \sum_{i \in I} c_i^{PM} x_{i,t}, \tag{24}$$

where c_i^{PM} denotes the preventive maintenance cost associated with machine i, and $x_{i,t}$ is the binary preventive maintenance decision variable. This term represents the direct maintenance expenditure generated by performing preventive maintenance actions during the planning horizon.

The second component corresponds to the expected corrective maintenance cost caused by machine failures

$$Z^{CM} = \sum_{t \in T} \sum_{i \in I} \tilde{p}_{i,t} c_i^{CM}, \tag{25}$$

where c_i^{CM} denotes the corrective maintenance cost associated with machine i, and $\tilde{p}_{i,t}$ represents the adjusted posterior failure probability after considering preventive maintenance effects. Since machine failures are uncertain events, the corrective maintenance cost is modeled in expected value form based on the estimated failure probability.

The third component represents the expected downtime cost

$$Z^{DT} = \sum_{t \in T} \sum_{i \in I} \tilde{p}_{i,t} c_i^{DT}, \tag{26}$$

where c_i^{DT} denotes the downtime cost associated with machine i. This term captures the economic loss caused by interrupted production, delayed manufacturing operations, or operational instability resulting from the equipment's failure.

Although minimizing maintenance-related costs is important, industrial production systems must also maintain acceptable reliability. Therefore, this study introduces a reliability penalty mechanism to discourage excessively risky maintenance schedules. The reliability penalty term is formulated as follows:

$$Z^{REL} = \Pi \cdot \sum_{t\in T} \sum_{i\in I} max\left(0, R_i^{min} - R_{i,t}\right), \tag{27}$$

where $R_{i,t}$ denotes the reliability level of machine i at period t, R_i^{min} represents the minimum acceptable reliability threshold, and Π is the reliability penalty coefficient. This formulation imposes an additional penalty whenever the machine's reliability falls below the required reliability threshold.

In practical industrial systems, excessive preventive maintenance actions performed within short intervals may generate unrealistic maintenance schedules and unnecessary operational interruption. To avoid this issue, the proposed framework introduces the following preventive maintenance interval penalty term:

$$Z^{PEN} = \sum_{i\in I} \sum_{t\in T} \Omega \cdot \mathbb{I}\left(d_{i,t} < G\right), \tag{28}$$

where Ω denotes the penalty coefficient associated with excessively frequent maintenance actions, G represents the minimum preventive maintenance interval, and $d_{i,t}$ denotes the time interval between two consecutive preventive maintenance actions for machine i. The indicator function $\mathbb{I}(\cdot)$ takes the value 1 if the maintenance interval violates the minimum maintenance gap requirement and 0 otherwise.

The proposed objective function integrates both economic and reliability considerations into a unified optimization framework. Compared with traditional maintenance scheduling models that focus solely on minimizing maintenance costs, the proposed formulation explicitly incorporates the stability of reliability and delayed information's robustness. Consequently, the model can generate more practical and stable maintenance schedules for smart manufacturing environments operating under uncertain and delayed information conditions.

3.7. Maintenance resource constraints

In practical industrial environments, preventive maintenance activities are constrained by limited maintenance resources, including maintenance crews, maintenance tools, spare parts, and operational maintenance capacity. Therefore, the proposed optimization model explicitly incorporates maintenance resource constraints into the scheduling process.

First, the number of preventive maintenance actions that can be performed during each planning period is restricted by the maintenance capacity limitations. Let M_t denote the maximum preventive maintenance capacity during period t. The maintenance capacity constraint is formulated as

$$\sum_{i\in I} x_{i,t} \leq M_t, \forall t \in T. \tag{29}$$

This constraint ensures that the total number of preventive maintenance actions performed during each period does not exceed the available maintenance capacity.

In addition to maintenance capacity limitations, industrial maintenance operations are often constrained by the maintenance crew's availability. Let q_i denote the maintenance crew requirement associated with machine i, and let Q_t represent the total available maintenance crew capacity during period t. The maintenance crew constraint is formulated as follows:

$$\sum_{i \in I} q_i x_{i,t} \leq Q_t, \forall t \in T. \tag{30}$$

This formulation ensures that the total maintenance crew requirement generated by preventive maintenance actions does not exceed the available workforce resources.

To avoid unrealistic maintenance schedules involving excessively frequent maintenance actions on the same machine, the proposed framework further imposes a minimum preventive maintenance interval constraint. Let G denote the minimum allowable maintenance interval between two consecutive preventive maintenance actions for the same machine. The maintenance interval constraint is expressed as

$$t_{i,k+1} - t_{i,k} \geq G, \forall i \in I, \tag{31}$$

where $t_{i,k}$ and $t_{i,k+1}$ denote two consecutive preventive maintenance periods associated with machine i.

Finally, the preventive maintenance decision variable must satisfy the following binary constraint:

$$x_{i,t} \in \{0, 1\}, \forall i \in I, t \in T. \tag{32}$$

The incorporation of these operational constraints significantly improves the practical applicability of the proposed maintenance scheduling framework. Unlike many theoretical predictive maintenance studies that assume unlimited maintenance resources, the proposed model explicitly captures real-world industrial maintenance limitations. Consequently, the generated preventive maintenance schedules are more suitable for practical implementation in industrial production systems.

3.8. Rolling-horizon predictive maintenance control

The proposed framework adopts a rolling-horizon predictive maintenance strategy to continuously update maintenance decisions as new operational information becomes available. Unlike static maintenance scheduling, the proposed approach predicts the future evolution of degradation and recursively updates maintenance decisions according to the latest machine conditions.

At each decision epoch, the current operational observations are first processed by the neural reliability prediction model to estimate the current failure probability. The updated degradation state, together with the degradation evolution model presented in Section 3.2, is then recursively propagated over the rolling prediction horizon to forecast future reliability trajectories. The predicted reliability sequence is expressed as

$$\{\hat{p}_{i,t+1}^{NN}, \hat{p}_{i,t+2}^{NN}, \ldots, \hat{p}_{i,t+H_r}^{NN}\}, \tag{33}$$

where H_r denotes the rolling prediction horizon. These predicted reliability states are subsequently refined through the Bayesian reliability updating mechanism before being incorporated into the preventive maintenance optimization model. Consequently, maintenance decisions are determined according to the predicted future evolution of degradation rather than solely the current condition of the machine.

For each decision stage s, the optimization problem is solved over the rolling horizon

$$T_s = \{s, s+1, \dots, s+H_r-1\}. \tag{34}$$

After implementing the maintenance decisions for the current period, the optimization horizon advances according to

$$s \leftarrow s+1. \tag{35}$$

The entire cycle of prediction–updating–optimization is then repeated using the latest machine information. The rolling-horizon strategy establishes a closed-loop predictive maintenance framework in which the evolution of degradation, neural-network-based reliability prediction, Bayesian reliability updating, and maintenance scheduling are continuously integrated. This mechanism improves the adaptability of maintenance under delayed information, enhances decisions' robustness in dynamically changing environments, and reduces the computational burden by decomposing a long-term scheduling problem into a sequence of smaller optimization problems.

3.9. Genetic algorithm-based optimization procedure

The preventive maintenance scheduling problem formulated in this study is a nonlinear combinatorial optimization problem involving binary maintenance decisions, dynamic reliability evolution, delayed information, and multiple operational constraints. Because exact optimization becomes computationally expensive for large-scale industrial systems, a genetic algorithm (GA) is adopted to solve the rolling-horizon maintenance scheduling problem.

In the proposed framework, each chromosome represents a preventive maintenance schedule over the rolling horizon, where each gene corresponds to the binary maintenance decision $x_{i,t}$ for machine i at decision period t. The initial population is randomly generated while satisfying the maintenance resource constraints. Each chromosome is evaluated using the objective function defined in Section 3.6, and its fitness is determined by the corresponding total expected operational cost.

The GA iteratively evolves candidate schedules through selection, crossover, mutation, and repair. Elitism preserves high-quality solutions, crossover and mutation enhance search diversity, and the repair operator ensures that the maintenance capacity and minimum maintenance interval constraints are satisfied. The optimization terminates when the predefined stopping criterion is reached, and the best feasible maintenance schedule is implemented within the current rolling horizon.

Compared with exact optimization methods, the proposed GA-based rolling-horizon framework provides greater computational scalability while maintaining the flexibility required for adaptive maintenance scheduling under dynamically evolving and delay-aware industrial environments.

4. Theoretical analysis and model characteristics

4.1. Analysis of the stability of reliability

In predictive maintenance systems operating under delayed industrial environments, maintaining the stability of reliability estimations is critically important for ensuring robust maintenance decisions. Since the proposed framework continuously updates machines' failure probabilities using neural networks' predictions, historical posterior states, and delayed reliability information, it is necessary to examine the theoretical stability characteristics of the proposed reliability updating mechanism.

Because the exact observation likelihood is unavailable, the implemented update is formulated as a convex approximate Bayesian filtering rule. It combines the current neural evidence, the most recent posterior estimate, delayed posterior information, and normalized machine criticality. The implemented update is expressed as follows:

$$\hat{p}_{i,t}^{B} = \lambda_1 \hat{p}_{i,t}^{NN} + \lambda_2 \hat{p}_{i,t-1}^{B} + \lambda_3 \hat{p}_{i,t-\tau_{i,t}}^{B} + \lambda_4 C_i, \tag{36}$$

where $\hat{p}_{i,t}^{B}$ denotes the approximate posterior failure probability estimate of machine i at period t, $\hat{p}_{i,t}^{NN}$ represents the current neural-network-based prediction of failure probability, $\hat{p}_{i,t-1}^{B}$ denotes the approximate posterior estimate of failure probability from the immediately preceding period, and $\hat{p}_{i,t-\tau_{i,t}}^{B}$ represents the delayed posterior estimate of failure probability associated with the time-varying observation delay $\tau_{i,t}$. Moreover, $c_i \in [0,1]$ is the normalized criticality score of machine i. The coefficients λ_1, λ_2, λ_3, and λ_4 are non-negative fusion weights assigned to the current neural evidence, the most recent posterior estimate, the delayed posterior estimate, and the machine's criticality, respectively.

To ensure consistency between the conceptual formulation and the implemented filtering rule, the fusion coefficients are parameterized as $\lambda_1 = \alpha(1-\zeta-\beta)$, $(1-\alpha)(1-\zeta-\beta)$, $\lambda_3 = \zeta$, and $\lambda_4 = \beta$, where $\alpha \in [0,1]$ controls the relative balance between the current neural network's prediction and the most recent posterior estimate, $\zeta \geq 0$ determines the contribution of delayed posterior information, and $\beta \geq 0$ controls the criticality contribution. Under the condition $\zeta + \beta \leq 1$, the four coefficients are non-negative and satisfy $\sum_{j=1}^{4} \lambda_j = 1$.

Proposition 1. Boundedness of posterior reliability

Suppose that the neural prediction, historical posterior reliability, delayed posterior failure-probability estimate, and machine criticality satisfy $0 \leq \hat{p}_{i,t}^{NN} \leq 1, 0 \leq \hat{p}_{i,t-1}^{B} \leq 1, 0 \leq \hat{p}_{i,t-\tau_{i,t}}^{B} \leq 1, 0 \leq C_i \leq 1$, and the approximate Bayesian filtering coefficients satisfy $\lambda_1, \lambda_2, \lambda_3, \lambda_4 \geq 0$, with $\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 = 1$. Then the posterior failure probability satisfies $0 \leq \hat{p}_{i,t}^{B} \leq 1$ for every decision period t.

Proof:

From the approximate Bayesian filtering equation, $\hat{p}_{i,t}^{B} = \lambda_1 \hat{p}_{i,t}^{NN} + \lambda_2 \hat{p}_{i,t-1}^{B} + \lambda_3 \hat{p}_{i,t-\tau_{i,t}}^{B} + \lambda_4 C_i$.

Since every component lies in the interval [0,1], $0 \leq \hat{p}_{i,t}^{NN}, \hat{p}_{i,t-1}^{B}, \hat{p}_{i,t-\tau_{i,t}}^{B}, C_i \leq 1$ multiplying each term by its non-negative coefficient gives $0 \leq \lambda_j x_j \leq \lambda_j, j = 1, \ldots, 4$, where x_j denotes the corresponding bounded variable.

Summing all four inequalities yields $0 \leq \hat{p}_{i,t}^{B} \leq \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 = 1$. Hence, $0 \leq \hat{p}_{i,t}^{B} \leq 1$.

Therefore, the posterior failure probability always remains within the physically meaningful probability interval.

Proposition 2. Stability under delayed information propagation

Assume that the neural prediction sequence is bounded, $0 \le \hat{p}_{i,t}^{NN} \le 1$, and $\lambda_2 + \lambda_3 < 1$. Then the recursive posterior reliability updating process remains bounded and asymptotically stable.

Proof:

The approximate Bayesian reliability updating equation can be rewritten as $\hat{p}_{i,t}^{B} = \lambda_1 \hat{p}_{i,t}^{NN} + \lambda_2 \hat{p}_{i,t-1}^{B} + \lambda_3 \hat{p}_{i,t-\tau}^{B} + \lambda_4 C_i$.

Define $M = \sup_t \left(\lambda_1 \hat{p}_{i,t}^{NN} + \lambda_4 C_i\right)$, which is finite because both the neural network's prediction and the machine's criticality are bounded. Then $\hat{p}_{i,t}^{B} \le M + (\lambda_2 + \lambda_3) max\left(\hat{p}_{i,t-1}^{B}, \hat{p}_{i,t-\tau}^{B}\right)$.

Since $\lambda_2 + \lambda_3 < 1$, the recursive gain associated with previous posterior states is strictly less than one.

Therefore, successive posterior reliability estimates remain bounded and any perturbation introduced by delayed observations gradually diminishes over time rather than being amplified.

Consequently, the posterior reliability updating process converges to a bounded trajectory under bounded neural prediction inputs, thereby ensuring asymptotic stability.

4.2. Interpretability and delay-aware characteristics

Although deep learning has demonstrated strong predictive capability in predictive maintenance, many existing approaches operate as black-box models that provide limited explanation of the reliability estimation process. In practical industrial maintenance, however, maintenance decisions must be both accurate and interpretable to support engineering judgments and operational planning.

The proposed dynamic Bayesian neural reliability network enhances interpretability by integrating neural-network-based reliability predictions, Bayesian temporal reasoning, and explicit delay-aware modeling within a unified decision framework. The neural-network-based prediction layer estimates the failure probability from physically meaningful operational variables, including the degradation level, load, temperature, vibration, delayed degradation observations, and effective machine age, thereby maintaining a clear connection between reliability predictions and the machines' operating conditions.

The approximate Bayesian filtering mechanism further improves interpretability by recursively incorporating historical posterior reliability and delayed observations, allowing maintenance engineers to understand how previous machine states influence current reliability estimations. In addition, the explicit modeling of time-varying communication delay, $\tau_{i,t}$, enables the framework to realistically represent the asynchronous industrial monitoring environments that are commonly encountered in cyber-physical manufacturing systems.

Finally, preventive maintenance decisions are generated through explicit optimization objectives and operational constraints rather than opaque decision policies. Consequently, the proposed framework combines nonlinear predictive capability with transparent reliability reasoning, providing an interpretable and practically deployable decision-support framework for delay-aware predictive maintenance.

4.3. Motivation for the hybrid Bayesian–neural architecture

Recent advances in deep learning have significantly improved predictive maintenance by enabling nonlinear reliability predictions from complex industrial data. Nevertheless, purely neural-network-based approaches often rely on instantaneous input–output mappings and generally lack explicit probabilistic reasoning, making them more sensitive to delayed observations, communication latency, and noisy sensor measurements. In addition, their black-box nature limits the interpretability required for practical maintenance decision-making.

To address these limitations, this study proposes a hybrid Bayesian–neural architecture that combines the strengths of neural-network-based learning and Bayesian reliability updating. The neural-network-based prediction layer captures nonlinear degradation–risk relationships from operational and degradation-related variables, whereas the approximate Bayesian filtering mechanism recursively incorporates historical posterior reliability and delayed observations to improve temporal consistency and the estimations' robustness.

By explicitly modeling time-varying communication delays, the proposed framework provides a more realistic representation of the evolution of reliability in cyber-physical manufacturing environments. Compared with purely neural approaches, the hybrid architecture enhances the robustness and interpretability of maintenance decisions while preserving strong predictive capability. Compared with traditional statistical reliability models, it also offers greater flexibility for modeling nonlinear degradation behavior without relying heavily on predefined degradation assumptions.

Overall, the proposed dynamic Bayesian–neural reliability network establishes an interpretable and adaptive reliability prediction framework that integrates nonlinear learning with probabilistic reasoning for delay-aware predictive maintenance.

4.4. Computational complexity analysis

The proposed predictive maintenance framework consists of two computational components: Reliability estimation and rolling-horizon maintenance optimization. The reliability estimation includes neural-network-based reliability prediction and Bayesian reliability updating, whereas the optimization stage determines preventive maintenance schedules using a GA.

Let N denote the number of machines, H be the planning horizon, F be the number of input features, P be the GA population size, G^{max} be the maximum number of generations, and H_r be the rolling-horizon length. The neural-network-based reliability prediction evaluates each machine at every decision period, resulting in a computational complexity of $O(NHF)$, while the Bayesian reliability updating recursively processes each machine–period observation using the current prediction and historical posterior information, yielding a complexity of $O(NH)$.

The dominant computational cost arises from the rolling-horizon GA optimization. During each optimization stage, all chromosomes are evaluated over the rolling horizon, leading to a complexity of $O(G^{max}PH_rN)$. Since the optimization is repeatedly performed throughout the planning horizon, the overall computational complexity becomes $O\left(\frac{H}{H_r}G^{max}PH_rN\right) = O(HG^{max}PN)$.

The analysis above indicates that the computational complexity increases linearly with the number of machines and planning periods under fixed GA settings. Furthermore, the rolling-horizon strategy decomposes the large-scale scheduling problem into a sequence of smaller optimization problems, thereby improving computational efficiency and making the proposed framework suitable for practical predictive maintenance applications involving multiple heterogeneous machines operating within delayed-information environments.

4.5. Industrial applicability and practical implications

The proposed delay-aware predictive maintenance framework is designed for industrial environments in which the equipment's degradation evolves dynamically under communication delays and uncertain operating conditions. It is particularly suitable for smart manufacturing systems equipped with distributed sensing infrastructure, cyber-physical production systems, and IIoT-enabled maintenance platforms.

Unlike conventional predictive maintenance approaches that assume instantaneous and complete condition monitoring, the proposed framework explicitly incorporates delayed degradation observations and Bayesian reliability updating to address communication latency, asynchronous sensor updates, and network-induced delays. Consequently, the framework provides a more realistic representation of how reliability evolves in practical industrial environments.

The proposed framework is also applicable to heterogeneous multiequipment systems operating under limited maintenance resources. By explicitly considering the maintenance capacity, workforce availability, and operational constraints, the rolling-horizon optimization generates maintenance schedules that are more consistent with practical industrial operations. Representative application domains include semiconductor manufacturing, automated production lines, petrochemical plants, intelligent machining systems, transportation equipment, and smart energy systems.

An additional advantage of the proposed framework is its interpretability. The integration of neural-network-based reliability prediction, Bayesian reliability updating, and explicit delay-aware modeling enables maintenance engineers to better understand the evolution of reliability and the rationale behind maintenance decisions, thereby improving confidence in maintenance planning.

Overall, the proposed framework provides an interpretable, adaptive, and practically deployable decision-support solution for predictive maintenance under delayed-information conditions, enabling maintenance managers to better balance a system's reliability, maintenance cost, and production continuity.

5. Numerical application and computation results

5.1. Industrial application scenario

To evaluate the effectiveness of the proposed DBNR-DAPMC framework, this study considers a smart manufacturing environment consisting of multiple heterogeneous industrial machines operating under dynamic production conditions and delayed information environments. The system represents an Industry 4.0-enabled manufacturing platform in which the machines' conditions are continuously monitored by distributed sensors and industrial communication networks.

The numerical experiments are conducted over a rolling planning horizon of 180 operational periods. The machines' operational information includes the degradation level, operating load, temperature, vibration, effective machine age, and delayed degradation observations. Owing to communication latency and asynchronous monitoring, the observed degradation state may differ from the actual condition of the machine, making reliability estimation and maintenance scheduling substantially more challenging. Unless otherwise specified, the machine-specific degradation coefficients, equipment criticality parameters, maintenance resource settings, and reliability updating parameters remained unchanged throughout all comparative experiments.

The proposed framework integrates neural-network-based reliability prediction, approximate Bayesian reliability updating, and rolling-horizon preventive maintenance optimization using a GA. The maintenance policy is compared with representative maintenance strategies commonly adopted in predictive maintenance studies, including pure Bayesian preventive maintenance, risk-threshold preventive maintenance, periodic preventive maintenance, and reactive maintenance.

The rolling-horizon optimization is solved using a GA with a population size of 100 and a maximum of 200 generations. Tournament selection and elitism are used to preserve high-quality solutions, while the crossover and mutation probabilities are set to 0.80 and 0.10, respectively. The optimization terminates when either the maximum number of generations is reached or no improvement is observed for 20 consecutive generations. These parameter settings provide stable convergence while maintaining satisfactory computational efficiency throughout the rolling-horizon optimization process.

Table 1 reports the principal parameter settings used in the numerical experiments. Machine-specific degradation and cost parameters were generated within the specified ranges to reflect the equipment's heterogeneity, whereas the filtering, maintenance, resource, and reliability parameters were fixed throughout the experiments. The reliability threshold was assigned according to the machines' criticality, and the approximate filtering weights were normalized to sum to one.

Table 1. Principal parameter settings used in the numerical experiments.

Parameter	Setting	Parameter	Setting
α_i	α_i~U (0.0006, 0.0018)	(α, ζ, β)	(0.8182, 0.10, 0.02)
β_i	β_i~U (0.0015, 0.0045)	ρ_i	(0.40), for all (i)
γ_i	γ_i~U (0.0004, 0.0018)	κ	(0.10)
V_i	V_i~U (0.0008, 0.0030)	Π	(8000)
η_i	η_i~U (0.0012, 0.0040)	Ω	(10)
σ_i	(0.0015)	R^{min}	$R_i^{min} \in \{0.68, 0.76, 0.84\}$
ϕ_0	(0.40)	c_i^{PM}	[1350, 2430]
ϕ_1	(1.80)	c_i^{CM}	[5980, 13666.25]
$(\lambda_1, \lambda_2, \lambda_3, \lambda_4)$	(0.72, 0.16, 0.10, 0.02)	c_i^{DT}	[1152, 2880]

Operational variables (load, temperature, and vibration) are generated within representative industrial operating ranges, whereas accumulated degradation and effective machine age evolve recursively according to the degradation model presented in Section 3.2. Communication delays are randomly generated to emulate asynchronous industrial monitoring environments, and the corresponding delayed degradation observations are incorporated into the Bayesian reliability updating mechanism.

To improve the transparency and reproducibility of the numerical experiments, Table 2 presents representative equipment records generated during the simulation process. The complete dataset contains operational records for multiple heterogeneous machines throughout the entire planning horizon, while only representative samples are presented here because of space limitations. Each record includes the operating conditions, communication delay, delayed degradation observation, accumulated degradation level, effective machine age, true failure probability, and the corresponding reliability of the machine.

Table 2. Example of equipment data for degradation.

Machine ID	Period	Load	Temperature	Vibration	Delay	Delayed degradation observation	Instantaneous degradation state	Effective age	True failure probability	True reliability
M01	0	0.5564	56.7179	0.4697	3	0.0372	0.0445	4.3702	0.0050	0.994995
M01	1	0.6283	50.3238	0.6582	2	0.0372	0.0596	4.8035	0.0047	0.995298
M01	2	0.5200	53.8003	0.4516	1	0.0445	0.0714	5.2293	0.0045	0.995539
…	…	…	…	…	…	…	…	…	…	…
M01	17	0.6385	58.3780	0.8548	4	0.2009	0.2653	11.6559	0.0120	0.988042
M01	18	0.6748	57.1460	0.9084	5	0.2009	0.2773	12.0823	0.0133	0.986669
…	…	…	…	…	…	…	…	…	…	…
M07	57	0.6531	56.7115	1.7199	1	0.7250	0.7561	27.7553	0.0508	0.949157
M07	58	0.8001	56.2263	1.7224	2	0.7250	0.7809	28.2096	0.0581	0.941876
…	…	…	…	…	…	…	…	…	…	…
M24	177	0.7162	58.4458	3.0376	5	1.5000	1.5000	82.1988	0.5681	0.431908
M24	178	0.6832	49.5954	3.1078	4	1.5000	1.5000	82.6601	0.5246	0.475411
M24	179	0.7354	45.8306	3.1120	3	1.5000	1.5000	83.1163	0.4935	0.506453

Note: "Instantaneous degradation state" denotes the actual machine degradation at the current decision period, whereas "delayed degradation observation" denotes the degradation information received after the communication delay, which is used for maintenance decision-making.

5.2. Time-varying delay environment

Figure 2 illustrates the time-varying observation delay generated in the simulated industrial monitoring environment. The delay represents the communication and sensing latency between the actual condition of the machine and the degradation information available to the predictive maintenance decision system. As shown in Figure 2, the average delay fluctuates approximately between 1.0 and 2.7 decision periods throughout the 180-period planning horizon, reflecting the dynamic communication conditions commonly encountered in industrial cyber-physical systems.

Although the magnitude of the delay appears moderate relative to the overall simulation horizon, its influence on predictive maintenance decisions should not be evaluated solely according to the total number of simulation periods. Because the proposed framework adopts a rolling-horizon decision mechanism, maintenance schedules are updated at every decision epoch using the latest available condition information. Consequently, even relatively short observation delays may lead to temporary discrepancies between the machine's actual degradation state and the information used for maintenance planning, thereby affecting short-term reliability estimation and maintenance decisions.

To address this issue, the proposed DBNR-DAPMC framework explicitly incorporates delayed observations into the Bayesian reliability updating mechanism. Instead of relying only on the latest neural-network-based prediction, the framework recursively integrates the current prediction, historical posterior reliability, and delayed condition information to obtain more robust reliability estimates under asynchronous observation environments. This mechanism reduces the sensitivity of maintenance decisions to temporary communication delays while improving the stability of rolling-horizon maintenance scheduling.

Overall, Figure 2 demonstrates the dynamic characteristics of the simulated delay environment and provides the basis for evaluating the effectiveness of the proposed delay-aware predictive maintenance framework under realistic industrial monitoring conditions.

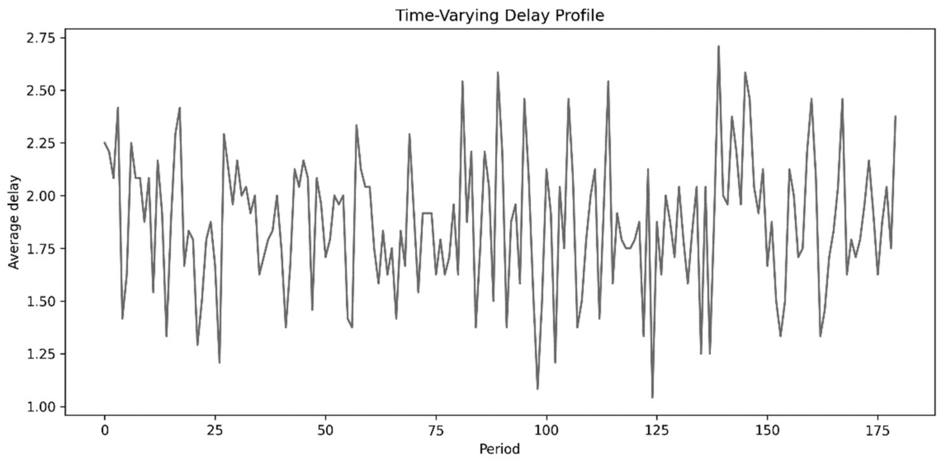

Figure 2. Time-varying information delay profile in the industrial monitoring environment.

5.3. Prediction performance evaluation

Before evaluating the effectiveness of the proposed maintenance optimization framework, it is first necessary to verify the predictive capability of the proposed dynamic Bayesian neural reliability (DBNR) model. Since the subsequent Bayesian reliability updating and rolling-horizon maintenance optimization directly rely on the machines' estimated failure probabilities, the quality of probability predictions fundamentally influences the effectiveness of maintenance decision-making. Therefore, this section first compares the prediction performance of the proposed model with several representative prediction methods before analyzing the maintenance scheduling results.

To evaluate the generalizability of different prediction models, a machine-holdout validation protocol is adopted. Instead of randomly partitioning individual observations, complete machines are separated into training, validation, and testing sets. Specifically, the proposed model is trained using Machines M01, M04, M07, M08, M10, M11, M16, M17, M18, M19, M20, and M24; validated using Machines M06, M12, M13, M15, and M21; and finally evaluated on the previously unseen Machines M02, M03, M05, M09, M14, M22, and M23. This evaluation protocol is considerably more challenging than conventional random sample partitioning because the prediction model must generalize to entirely unseen machines with different degradation characteristics rather than merely interpolating previously observed operating conditions.

Table 3 summarizes the prediction performance of the proposed DBNR model and four representative benchmark methods. Since the proposed framework estimates continuous failure probabilities that are subsequently incorporated into Bayesian reliability updating and rolling-horizon maintenance optimization, probability-based evaluation metrics are adopted instead of threshold-dependent binary classification metrics. Specifically, the mean absolute error (MAE), root mean square error (RMSE), Brier score, and expected calibration error (ECE) evaluate the accuracy and calibration quality of probabilistic predictions, while the area under the curve (AUC) and area under the precision–recall curve (PR-AUC) assess the ability to discriminate between impending failure and normal operating conditions. The mean early warning time measures how early potential failures can be detected before failure occurs, whereas the false alarm rate evaluates the frequency of unnecessary maintenance warnings.

It should be noted that the F1-score is intentionally not adopted in this study. Unlike conventional binary classification problems, predictive maintenance requires accurate estimations of continuous failure probabilities rather than simply classifying machines into failure and nonfailure categories. The F1-score requires the conversion of predicted probabilities into binary decisions using a predefined classification threshold, making the resulting performance highly dependent on the selected threshold value. In contrast, the proposed maintenance framework directly utilizes predicted failure probabilities within the Bayesian reliability updating mechanism and the rolling-horizon maintenance optimization process. Consequently, the quality of probability estimation, calibration performance, and probability ranking capability provide a more meaningful evaluation than threshold-dependent classification metrics.

As shown in Table 3, the proposed DBNR model achieves excellent overall prediction performance. Although XGBoost produces slightly lower MAE, RMSE, Brier score, and ECE values, the proposed framework achieves the highest AUC (0.9813) and PR-AUC (0.7702), indicating superior capability in distinguishing potential failure events, particularly under the highly imbalanced operating conditions commonly encountered in predictive maintenance applications. Since machine failures occur much less frequently than normal operating conditions, PR-AUC provides a more informative assessment of rare-event prediction performance than AUC alone. To directly evaluate the contribution of the proposed reliability updating mechanism, Table 3 additionally reports the prediction performance of the neural-network-based predictor before updating reliability. The comparison indicates that the updating layer is primarily intended to improve the robustness and temporal consistency of reliability estimations under delayed observations, rather than to uniformly improve every pointwise prediction metric. Compared with the neural-network-based predictor alone, the proposed reliability updating mechanism produces a slightly larger MAE, RMSE, Brier score, and ECE, while improving AUC, PR-AUC, mean early warning time, and reducing the false alarm rate. These results indicate that the proposed updating layer is primarily designed to improve the robustness and reliability of maintenance-oriented probability estimation rather than minimizing every pointwise prediction error metric.

From the maintenance perspective, the false alarm rate is particularly important because each false alarm may trigger unnecessary inspections, preventive maintenance activities, machine downtime, spare part replacement, and production interruptions. Excessive false alarms therefore increase maintenance costs while reducing production efficiency. The proposed DBNR model achieves the lowest false alarm rate (5.13%), corresponding to only 4 false maintenance warnings throughout the entire experiment, compared with 5, 6, and 22 false warnings generated by XGBoost, Random Forest, and Weibull reliability predictions, respectively. This result demonstrates that the proposed framework produces more reliable maintenance recommendations while effectively avoiding unnecessary maintenance interventions.

The proposed model also achieves a favorable balance between early warning capability and decision reliability. Although the Weibull reliability model provides a slightly longer average warning time, it simultaneously generates substantially more false alarms, indicating that many of its early warnings are unnecessary. In contrast, the proposed DBNR model maintains an average early warning time of 8.735 decision periods while producing the lowest false alarm rate among all competing methods. Such a balance provides maintenance planners with sufficient preparation time without introducing excessive maintenance interventions.

Overall, the experimental results demonstrate that the proposed DBNR model does not necessarily achieve the minimum prediction error for every individual metric. Nevertheless, it consistently provides well-calibrated probability estimation, superior rare-event discrimination capability, sufficiently early maintenance warning, and the lowest false alarm rate among the competing methods. These characteristics are particularly desirable for predictive maintenance because maintenance decisions are driven by probabilistic reliability estimations rather than binary classification labels. Consequently, the proposed prediction model provides a reliable foundation for the subsequent Bayesian reliability updating mechanism and the rolling-horizon maintenance optimization framework.

Table 3. Comparative evaluation of predicted probability, calibration quality, risk discrimination, and early warning performance using the machine holdout validation protocol.

Model	Training machines	Validation machines	Test machines	MAE	RMSE	Brier score	ECE	AUC	PR-AUC	Mean early warning time	False alarm rate	Total warnings	Total false warnings
Proposed DBNR	M01 M04 M07 M08 M10 M11 M16 M17 M18 M19 M20 M24	M06 M12 M13 M15 M21	M02 M03 M05 M09 M14 M22 M23	0.02526	0.03712	0.00138	0.13128	0.9813	0.7702	8.735	0.05128	78	4
Neural predictor only	M01 M04 M07 M08 M10 M11 M16 M17 M18 M19 M20 M24	M06 M12 M13 M15 M21	M02 M03 M05 M09 M14 M22 M23	0.02458	0.03648	0.00132	0.12649	0.9798	0.7518	8.381	0.06410	82	5
XGBoost	M01 M04 M07 M08 M10 M11 M16 M17 M18 M19 M20 M24	M06 M12 M13 M15 M21	M02 M03 M05 M09 M14 M22 M23	0.02113	0.03519	0.00124	0.12461	0.9758	0.6821	8.208	0.07143	70	5
Random Forest	M01 M04 M07 M08 M10 M11 M16 M17 M18 M19 M20 M24	M06 M12 M13 M15 M21	M02 M03 M05 M09 M14 M22 M23	0.02252	0.03686	0.00136	0.12762	0.9726	0.6407	8.735	0.07500	80	6
Weibull reliability	M01 M04 M07 M08 M10 M11 M16 M17 M18 M19 M20 M24	M06 M12 M13 M15 M21	M02 M03 M05 M09 M14 M22 M23	0.23723	0.32066	0.10283	0.32512	0.9496	0.4286	9.721	0.16418	134	22

Note: Lower values indicate better performance for the MAE, RMSE, Brier score, ECE, and false alarm rate, whereas higher values indicate better performance for AUC, PR-AUC, and mean early warning time.

5.4. Policy-related analysis of the evolution of reliability

Following the verification of the prediction capability of the proposed dynamic Bayesian–neural reliability (DBNR) model, this subsection evaluates how different maintenance decision mechanisms influence the long-term evolution of reliability of the manufacturing system. Since maintenance scheduling directly determines subsequent propagation of degradation, the reliability trajectories provide an intuitive assessment of the effectiveness of different maintenance policies before analyzing the corresponding maintenance schedules and economic performance.

Figure 3 compares the mean reliability trajectories of the system generated by the proposed DBNR-DAPMC framework and four representative benchmark policies, namely periodic preventive maintenance, pure Bayesian preventive maintenance, reactive maintenance, and risk-threshold preventive maintenance. The horizontal axis represents the operational period, whereas the vertical axis denotes the average reliability of the 24-machine manufacturing system.

Overall, all maintenance policies exhibit a gradual reduction in the system's reliability as machine degradation accumulates throughout the planning horizon. Nevertheless, the proposed DBNR-DAPMC framework consistently maintains a system with higher mean reliability than the benchmark policies during most operational periods. This behavior indicates that the proposed framework is capable of preserving the system's reliability more effectively under continuously evolving degradation conditions.

The primary reason for this improvement is that the proposed framework does not rely solely on the current condition of the machines when determining maintenance actions. Instead, neural-network-based reliability prediction and Bayesian reliability updating jointly estimate the future degradation tendency by integrating current observations, historical reliability information, and delayed monitoring data. Consequently, the rolling-horizon optimization mechanism is able to identify machines that are approaching accelerated degradation and can schedule preventive maintenance before a significant decline in reliability occurs. As a result, the reliability trajectory remains consistently above those generated by the conventional maintenance strategies.

The differences among the benchmark policies further illustrate the importance of predictive maintenance. Periodic preventive maintenance performs maintenance according to fixed intervals and therefore cannot respond to heterogeneous degradation behaviors among different machines. Reactive maintenance postpones maintenance until severe degradation has already occurred, leading to a more rapid decline in reliability during the later operational stages. The pure Bayesian preventive maintenance policy utilizes posterior reliability information but lacks the predictive state propagation and rolling-horizon optimization incorporated in the proposed framework, thereby limiting its ability to anticipate the future evolution of degradation. Although the risk-threshold preventive maintenance policy maintains relatively high reliability through threshold-triggered maintenance, its reliability trajectory exhibits frequent oscillations, indicating repeated maintenance interventions whenever the reliability approaches the predefined threshold.

Unlike these benchmark approaches, the proposed DBNR-DAPMC framework proactively schedules maintenance according to the predicted evolution of degradation rather than reacting to a deterioration in reliability after it has already occurred. Consequently, degradation of reliability is mitigated before entering the rapid deterioration stage, enabling the proposed framework to maintain a more stable and consistently higher reliability trajectory throughout the planning horizon.

It should be emphasized that the objective of the proposed framework is not simply to maximize instantaneous reliability through excessive maintenance. Instead, the proposed approach seeks to preserve the system's reliability by performing maintenance at appropriate decision periods identified through predictive degradation analysis, Bayesian reliability updating, and rolling-horizon optimization. This predictive maintenance philosophy enables the framework to maintain superior reliability while avoiding unnecessary maintenance interventions.

Overall, Figure 3 demonstrates that integrating neural-network-based reliability prediction, Bayesian reliability updating, delayed-information modeling, and rolling-horizon optimization enables the proposed framework to anticipate accelerated degradation and implement preventive maintenance before substantial deterioration in reliability occurs. The resulting evolution of reliability provides the foundation for the adaptive maintenance schedules presented in the following subsection.

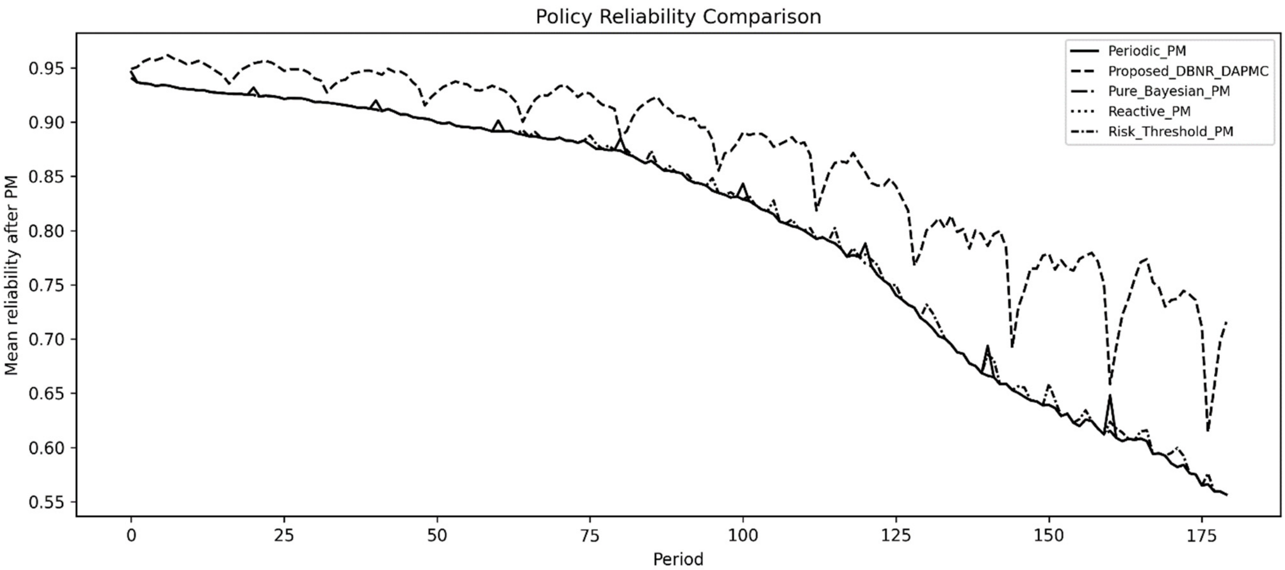

Figure 3. Mean reliability of the system under different preventive maintenance policies.

5.5. Posterior failure risk monitoring

While Figure 3 compares the evolution of overall reliability under different maintenance policies, Figure 4 provides a machine-level view of posterior failure risk throughout the planning horizon, enabling maintenance engineers to monitor the degradation status of individual machines. The horizontal axis represents the operational period, whereas the vertical axis corresponds to the machine index. Darker regions indicate higher posterior failure probabilities estimated by the proposed Bayesian reliability updating mechanism.

Several important observations can be drawn from Figure 4. First, failure risk evolves differently across machines, reflecting the heterogeneous degradation characteristics commonly encountered in industrial production systems. While some machines experience gradual deterioration in reliability, others exhibit accelerated increases in posterior failure probability after extended operation. These heterogeneous degradation patterns indicate that maintenance decisions should be determined according to equipment-specific reliability conditions rather than fixed maintenance intervals.

Second, the posterior failure risk matrix provides valuable decision-support information for proactive maintenance management. By continuously monitoring the temporal evolution of failure probability, maintenance engineers can identify machines approaching rapid degradation, anticipate when failure risk is likely to exceed an acceptable level, and prioritize their maintenance resources accordingly. Such information facilitates maintenance scheduling, spare part preparation, and workforce allocation before failures occur.

Furthermore, because the posterior failure probabilities are obtained through Bayesian reliability updating that integrates neural-network-based prediction, historical reliability information, and delayed observations, the resulting risk trajectories exhibit smooth temporal continuity while preserving the underlying degradation trends. This improves the robustness of maintenance decisions in delayed-information environments, where sensors' measurements may be incomplete or asynchronously updated.

Overall, Figure 4 demonstrates that the proposed framework serves not only as a model for predicting the probability of failure but also as an effective visual risk-monitoring tool. The posterior failure risk matrix enables maintenance engineers to identify high-risk equipment, monitor the progression of degradation, and allocate maintenance resources more efficiently. The corresponding evolution of machine-level reliability after maintenance implementation is presented in the following subsection.

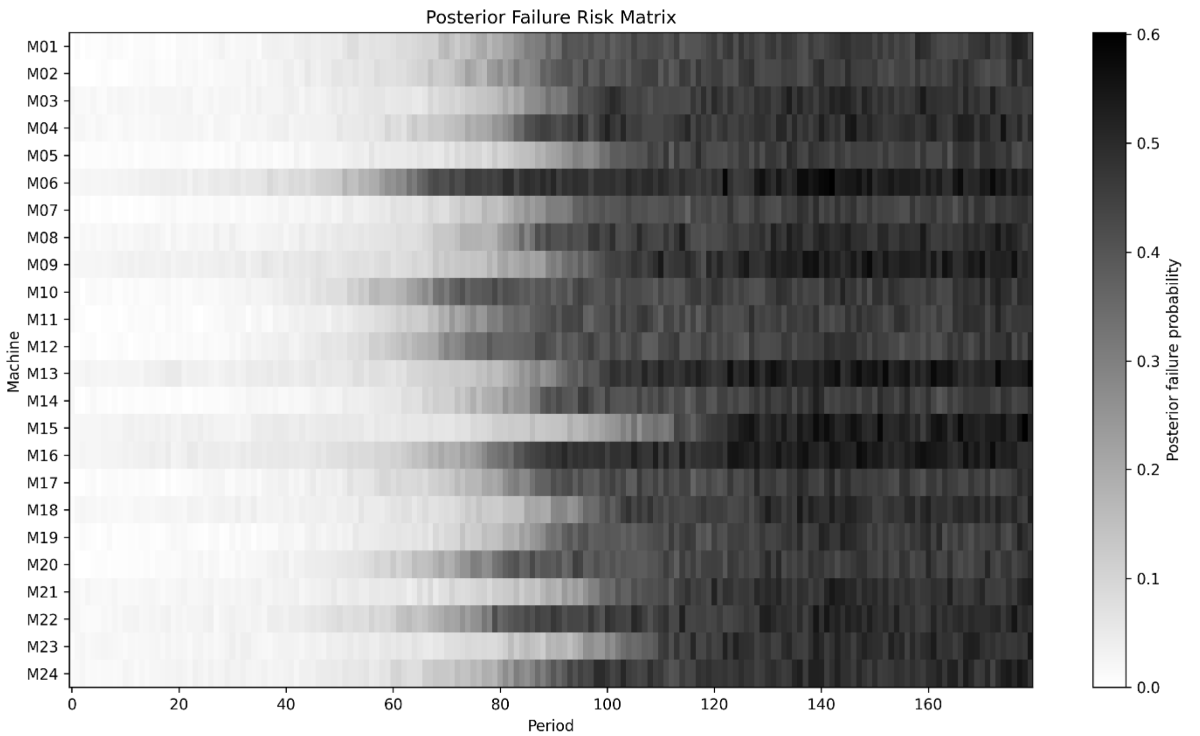

Figure 4. Evolution of posterior failure risk of the 24-machine manufacturing system under the proposed DBNR-DAPMC framework.

5.6. Evolution of machine-level reliability

While Figure 4 visualizes the evolution of posterior failure risk, Figure 5 illustrates how preventive maintenance influences the reliability trajectory of each machine under the proposed DBNR-DAPMC framework. Each subplot corresponds to an individual machine, where the horizontal axis represents the operational period and the vertical axis denotes the machine's reliability. The dashed horizontal line indicates the minimum reliability threshold adopted in the maintenance decision model, whereas the vertical dashed lines represent preventive maintenance actions.

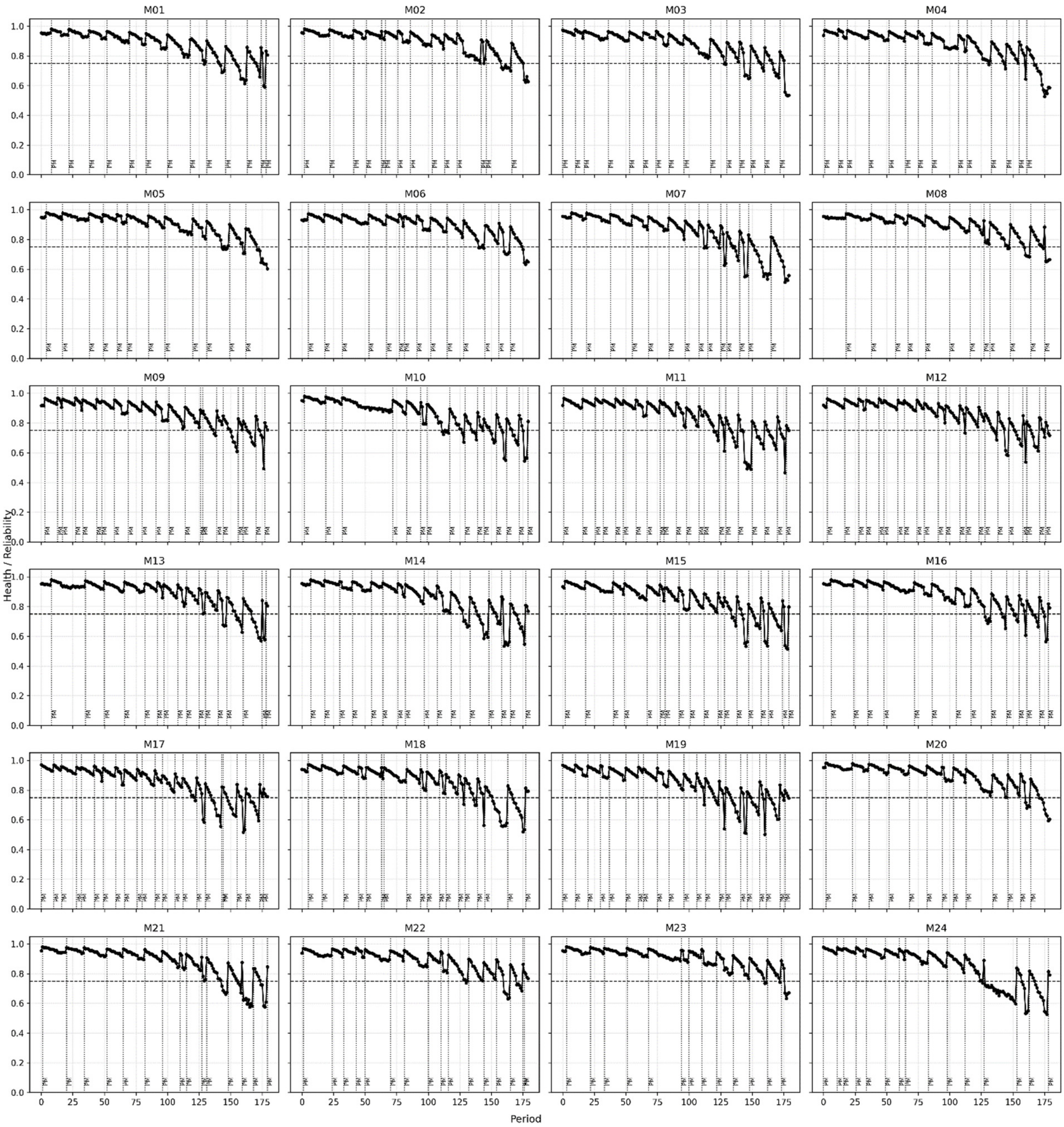

Figure 5. Evolution of machine-level health and reliability under the proposed DBNR-DAPMC framework.

As degradation accumulates during operation, machines' reliability gradually decreases until preventive maintenance is performed. Following maintenance, reliability partially recovers before entering another degradation cycle. Because the proposed framework assumes imperfect maintenance, the equipment is not restored to an as-new condition, resulting in realistic degradation–recovery patterns as commonly observed in industrial practice.

A notable observation is that maintenance actions are distributed differently across machines. Equipment experiencing faster degradation receives maintenance earlier or more frequently, whereas relatively stable machines require fewer interventions. This adaptive scheduling behavior demonstrates that maintenance decisions are determined according to the predicted evolution of degradation and updated posterior reliability rather than fixed maintenance intervals.

Figure 5 also provides valuable operational information for maintenance management. By simultaneously displaying the degradation in reliability, maintenance timing, and post-maintenance recovery, engineers can readily identify machines approaching critical reliability levels, evaluate maintenance's effectiveness, and adjust maintenance intervals or resource allocation when necessary. Such information supports more proactive maintenance planning and improves the utilization of limited maintenance resources.

Together with the system-level comparison presented in Figure 3 and the posterior risk monitoring shown in Figure 4, Figure 5 demonstrates how the proposed framework translates reliability predictions into adaptive maintenance actions at the individual machine level. Consequently, most machines remain above the predefined reliability threshold for the majority of the planning horizon while avoiding unnecessary maintenance interventions.

Overall, the results demonstrate that the proposed framework provides an effective machine-level decision-support mechanism that continuously coordinates degradation prediction, Bayesian reliability updating, and preventive maintenance scheduling within delayed-information environments.

5.7. Preventive maintenance scheduling analysis

Following the analysis of the evolution of machine-level reliability presented in the previous subsection, this section investigates how the proposed DBNR-DAPMC framework transforms reliability predictions into practical maintenance scheduling decisions. While Figure 3 demonstrates the system-level reliability advantage of the proposed framework and Figure 5 illustrates the recovery of machine-level reliability, Figure 6 further shows how these improvements are achieved through adaptive scheduling of preventive maintenance over the rolling planning horizon.

Figure 6 presents the preventive maintenance schedules generated for the 24-machine manufacturing system. The horizontal axis represents the operational periods, whereas the vertical axis denotes the machine index. Each marker indicates that preventive maintenance is scheduled for the corresponding machine during that decision period. Unlike conventional maintenance schedules based on fixed intervals, the generated maintenance actions are dynamically determined according to the predicted evolution of degradation, posterior reliability estimation, and resource availability.

The maintenance schedules reveal that preventive maintenance actions are distributed throughout the planning horizon rather than concentrated at predetermined intervals. This behavior demonstrates that the proposed rolling-horizon optimization framework continuously updates maintenance decisions according to newly available information on the machines' condition instead of relying on static maintenance plans. As the machine's degradation evolves over time, maintenance priorities are recursively adjusted, enabling the scheduling strategy to adapt to changing operational conditions.

Another important observation is that different machines receive substantially different maintenance frequencies. Machines exhibiting faster degradation rates or more rapidly increasing posterior failure probabilities are scheduled for preventive maintenance earlier and more frequently than machines operating under relatively stable conditions. This adaptive allocation reflects the heterogeneous degradation characteristics of the manufacturing system and demonstrates that maintenance decisions are driven by the predicted health condition of individual machines rather than by uniform maintenance intervals.

The scheduling pattern also illustrates the advantage of integrating Bayesian reliability updating with rolling-horizon optimization. Because posterior reliability estimates incorporate delayed monitoring information and historical reliability states, maintenance decisions are less sensitive to temporary fluctuations caused by communication latency or incomplete observations. Consequently, maintenance actions are triggered according to the long-term degradation tendency rather than isolated variations in sensors' measurements, thereby improving the robustness of the maintenance scheduling process.

Furthermore, the generated maintenance schedules exhibit no excessive clustering of maintenance actions within short operational periods. This behavior indicates that the optimization model successfully coordinates maintenance activities across multiple machines while satisfying maintenance-related resource constraints and minimum maintenance interval requirements. Such balanced scheduling not only improves the feasibility of maintenance but also reduces production interruptions that may occur when numerous machines require maintenance simultaneously.

More importantly, the scheduling results provide direct evidence supporting the reliability evolution observed in Figures 3 and 5. Since the proposed DBNR-DAPMC framework predicts the onset of accelerated degradation before substantial deterioration in reliability occurs, preventive maintenance can be scheduled proactively rather than reactively. As a result, reliability recovery is achieved before machines enter the rapid degradation stage, allowing the system's reliability trajectory to remain consistently above those of the benchmark maintenance strategies throughout most of the planning horizon.

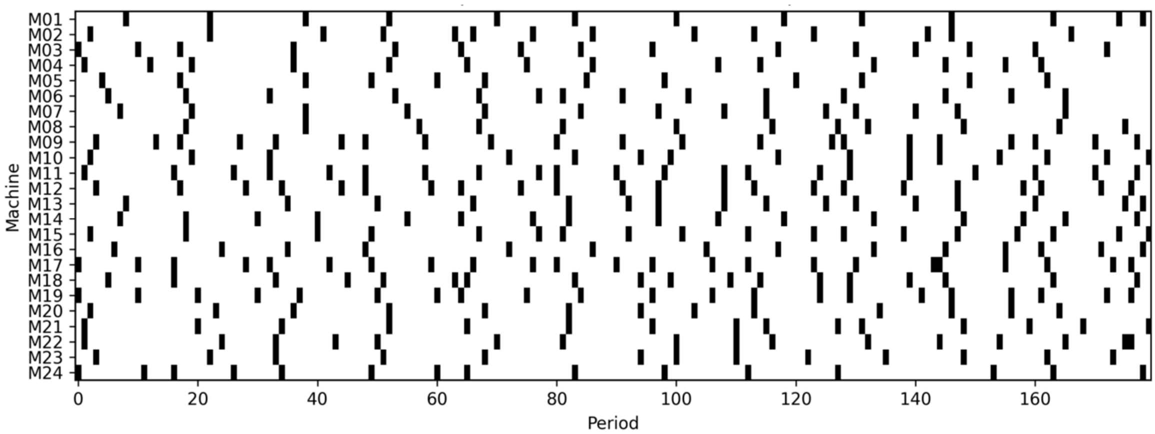

Figure 6. Preventive maintenance schedules generated by the proposed rolling-horizon optimization framework (Note: The density of maintenance markers reflects the dynamic maintenance frequency determined by the proposed rolling-horizon optimization rather than fixed periodic scheduling).

Overall, Figure 6 demonstrates that the proposed framework effectively transforms probabilistic reliability predictions into executable maintenance schedules through the integration of neural-network-based reliability prediction, Bayesian reliability updating, degradation state propagation, and rolling-horizon optimization.

5.8. Overall maintenance performance and cost analysis

Figure 7 and Table 4 present the overall performance comparison of the proposed DBNR-DAPMC framework and four representative benchmark maintenance policies.

As illustrated in Figure 7, the proposed DBNR-DAPMC framework achieves the lowest total operational cost among the evaluated maintenance strategies while simultaneously maintaining superior reliability.

According to Table 4, Neural-GA and Weibull-GA achieved lower total costs than the rule-based benchmark policies owing to their optimization-based maintenance scheduling. Nevertheless, the proposed DBNR-DAPMC framework achieved the lowest overall cost. Specifically, Neural-GA and Weibull-GA incurred approximately 11.55% and 15.98% higher total costs than the proposed method, respectively. Although Neural-GA directly incorporated data-driven failure predictions and Weibull-GA combined parametric reliability estimation with GA optimization, both methods produced higher failure, downtime, and reliability penalty costs. These results indicate that the cost advantage of DBNR-DAPMC may be attributed to the integrated effects of delay-aware neural-network-based prediction, recursive reliability updating, and rolling-horizon maintenance optimization.

Although the proposed framework performs a substantially larger number of preventive maintenance actions than several benchmark strategies, this does not indicate excessive maintenance. Instead, the additional preventive maintenance interventions effectively avoid expensive corrective maintenance, catastrophic failures, and prolonged production interruptions. Consequently, the increase in preventive maintenance cost is more than compensated by the significant reduction in failure cost, downtime cost, and reliability penalty cost, leading to a lower overall operational cost.

It is worth emphasizing that the superior performance of the proposed framework is achieved through the integration of multiple complementary decision mechanisms rather than by relying on a single prediction model. Neural-network-based reliability prediction provides early identification of accelerated degradation, Bayesian reliability updating improves the robustness of reliability estimations within delayed-information environments, and rolling-horizon optimization continuously adjusts the maintenance schedules according to the predicted future degradation states. The interaction of these components enables preventive maintenance to be implemented before machines enter the rapid deterioration stage, thereby preserving the system's reliability while avoiding unnecessary corrective maintenance.

Although the pure Bayesian preventive maintenance strategy utilizes posterior reliability information, it lacks the predictive degradation propagation and rolling-horizon optimization incorporated in the proposed framework. Consequently, maintenance decisions become less adaptive to future evolution of degradation, resulting in higher operational costs, lower reliability of the system, and substantially more high-risk operating periods.

Overall, the numerical results consistently demonstrate that the proposed DBNR-DAPMC framework provides the most balanced maintenance strategy among the evaluated approaches. Rather than maximizing reliability through excessive maintenance or minimizing the maintenance frequency at the expense of increased failures, the proposed framework effectively balances predictive capability, preservation of reliability, maintenance adaptability, and long-term operational cost under delayed-information environments. These results confirm that integrating neural-network-based reliability prediction, Bayesian reliability updating, the evolution of degradation, and rolling-horizon optimization significantly improves predictive maintenance performance for heterogeneous multiequipment manufacturing systems.

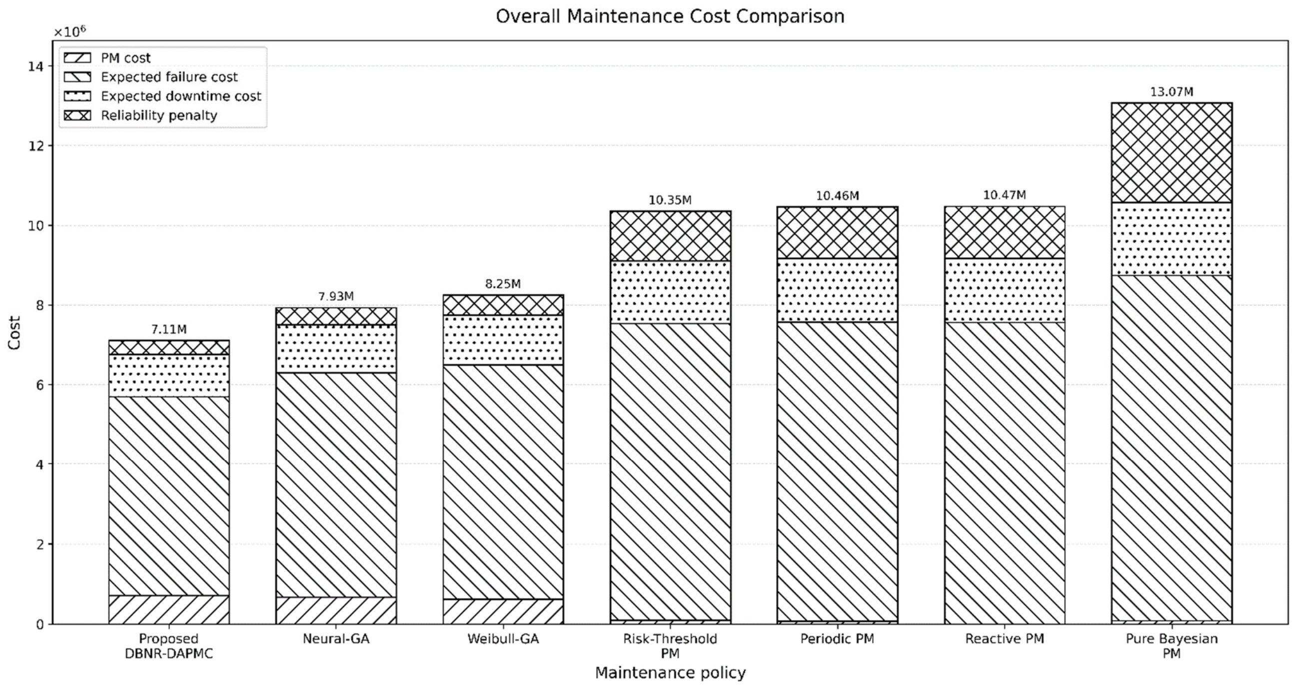

Figure 7. Cost component comparison among different maintenance strategies.

Table 4. Overall maintenance performance and cost analysis.

Method	Total cost	PM cost	Failure cost	Downtime cost	Reliability penalty	PM actions	Mean reliability	Minimum reliability	High-risk observations
Proposed DBNR_DAPMC	7,109,359	717,131	4,976,598	1,060,587	355,042	385	0.86895	0.46650	530
Neural-GA	7,930,420	670,842	5,630,437	1,200,276	428,865	360	0.85462	0.45071	642
Weibull-GA	8,245,682	625,315	5,867,176	1,251,409	501,782	335	0.84086	0.43984	748
Risk threshold PM	10,352,291	94,415	7,437,643	1,578,918	1,241,314	50	0.80558	0.43926	1253
Periodic PM	10,456,793	67,184	7,506,145	1,592,460	1,291,003	36	0.80387	0.43926	1290
Reactive_ PM	10,472,740	0	7,561,280	1,602,860	1,308,600	0	0.80267	0.43926	1303
Pure Bayesian PM	13,065,384	84,815	8,654,529	1,828,503	2,497,537	45	0.77300	0.32673	1534

Notes: Proposed DBNR-DAPMC, delay-aware Bayesian–neural predictive maintenance with rolling-horizon optimization; Neural-GA, neural prediction with GA optimization; Weibull-GA, Weibull reliability with GA optimization; periodic PM, fixed maintenance intervals; reactive PM, maintenance after failure only; risk threshold PM, maintenance triggered when the estimated failure probability exceeds a preset threshold; pure Bayesian PM, Bayesian reliability updating without neural prediction. PM, predictive maintenance.

6. Conclusions

This study proposed a delay-aware predictive maintenance and reliability control framework for multimachine industrial systems operating in dynamic and uncertain environments. The proposed DBNR-DAPMC framework integrates multilayer neural-network-based reliability prediction, Bayesian reliability updating, time-varying delay modeling, and rolling-horizon GA optimization into a unified predictive maintenance architecture. Unlike conventional maintenance approaches that rely primarily on instantaneous observations or fixed maintenance intervals, the proposed framework explicitly incorporates delayed information propagation and dynamic evolution of reliability to support adaptive maintenance decision-making.

Extensive numerical experiments demonstrated that the proposed framework effectively coordinates reliability prediction and preventive maintenance scheduling under practical resource constraints. The results indicate that the proposed approach achieves competitive prediction performance while providing improved robustness through Bayesian reliability updating and explicit delay-aware modeling. Furthermore, adaptive maintenance scheduling successfully reduces operational risk, maintains the system's satisfactory reliability, and allocates maintenance resources more efficiently than conventional maintenance strategies.

An important contribution of this study is the explicit incorporation of communication delays into the predictive maintenance process. By integrating delayed observations with historical posterior reliability information, the proposed framework improves the robustness of reliability estimation and maintenance decision-making under asynchronous industrial monitoring environments. In addition, the rolling-horizon optimization strategy enables maintenance schedules to be continuously updated according to evolving equipment conditions, thereby enhancing the adaptability of maintenance planning in dynamic production systems.

From a practical perspective, the proposed framework provides an interpretable decision-support tool for industrial maintenance management. The posterior failure risk monitoring and machine-level reliability analysis enable maintenance engineers to identify high-risk equipment, prioritize maintenance activities, and allocate limited maintenance resources more effectively. These capabilities are particularly valuable for Industry 4.0 and IIoT-enabled manufacturing systems, where communication latency and heterogeneous equipment conditions are frequently encountered.

Several limitations should be acknowledged. The present study evaluates the proposed framework using simulated industrial operating conditions, and maintenance's effectiveness is assumed to remain relatively stable throughout the planning horizon. Future research may incorporate real industrial datasets to further validate the proposed framework, investigate adaptive maintenance's effectiveness under varying operating conditions, and extend the optimization model to jointly consider production scheduling, energy consumption, and sustainability objectives. The integration of advanced learning architectures and digital twin technologies also represents a promising direction for real-time predictive maintenance in cyber-physical manufacturing systems.

Overall, the proposed DBNR-DAPMC framework establishes an interpretable, adaptive, and practically deployable predictive maintenance solution that integrates reliability prediction, Bayesian reasoning, delay-aware modeling, and maintenance optimization within a unified decision-support framework. The proposed methodology provides a practical foundation for reliability-centered maintenance management in modern smart manufacturing systems operating within delayed and uncertain industrial environments.

Use of AI tools declaration

The authors declare they have not used artificial intelligence (AI) tools in the creation of this article.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (Grant No. 72541160280) and the Guangdong Basic and Applied Basic Research Foundation (Grant No. 2024A0505050040).

Conflict of interest

The authors declare there is no conflict of interest.

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