

Review

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Bioinspired intelligence for situation awareness and health management of hydroelectric units: perspective of reliability-centered maintenance

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Abstract

As fundamental prerequisites for the operation and maintenance (O&M) of hydroelectric units, situation awareness and health management have emerged as research hotspots in recent years. Bioinspired intelligence, with advantages such as high efficiency, environmental adaptability, robust performance, and transferability, provides new research ideas, methods, and applications for the O&M of hydroelectric units, especially in situation awareness and health management. This paper reviews the prospects, current applications, and technical challenges of bioinspired intelligence in situation awareness and health management of hydroelectric units from the perspective of reliability-centered maintenance (RCM). First, the technical requirements and features of situation awareness and health management for hydroelectric units in RCM are elucidated. Next, the technical frameworks of hydroelectric units are reviewed from the perspective of bioinspired intelligence. A detailed discussion is then provided regarding the relevant implementation strategies in multiple domains, including real-time monitoring, multi-source signal fusion, state characteristic extraction, intelligent health diagnostics,



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maintenance decision-making optimization, and smart O&M systems. Finally, future trends and development opportunities in applying bioinspired intelligence to situation awareness and health management of hydroelectric units are proposed: integrating the advantages of bioinspired intelligence with the engineering requirements of RCM and innovating approaches for intelligent O&M, which would provide further support for safe, reliable, and efficient energy systems.

Keywords: Hydroelectric units, bioinspired intelligence, reliability-centered maintenance (RCM), situation awareness, health management

1. INTRODUCTION

Hydroelectric energy is a renewable, clean source that plays a vital role in the global energy system due to its efficiency, stability, and regulation capacity^[1,2]. The operational status of hydroelectric units directly affects energy security, generation efficiency, and economic returns. Modern large-scale units feature high water heads, multiple turbines, long diversion pipelines, and large water flow inertia. A typical structure of Francis turbine-generator units is shown in Figure 1^[3]. During operation, these units exhibit complex hydro-mechanical-electrical coupling, producing vibration signals with non-stationary and non-linear features^[4]. Harsh environments, frequent regulation, and variable conditions further accelerate equipment deterioration, creating major challenges for operation and maintenance (O&M). The maintenance of hydroelectric units incurs substantial costs and involves technical barriers, including insufficient understanding of the physical properties of the equipment and a lack of effective, condition-specific maintenance strategies, all of which render it difficult for operators to develop targeted maintenance plans.

Currently, hydropower stations predominantly adopt a planned maintenance-oriented strategy; this approach frequently encounters under-maintenance or over-maintenance issues, failing to meet the requirements of modern power systems for power supply-side adaptability and supporting the high-quality development demands of the power industry^[5]. The reforms introduced in maintenance practices have transitioned from reactive models and periodic models to condition-based maintenance (CBM) or further advanced maintenance philosophies. However, in practice, many power generation facilities lack clear implementation roadmaps, involve imbalanced development of software and hardware technologies, and encounter economic and technical limitations, leading to slow progress in operational upgrades.

Under the Industry 4.0 framework, CBM has emerged as a prominent trend in power generation^[6,7]. By leveraging the operational data from units, comprehensive unit status assessments are achieved through information processing and analysis. This enables the formulation of efficient, precise, and reliable maintenance plans on the basis of health monitoring and performance predictions. Nevertheless, the challenges related to overcoming organizational coordination barriers, cost-benefit trade-offs, and limitations of traditional practices that rely on manual inspections, expert experience, and single-parameter monitoring for health evaluation persist^[8,9].

Units encounter multifaceted challenges, including complex operating conditions, stochastic disturbances, and latent failures from prolonged service, which critically undermine the effectiveness of conventional prognostics and health management (PHM) systems. This research has four persistent technical limitations:

- (1) Insufficient sensor deployment, with environmentally induced data degradation and latency issues.
- (2) Ineffective integration of multi-source heterogeneous data, coupled with rigid feature extraction frameworks.
- (3) Post-failure diagnostic approaches that inadequately address early-stage performance degradation.
- (4) Disjointed maintenance planning that lacks systematic PHM integration.

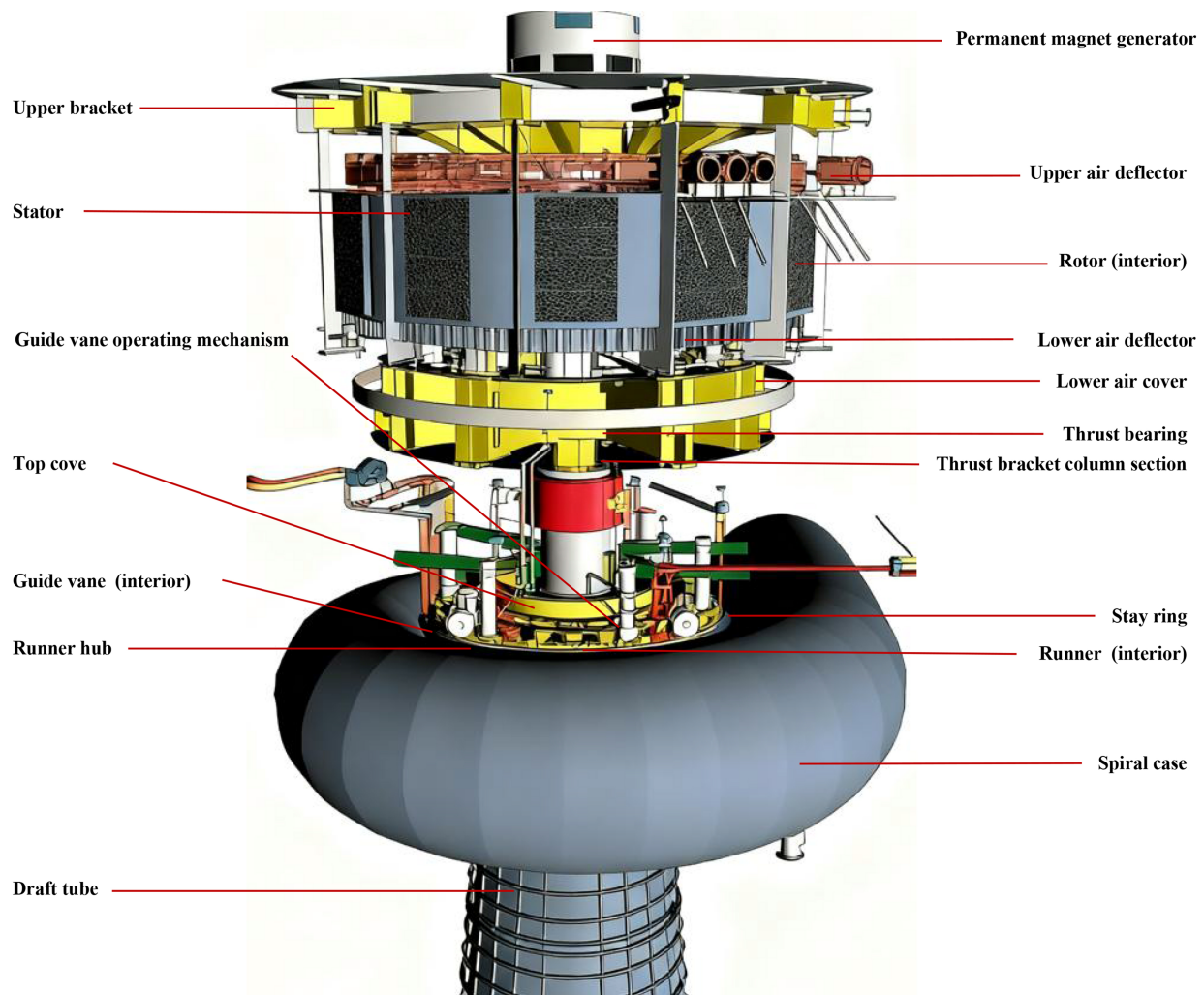


Figure 1. Structural schematic for hydroelectric units. Copyright © 2024, IEEE (Adapted from^[3]).

With the rise of the industrial Internet of Things and big data, artificial intelligence (AI) has become a key tool in PHM, improving safety and operational efficiency. Bioinspired intelligence, the foundation of AI, is widely applicable in hydropower, including hydraulic machinery design, sensor deployment for monitoring, signal processing, and multi-fault identification across hydraulic, mechanical, and electrical systems. These applications enhance intelligence, precision, and efficiency in O&M while overcoming the limitations of traditional methods under uncertain conditions^[10,11]. Distinct advantages include:

- (1) Distributed coordination and parallel processing for optimized monitoring.
- (2) Dynamic optimization and adaptive learning for non-linear fault recognition.
- (3) Improved critical data weighting and global optimization.
- (4) Efficient environmental interaction with anti-interference and resource-task optimization.

Applied to situation awareness and health management, bioinspired intelligence integrates historical and real-time data to improve signal processing, feature extraction, health assessment, performance prediction, and maintenance decision-making. Specifically:

- (1) Effective data acquisition is essential for condition understanding.
- (2) Feature parameterization supports health assessment.
- (3) Health indicators reflect unit degradation.
- (4) Maintenance frameworks ensure new maintenance paradigms.

Given the shortcomings of current models, development needs, and the strengths of bioinspired intelligence, this study adopted a reliability-centered maintenance (RCM) approach^[12], explored the O&M architecture of units, as shown in [Figure 2](#), it established a research framework for situation awareness and health management of hydroelectric units.

The framework aims to precisely grasp the health status of units and predict the remaining useful life (RUL) of the equipment based on performance changes to derive optimal maintenance strategies, achieve closed-loop maintenance for the units, and fill the gaps in previous research, which focused on improving the accuracy of health assessment and prediction results but neglected applicability methods in maintenance decision-making. This addresses the shortcomings of traditional maintenance models in terms of reliability and economy.

This paper combines bioinspired intelligence with situation awareness and health management, overcomes the shortcomings of traditional predictive maintenance, and provides a foundation for the future technological path of O&M. The remaining part is organized as follows. Section 2 introduces the RCM for situation awareness and health management. Section 3 examines the development and characteristics of bioinspired intelligence and its adaptability in the O&M. Section 4 proposes key technologies on the basis of bioinspired intelligence and analyzes the prospects for these technologies. Finally, Section 5 summarizes the entire content.

2. RCM-BASED FRAMEWORK FOR THE SITUATION AWARENESS AND HEALTH MANAGEMENT OF HYDROELECTRIC UNITS

This section introduces the necessity of RCM for situation awareness and health management. First, the concepts and operational workflow are discussed, and an integrated system architecture is proposed. Next, a review of the existing technologies embedded within the framework is provided.

2.1. Basic concepts and research framework

RCM originated in the civil aviation industry in the 1970s and was later adopted by the power sector. Its predominance stems from a reliability-centered framework that integrates CBM with advanced situation awareness and health management. This integration balances reliability, cost-effectiveness, and technological advancements, while also allowing for future incorporation of environmental considerations to establish a comprehensive maintenance mode^[13].

Traditional maintenance relied mainly on empirical data and statistical methods, often neglecting proactive failure prediction through functional analysis and data-driven diagnostics. As hydroelectric units grow in capacity, complexity, and intelligence, operational disruptions lead to higher costs, with maintenance comprising a large share of plant budgets. RCM-based situation awareness and health management improve safety and significantly reduce costs, shifting the focus from time-based preventive maintenance toward CBM, as illustrated in [Figure 3](#).

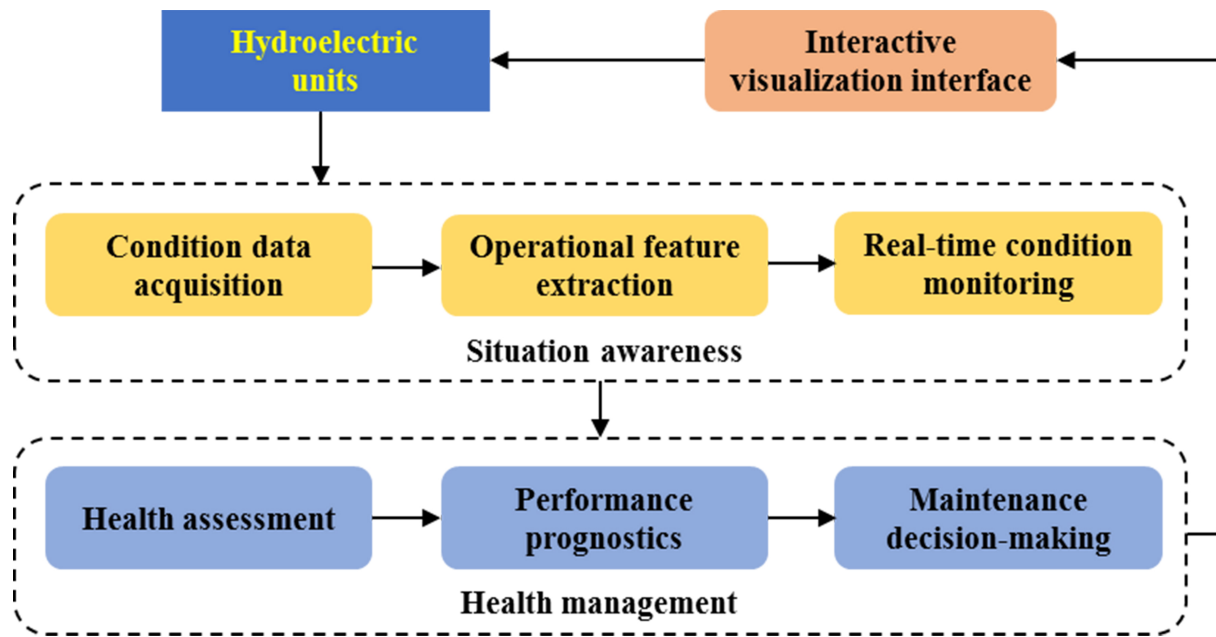


Figure 2. Situation awareness and health management of hydroelectric units.

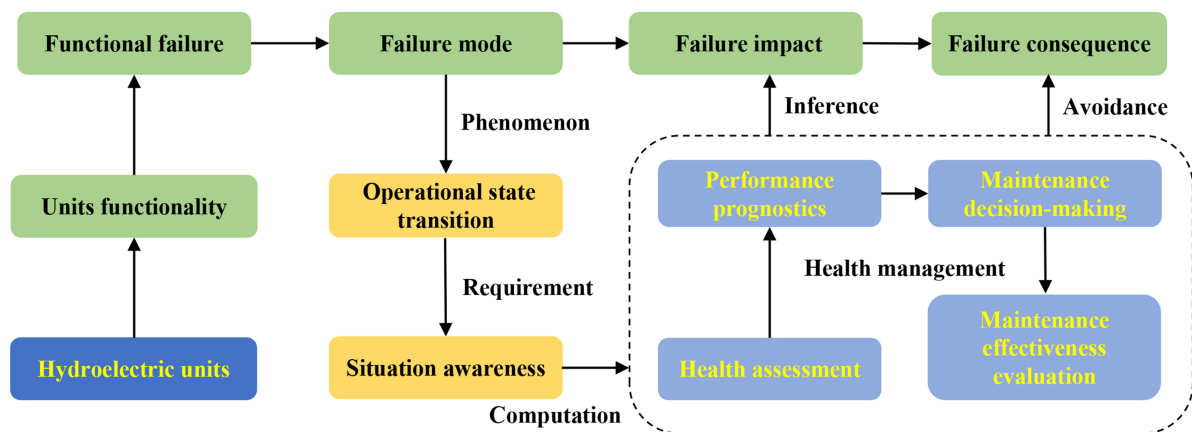


Figure 3. Workflow for the O&M of hydroelectric units. O&M: Operation and maintenance.

Situation awareness refers to the acquisition of units' operation parameters via sensor networks, followed by state characterization via feature extraction processes. This approach enables continuous condition monitoring and operational status reflection, thereby establishing the foundational dataset for the subsequent workflow^[14]. Health management encompasses the evaluation of degradation states, predictive analysis of performance, and RUL estimation of equipment to formulate optimal maintenance strategies that ensure reliability, safety, and cost efficiency. Situation awareness provides the informational infrastructure for health management, which reciprocally optimizes sensing configurations through feedback mechanisms, and this closed-loop architecture enhances the diagnostic accuracy of determining the current health status. Therefore, dynamic adjustments in monitoring focus and maintenance scheduling are achieved. The RCM-based framework for unit maintenance is presented in Figure 4.

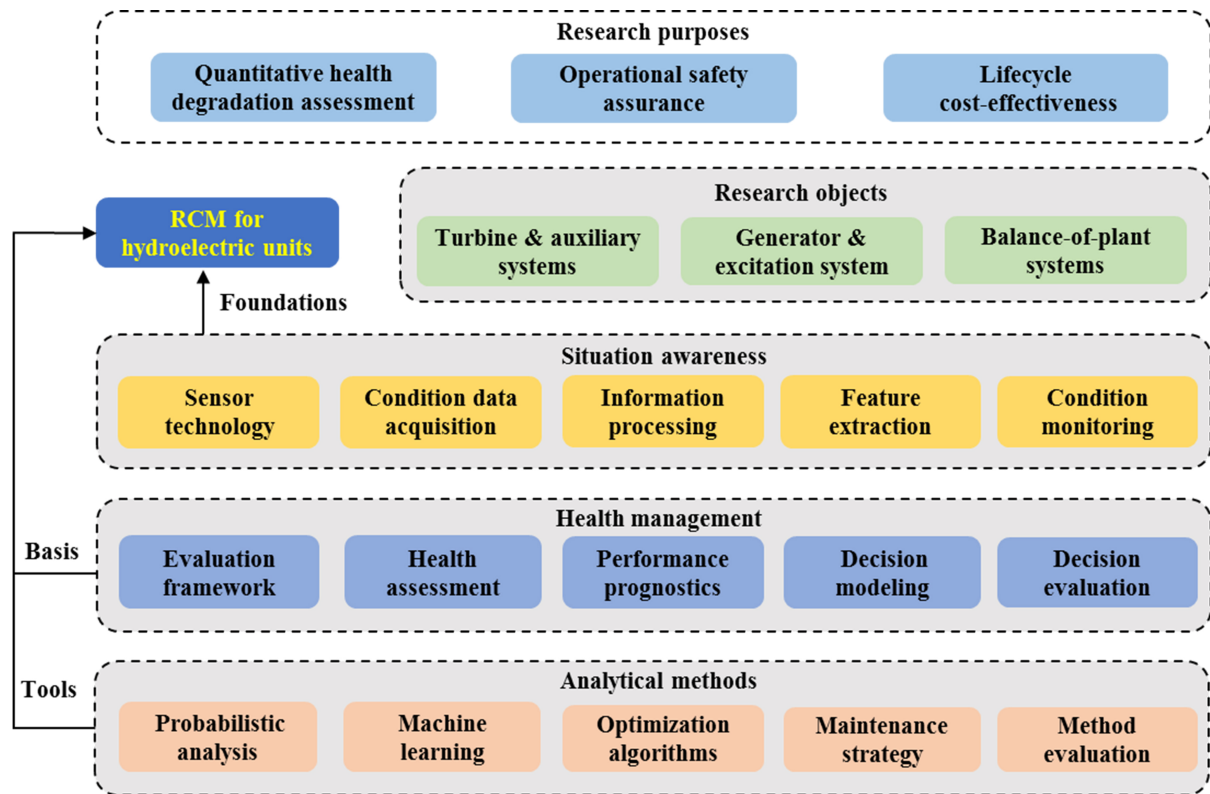


Figure 4. RCM-based holistic maintenance framework for hydroelectric units. RCM: Reliability-centered maintenance.

This framework maps the interdependence between maintenance processes and methodological components. The RCM and data-driven core integrate analytical methods and technical protocols with the basics of situation awareness to formulate evidence-based maintenance strategies.

2.2. Current research and application

This subsection examines the progress in current research and identifies the existing limitations across four technical dimensions: sensing technology and data acquisition, information processing and feature extraction, condition monitoring and health assessment, and performance prediction and decision.

2.2.1. Sensor technology and data acquisition

Sensors serve as the input interface for situation awareness, determining monitoring reliability through the acquisition and transmission of signals such as pressure, temperature, current, and voltage. Failures often result from poor sensor selection, leading to signal distortion. The number and placement of sensors affect accuracy: too few reduce credibility, while too many cause redundancy, inefficiency, higher costs, complexity, and fragility^[15].

Data acquisition includes filtering, noise removal, direct current (DC) isolation, amplification, and modulated transmission. Equipment degradation is reflected in vibration or other parameters, captured as numerical, semantic, or graphical features. Accurate acquisition of both structured and unstructured data underpins situation awareness^[16]. Conventional empirical and single-source models cannot process massive, multi-format, interrelated data. Multi-sensor fusion, inspired by the human brain, overcomes this limitation. Bioinspired intelligence enables precise and comprehensive use of multi-source information, surpassing single-perspective cognition^[17].

2.2.2. Information processing and feature extraction

Data undergo preprocessing such as outlier removal, missing data imputation, normalization, and cleansing to ensure integrity and reduce noise. Clustering with algorithms such as K-means, fuzzy C-means, and density-based spatial clustering of applications with noise (DBSCAN) partitions data^[18], but is limited by centroid sensitivity, difficulty detecting irregular shapes, local optima issues, and the need for feature reduction in high-dimensional data.

Signal processing applies time-, frequency-, and time-frequency-domain analyses to link signals with operational states, though environmental uncertainties hinder feature–health mapping. Vibration coupling produces non-stationary, low-signal-to-noise ratio (SNR) signals with noise and interference. Modal decomposition methods - wavelet transform (WT)^[19,20], empirical mode decomposition (EMD)^[21,22], variational mode decomposition (VMD)^[23,24], singular value decomposition (SVD)^[25,26] and independent component analysis - aid non-stationary feature extraction but often fail under complex dynamics, issues mitigated by bioinspired intelligence through adaptive optimization and noise robustness^[27].

Multimodal processing also includes semantic feature extraction from text via word2vec^[28] and convolutional neural network (CNN)-based classification of axle center trails^[29,30]. Selection criteria and applicability of these methods are summarized in Table 1.

2.2.3. Condition monitoring and health assessment

Condition monitoring uses real-time or periodic data to track operational evolution and increase availability. Hydraulic turbine monitoring focuses on efficiency, stability, and cavitation erosion^[31], employing pressure transducers for head measurement and ultrasonic or spiral-case differential pressure techniques for flow monitoring. Strategic sensor placement captures shaft runout and pressure pulsations, whereas confined flows necessitate indirect cavitation detection via vibration anomalies, acoustic emissions, or efficiency fluctuations and localization by leveraging abnormal vibrations, ultrasonic bubble analysis, or noise spectra. Advanced monitoring tracks crack propagation in flow components and sediment-induced wear^[32,33], although challenges persist in low-frequency vibration signal distortion mitigation. Generator monitoring employs air-gap systems to quantify stator–rotor clearance variations for misalignment or eccentricity detection, whereas shaft voltage pulse monitoring can be used to diagnose magnetic imbalance faults^[34]. Rotor temperature assessment has evolved from empirical estimates to wireless thermal mapping, and partial discharge (PD) monitoring uses multiple coupling methods but struggles with electromagnetic interference isolation^[35,36].

At present, the monitoring systems of units are undergoing rapid technological updates. For the industry, there is a problem of signal distortion in sensor collection. The causes can be attributed to sensor defects, aging, and installation issues, as well as electromagnetic, mechanical, and temperature–humidity interference; insufficient collection frequency; and signal attenuation during transmission. On an edge computing platform, real-time data processing is implemented at the collection end, which reduces the amount of transmission, decreases latency, and subsequently reduces the computational burden^[37].

Health assessment employs a multidimensional framework for quantifying long-term degradation, where conventional knowledge-based methods and physics-based approaches are superseded by data-driven methodologies. Degradation-driven analysis uses probabilistic and stochastic modeling^[38], including integrated PHM-semi-Markov frameworks^[39] and multi-source uncertainty integration^[40], but excessive probabilistic reliance risks inaccuracies under dynamic conditions^[41], exacerbated by hydrological variations. Machine learning approaches such as logistic regression, support vector regression (SVR), and

Table 1. Comparison of various methods

Methods	Limitations	Performs well in	Performs poorly in
K-means Fuzzy C-means ^[17]	Hard with non-spherical clusters Noise sensitive	Low-dim Spherical cluster Little noise	Hi-dim data Irregular clusters High noise
DBSCAN ^[17]	Sensitive to parameter choice	Noisy data Irregular shapes Unknown cluster count	Data with varying densities
WT ^[18,19] EMD ^[20,21] VMD ^[23,24]	Need expert parameter tuning EMD may mix modes	Non-stationary vibes Fault timing detection	Bad parameter choices lead to failure
SVD ^[25,26]	Fail under complex dynamics or strong noise	SVD: denoising	When signals don't meet algorithm assumptions
Word2Vec ^[28]	Needs lots of quality text data	Mining historical reports	Little or no non-standard text data
CNN ^[29,30]	Needs lots of labeled images	Classifying abundant labeled images	Lack of quality or unbalanced training data

DBSCAN: Density-based spatial clustering of applications with noise; WT: wavelet transform; EMD: empirical mode decomposition; VMD: variational mode decomposition; SVD: singular value decomposition; CNN: convolutional neural network.

recurrent neural networks (RNNs) extract degradation features^[42] to compute [0, 1]-normalized health indices via regression mapping, with neural networks enabling hierarchical feature abstraction for latent indicator extraction.

2.2.4. Performance prediction and decision-making

CBM formulates maintenance decisions based on the operational states while remaining reactive in nature. In contrast, prediction-based maintenance (PBM)^[43] proactively schedules interventions by leveraging degradation trend forecasting, thereby achieving preemptive maintenance optimization. This paradigm integrates fault progression predictions derived from time series forecasting models or fatigue damage models to enable the prognostics of future operational states and RULs for critical equipment. As illustrated in Figure 5, conventional prediction methods, such as physics-based, statistical, or hybrid approaches, underperform compared with deep learning architectures when handling complex multi-source data. Bioinspired intelligence has emerged as a critical enabler for data-driven methodologies, enhancing both the computational adaptability and autonomous decision-making of prognostic frameworks.

The maintenance strategy formulation uses operational data and failure mode studies to inform decision-making. With advancements in RCM, their application in the field of equipment maintenance has evolved to optimize resource allocation, minimize repair costs, and preserve operational safety and reliability. The RCM begins with the failure mode and effects analysis (FMEA)^[44,45] as follows:

- (1) Define the system component functionalities.
- (2) Identify the potential failure modes, root causes, and consequences.
- (3) Establish the foundational information for selecting context-appropriate maintenance actions.

Traditionally, RCM relies on experiential knowledge or qualitative assessments and lacks systematic justification. For example, fault tree analysis (FTA) enhances the logical rigor of the RCM through bottom-up deductive reasoning, graphically modeling the causal relationships between system failures and the contributing factors^[46]. This methodology quantifies how basic events influence top-level system failures for maintenance planning optimization. However, pre-failure decision-making in conventional approaches remains constrained for the following reasons:

- (1) Reliance on failure pattern analysis and statistical modeling.
- (2) Incomplete transition from time-based maintenance frameworks.
- (3) Limited adherence to genuine RCM.

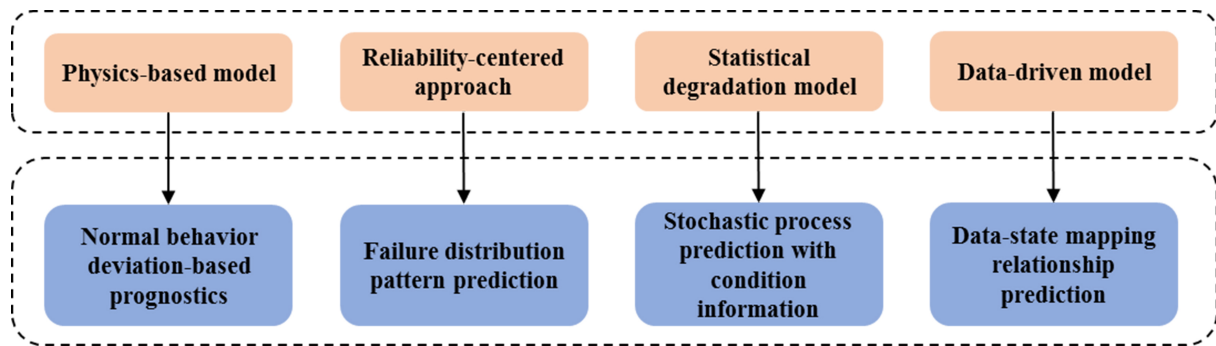


Figure 5. Comparison of the performances of different prediction methods.

Maintenance decision-making on the basis of bioinspired intelligence addresses the above limitations by incorporating multiple constraints and enabling solutions that approach theoretically optimal maintenance timing.

3. BIOINSPIRED INTELLIGENCE AND APPLICATIONS

This section focuses on the characteristics of bioinspired intelligence to trace its evolutionary trajectory, categorizes the methodological approaches used, and highlights its advantages. This study substantiates the technical feasibility of integrating bioinspired intelligence into situation awareness and health management.

3.1. Development history

The integration of computer science and bionics has fostered bioinspired intelligence, a paradigm that emulates biological behaviors to advance research and engineering. As a branch of AI, it addresses complex problems by mimicking biological architectures, behavioral patterns, and evolutionary mechanisms, with development spanning from neural models to swarm intelligence systems^[47].

Bioinspired intelligence's evolution followed distinct phases. The early stage began with McCulloch and Pitts' neuron model^[48], Hebb's synaptic plasticity theory^[49] and Rosenblatt's perceptron^[50], establishing mathematical models of neurons. In the 1960s–1970s, Holland's genetic algorithms (GAs) simulated Darwinian evolution^[51], while neural networks stagnated due to computational limits and Minsky's critique^[52], shifting focus to population-based optimization. The algorithmic renaissance introduced Hopfield's recurrent networks^[53], Rumelhart's backpropagation^[54], Dorigo's ant colony optimization^[55], and Kennedy and Eberhart's particle swarm optimization (PSO)^[56], advancing theory into real-world applications and establishing swarm intelligence. Since 2000, Hinton's deep belief networks^[57,58] spurred deep learning, while current frontiers explore brain-inspired computing for low-power systems^[59–61], biohybrid designs, molecular biocomputing, and cortical emulation^[62], driving interdisciplinary convergence across scales.

3.2. Technical characteristics

Bioinspired intelligence emulates the adaptive learning, evolutionary abilities, and problem-solving behaviors of organisms in complex environments, creating systems with similar traits of self-adaptation and optimization. It shows strong potential for applications such as situation awareness and health management to improve reliability and safety in equipment maintenance. Based on natural phenomena and biological behaviors, it can be classified into four categories: natural selection and evolution, swarm intelligence,

immune systems, and neural networks^[63]. A summary of bioinspired intelligence is provided in [Table 2](#).

Bioinspired intelligence solves problems through natural mechanism simulation. Evolutionary algorithms optimize via selection, crossover, and mutation, inspired by natural selection. Swarm intelligence enables global optimization through decentralized collaboration, mimicking collective animal behaviors for path planning and task scheduling. Artificial immune systems replicate immune functions such as antigen–antibody recognition and immune memory for anomaly detection in fault diagnosis. Neural networks simulate biological nervous systems with adaptive weighted neurons for non-linear mapping. While shallow networks risk local optima, deep learning employs multilayered architectures for automated feature extraction from image, audio, and time-series data. Despite high demands for labeled data and computation, they are widely applied in industrial diagnostics^[72-81].

3.3. Applicability analysis

Traditional AI generally refers to AI systems based on mathematical modeling, symbolic logic, statistics, and classical machine learning methods, which distinguish them from bioinspired intelligence. However, in situation awareness and health management, these two approaches coexist in a complementary relationship, as illustrated in [Figure 6](#). This image demonstrates the application domains of traditional AI, which are currently limited to the state perception level of hydroelectric units. Integrating bioinspired intelligence to extend capabilities into health management can enhance the reliability of unit O&M.

Bioinspired intelligence offers the advantages of processing complex data, adapting to environmental variations, achieving multi-objective optimization, and addressing uncertainties. Therefore, its application to units is highly feasible, as depicted in [Figure 7](#). This diagram concisely illustrates the role of bioinspired intelligence in equipment O&M, along with its specific application domains, and presents the applicable boundaries of different methods.

For hydroelectric units requiring real-time monitoring of multiple parameters, bioinspired intelligence optimizes sensor network layouts by emulating biological perception mechanisms. The encoder–decoder architecture in neural networks can integrate multi-source heterogeneous data, reduce noise interference, and achieve high-precision condition monitoring. In large-scale hydropower stations, swarm intelligence optimization algorithms are employed to enhance path planning for wireless sensor networks, minimizing communication latency. For edge computing scenarios, locally deployed intelligent diagnostic terminals are implemented, which leverage optimization algorithms to reduce the consumption of computational resources. By simulating the self-repair mechanisms of biological immune systems, adaptive fault diagnosis models can autonomously induce antibody generation processes upon anomaly detection, thereby enabling rapid fault localization. Traditional monitoring systems pose safety risks if sensor failures remain undetected, whereas immune algorithms and swarm intelligence demonstrate fault tolerance and maintain system stability through redundancy mechanisms even during partial sensor failures, thereby ensuring strong robustness. Intelligent optimization algorithms such as Non-dominated Sorting Genetic Algorithm (NSGA-II) facilitate the multi-objective optimization of maintenance decisions, balancing cost, downtime, and equipment reliability^[82].

When different types of bioinspired intelligence are selected for specific technical applications within the framework, the implementation of situation awareness and health management can adopt a layered technical architecture aligned with bioinspired intelligence, which can be divided into three tiers:

- (1) Perception Layer - focusing on the dynamic response and noise immunity.
- (2) Analysis Layer - Emphasizing data fusion and model evolution.
- (3) Decision Layer - Prioritizing multi-objective optimization and adaptability.

Table 2. Summary and comparison of bioinspired intelligence methods

Algorithm category	Evolutionary algorithms ^[64]	Swarm intelligence ^[65-67]	AIS ^[68]	Neural networks ^[69-71]
Biological principles	Natural selection and genetic mechanisms	Collective animal behavior	Biological immune defense	Biological nervous system
Core mechanism	Iterative optimization via selection-crossover-mutation	Global optimization through distributed local collaboration	Antigen-antibody recognition and immune memory	Adaptive weight adjustment of neurons
Typical applications	General optimization, symbolic expression refinement	Path planning, task scheduling	Fault diagnosis, intrusion detection	Non-linear mapping, adaptive learning
Applicability in hydropower	Plant economic dispatch, maintenance scheduling, units commitment	PSO: controller tuning, design optimization ACO: maintenance routing, resource allocation	Equipment fault detection and diagnosis (SCADA security)	Power forecasting, condition monitoring, vibration analysis
Advantages	Global search, good for non-linear problems	PSO: simple, fast convergence ACO: excellent for combinatorial problems	Strong anomaly detection, online learning potential	Excellent prediction and classification, automatic feature learning
Disadvantages	Slow convergence, parameter tuning, premature convergence	PSO: local optima stagnation ACO: slow, complex for continuous variables	Complex structure, less intuitive parameters	Black-box, needs big data, overfitting
Computational Req.	Medium-High	Low-medium	Medium	Train: high Use: low
Interpretability	Low (Black-box)	Low (Black-box)	Medium (Pattern-based)	Very low (Black-box)
Maturity (TRL)	TRL 7-8	PSO: TRL 7-8 ACO: TRL 5-6	TRL 4-5	TRL 7-9

AIS: Artificial immune system; PSO: particle swarm optimization; ACO: Ant Colony optimization; TRL: technology readiness level.

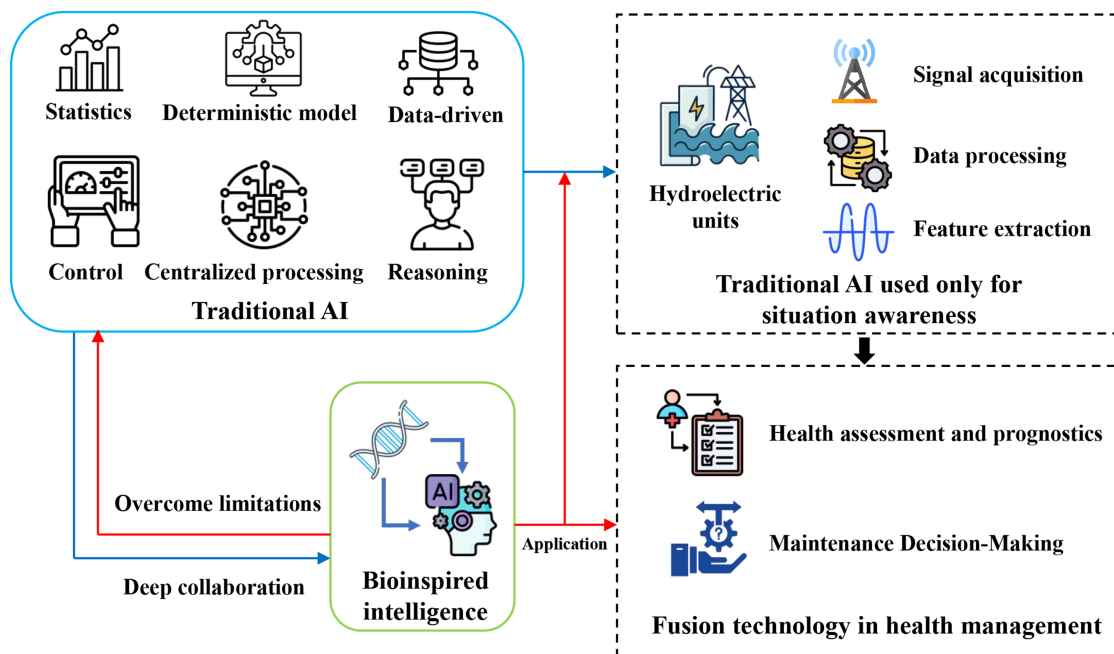


Figure 6. Relationship and applications of bioinspired intelligence and traditional AI. Icon made by Three musketeers, syafii5758, kliwir art, Vectors Tank, Uniconlabs, Aficons studio, Freepik, Vitaly Gorbachev, srip, bsd, Dewi Sari, Ehtisham Abid, Iconic Artisan from Flaticon. AI: Artificial intelligence.

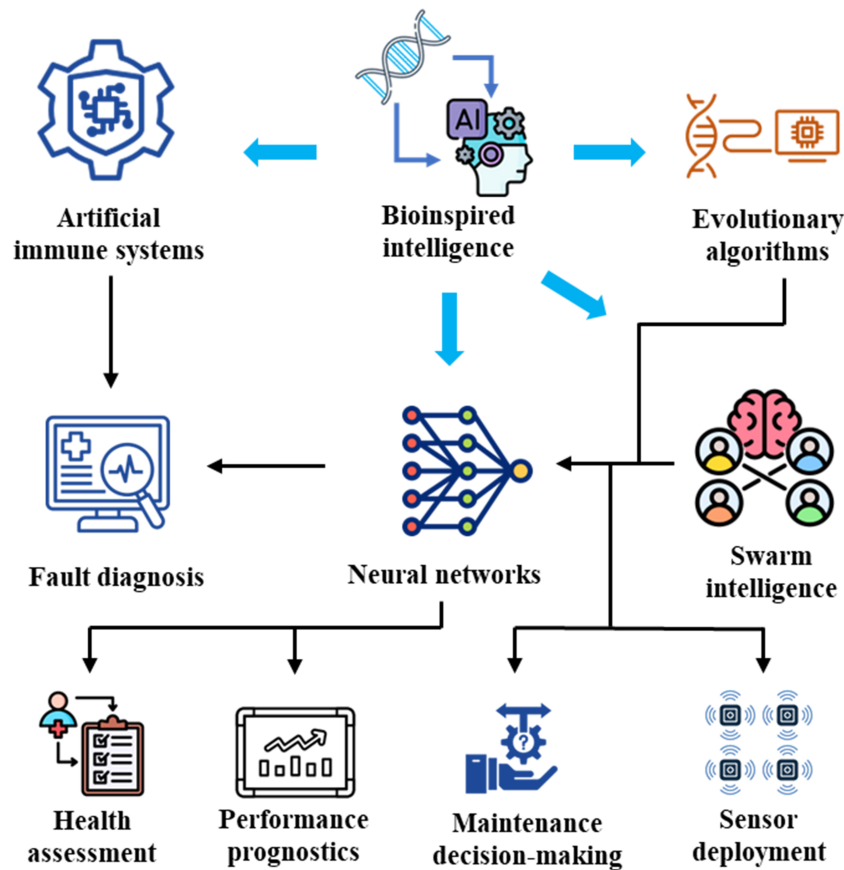


Figure 7. Applicable structure of bioinspired intelligence for hydroelectric units O&M. Icon made by -the Manggolo's-, Dewi Sari, varianicon, Freepik, Arkinasi, Dewi Sari, Ehtisham Abid, Iconic Artisan from Flaticon. O&M: Operation and maintenance.

This is achieved through a “problem-biological trait-algorithm” triad matching logic to precisely map bioinspired intelligence to engineering requirements. The selection process is as follows:

- (1) Define the technical objectives.
- (2) Select candidate methods.
- (3) Tune parameters.
- (4) Iterate dynamically.

4. SITUATION AWARENESS AND HEALTH MANAGEMENT OF HYDROELECTRIC UNITS BASED ON BIOINSPIRED INTELLIGENCE

This section integrates conventional techniques and bioinspired intelligence to analyze critical solutions addressing operational needs and technical challenges. The assessment encompassed four domains: (1) real-time monitoring with multi-source signal fusion; (2) operational factor simplification with state feature extraction; (3) intelligent health diagnosis and performance prediction; and (4) maintenance decision-making.

4.1. Key technologies

To achieve refined PHM, it is essential to delineate the operational stages of the units first, and the lifecycle of unit operation is divided into three phases, as illustrated in [Figure 8](#).

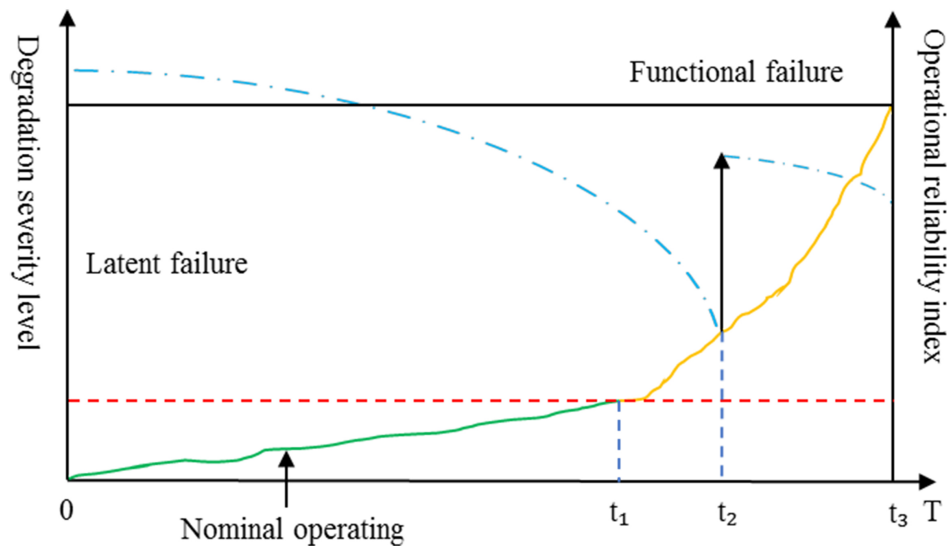


Figure 8. Lifecycle and condition maintenance times.

The solid line represents the degradation curve of the equipment, whereas the dashed line indicates its reliability, t_1 denotes the onset of a potential failure, t_2 marks the completion of maintenance, after which equipment reliability improves but does not fully return to the initial state, and t_3 signifies the point of complete equipment failure. Situation awareness and health management focus primarily on the interval between t_1 and t_3 , ensuring proactive hazard mitigation prior to failure. The key bioinspired intelligence technological system for the situation awareness and health management of hydroelectric units is illustrated in Figure 9.

This system clarifies the interdependence of maintenance steps and integrates constraint conditions and cost function models in line with RCM principles, including structural analysis, equipment criticality assessment, FMEA, and failure consequence evaluation. Using condition monitoring, it applies health assessment and performance prediction models to implement component-condition-based opportunistic maintenance, ultimately generating RCM decision plans for hydroelectric units. Bioinspired intelligence is employed in specific phases for modeling or optimization, forming a comprehensive framework for operation, maintenance, and inspection. The data acquisition, processing, and health assessment described in^[40] provide strong support for establishing this system. A project on real-time state evaluation and lifecycle prediction of turbine runners demonstrated the feasibility of applying situation awareness and health management to hydroelectric units. However, current processes underutilize bioinspired intelligence, limiting the advantages of each technical component. The technical architecture processes distributed operational data and maintenance records covering nearly all parameters, including sensitive grid dispatch strategies and proprietary equipment specifications. This requires strict information flow protocols with directional transmission controls to ensure cryptographic integrity. Building on existing monitoring infrastructure, progressive hardware and software integration will preserve coherence and compatibility while providing scalability. If the system becomes inoperable, fallback conservative maintenance protocols are automatically activated through predefined logic circuits, ensuring baseline safeguards.

Implementation of maintenance strategies and their effectiveness evaluation represent the culmination of condition perception and health management. By optimizing sensor configuration, maximizing asset utilization, improving generation efficiency, reducing maintenance scope and frequency, and preventing unplanned downtime, the system delivers significant economic benefits to hydropower stations.

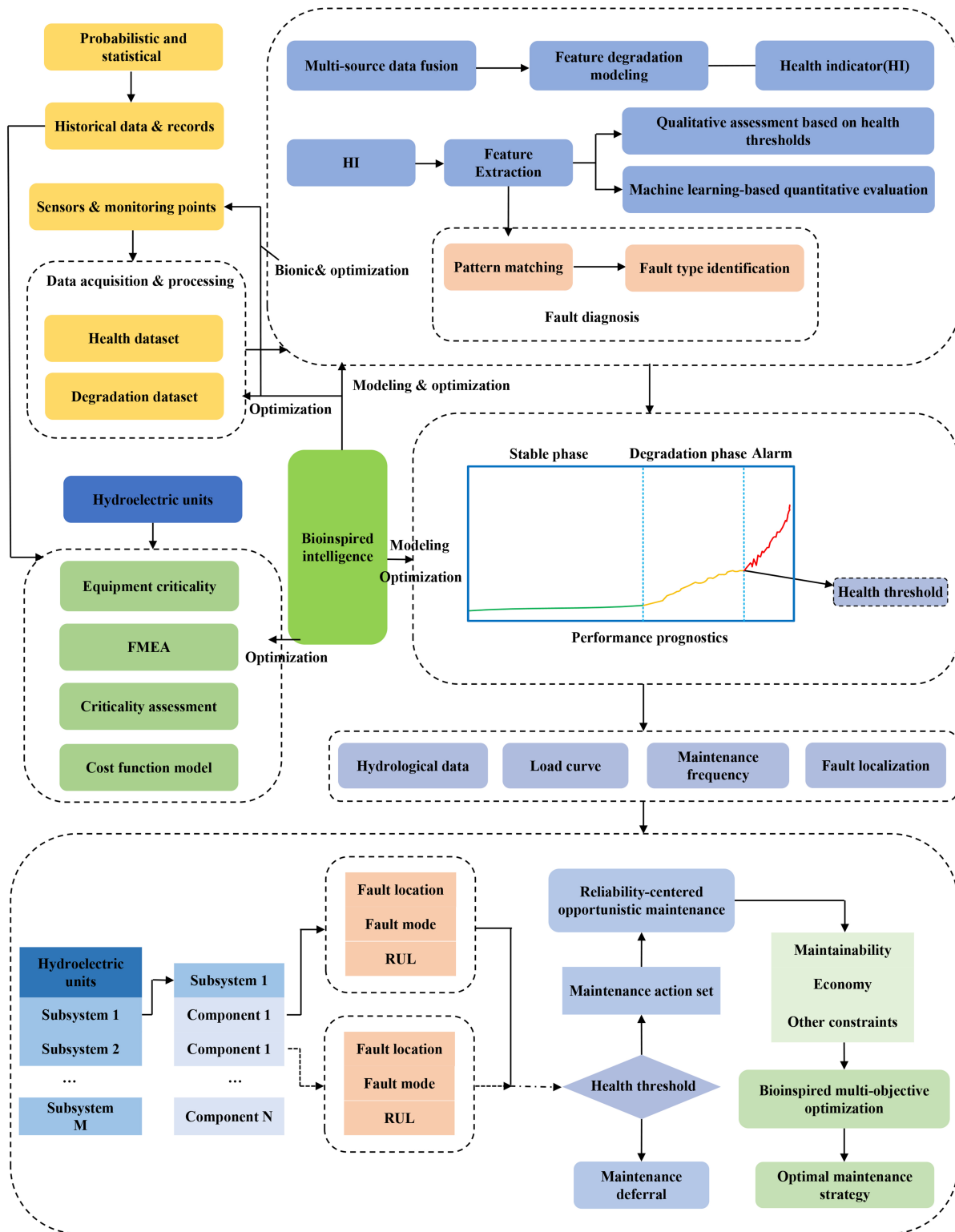


Figure 9. Key bioinspired intelligence technological system for the situation awareness and health management of hydroelectric units.

The following subsection elaborates on principles and research cases across different stages of the technical framework to demonstrate the system's practical applicability.

4.2. Major application prospects

Addressing the limitations identified in Section 2, bioinspired intelligence provides corresponding solutions. This section discusses the current research on its applications in maintenance practices, as shown in Table 3, followed by a critical examination of the technical challenges and future research directions for implementing bioinspired intelligence in next-generation hydroelectric unit O&M systems.

4.2.1. Real-time monitoring optimization and multi-source signal fusion

To reduce reliance on empirical approaches in monitoring point placement, bioinspired intelligence automates sensor location optimization using operational data, equipment characteristics, and environmental factors. The process searches for the optimal monitoring point combination, ensuring comprehensive coverage while avoiding redundancy. Using PSO, monitoring points are modeled as particle positions in multidimensional space. A multi-constraint fitness function incorporating effectiveness, cost, and risk evaluates candidate positions, and particle velocities are iteratively updated until convergence, yielding an optimal configuration.

Studies have shown the effectiveness of intelligent optimization algorithms for sensor placement in improving health monitoring reliability. Early research established optimization criteria^[100] defining performance metrics for measurement points. Later, bioinspired methods were widely applied to layout design. Zhang *et al.* proposed a Pareto multi-objective artificial fish swarm algorithm for structural health monitoring, optimizing distribution to ensure comprehensive data with minimal redundancy^[83]. Tripathi *et al.* developed a hybrid method combining genetic programming and GA for optimal deployment of wireless nodes^[101]. A comparative study found the bat algorithm (BA) outperformed PSO with higher efficiency, stronger global search, and superior precision in placement optimization^[84].

Current sensor configurations monitor vibration signals in X-, Y-, and Z-directions of the upper frame, stator frame, lower frame, and top cover, as well as horizontal and vertical vibrations of the stator core and stator coil plates. Swing signals are measured in the X- and Y-directions of the upper guide, lower guide, and hydro guide bearings. Pressure pulsations are recorded at the volute inlet, top cover, guide vane front, and draft tube inlet. Additional points include main shaft displacement, PD, and air gaps; the monitoring points of the hydroelectric units are shown in Figure 10^[102]. However, these monitoring points remain insufficient to capture full system dynamics. Future work should optimize sensor placement using field conditions and new technologies, such as alignment with bearing orientations or multifunctional sensors, to identify points that better reflect unit health.

Multi-sensor fusion technology integrates heterogeneous parameters into a unified framework, which allows holistic reflection of the operational status of the electromechanical equipment. For multicomponent systems involving intricate multiphysics couplings, such as hydroelectric units, distributed sensor networks inspired by bionic sensing mechanisms and bioinspired intelligence enable collaborative multinode perception. These networks significantly enhance both spatial coverage and measurement accuracy for condition monitoring. On the basis of biological signal acquisition principles, researchers have developed ultrasonic-based vibration monitoring systems that mimic bat echolocation and are capable of extracting critical signal features in data from high-noise environments^[85]. These sonar-based detection systems suffer performance degradation in sediment-laden or turbid water because of severe acoustic scattering attenuation, for which bioinspired solutions have emerged; however, low-power electromagnetic sensors,

Table 3. Application of bioinspired intelligence in unit maintenance

Hydroelectric units maintenance Issue	Bioinspired intelligence		Non-BI Bionic sensor
	Neural network	Intelligent optimization algorithm	
Function	Modeling	Optimization	Simulation
Overcoming empirical assumptions ^[83,84]	×	√	×
Bionic sensor ^[85]	×	×	√
Data cleaning accuracy ^[86-88]	×	√	×
Multi-source data fusion ^[29,30]	√	√	×
High-precision feature extraction and selection ^[89-91]	√	√	×
Data dimensionality reduction ^[92]	√	√	×
Model optimization ^[92-94]	×	√	×
Pattern recognition accuracy ^[68,92-95]	√	√ (AIS)	×
RUL ^[96,97]	√	√	×
Objective function optimization ^[98,99]	×	√	×

AIS: Artificial immune system; RUL: remaining useful life.

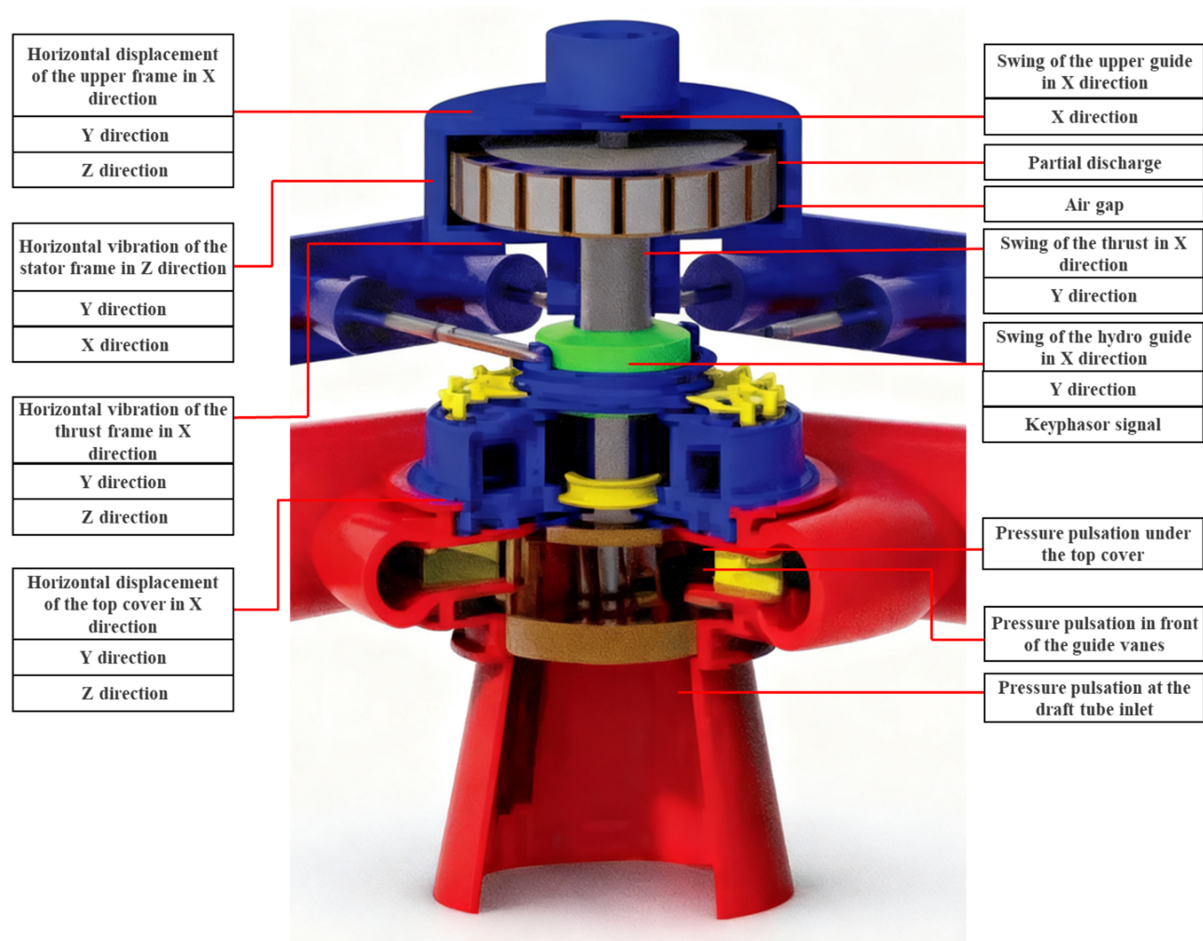


Figure 10. Monitoring points of hydroelectric units. Copyright © 2025, IEEE (Adapted from^[102]).

which employ the weak electric field detection capabilities of electric fish, demonstrate enhanced sensitivity for subaqueous weak electric field measurements, overcoming the limitations of traditional sonar systems.

Compared with simulation technology, physical sensors, although not falling within the category of bioinspired intelligence, have seen advancements that have enhanced the reliability and applicability of bioinspired intelligence.

Multi-source information fusion technology should be applied at different stages depending on the type of data. Sensors of the same type can achieve correlation at the data level, which helps to better preserve the original information. For heterogeneous data types, fusion needs to be implemented at the feature level or decision level to reduce the communication bandwidth requirements and facilitate real-time processing. Compared with random models and least squares-based fusion methods, bioinspired intelligence fusion avoids the need for in-depth studies on fault mechanisms by establishing multi-input multi-output black-box systems that operate at the feature level, such as transformers, and it learns complementary information across these diverse data sources. However, training neural networks requires sufficient input–output matching information to ensure reliability.

Nevertheless, bioinspired intelligence still faces several challenges. First, existing conclusions are dependent on the design of fitness functions and parameter settings, but lack unified benchmark standards. Second, in high-dimensional spaces with multiple monitoring points and constraints, bioinspired intelligence encounters the curse of dimensionality. Additionally, current research predominantly focuses on centralized processing models, leaving a need to explore the deployment of optimization algorithms on edge nodes to achieve adaptive sensor scheduling and network topology adjustments on the basis of real-time operating conditions. At present, most studies remain at the laboratory validation stage, whereas industrial cases where such systems are reliably integrated into power plant monitoring are extremely rare. Furthermore, algorithm performance depends on high-quality data, yet extreme operating conditions and rare fault samples over the full lifecycle of units are scarce.

4.2.2. Simplified representation of factors and extraction of state features

Section 2 highlighted the limitations of single clustering algorithms, which have been mitigated by bioinspired optimization approaches. Kumar *et al.* applied PSO to reduce the sensitivity of FCM in selecting clustering centers^[103]. Niknam *et al.* developed a hybrid evolutionary algorithm combining Ant Colony optimization (ACO) and simulated annealing (SA), which significantly improved classification accuracy^[87]. To address missing data prediction, Zhang *et al.* introduced an improved sparrow search algorithm (SSA) for optimizing a deep extreme learning machine (DELM), which outperformed the PSO-enhanced DELM^[88].

When techniques such as EMD or VMD are used to extract features such as frequency and amplitude, bioinspired intelligence can optimize sampling frequency to balance accuracy and computational efficiency. PSO searches feature space for optimal subsets, rapidly identifying the most relevant features. Tyagi *et al.* used PSO to select the optimal envelope window for vibration signals, enhancing fault diagnosis^[89]. GA can also identify optimal subsets and remove redundancy. Cerrada *et al.* applied GA to extract optimal time-, frequency-, and time-frequency-domain parameters, improving robustness in fault diagnosis^[90]. For comprehensive state characterization, Cao *et al.* proposed an integrated multi-sensor genetic programming (IMSGP) method, combining feature construction with a weighted Euclidean metric to provide early fault warnings in hydroelectric units. Overall, bioinspired intelligence improves global search, avoids local optima, and adapts to varied data scales without manual tuning. Unlike principal component analysis (PCA) and linear discriminant analysis (LDA), which rely on linear assumptions, it handles non-linear data and remains robust to noise and missing values. This allows meaningful feature extraction even under partial data loss^[91].

However, optimization algorithms are influenced by hyperparameters such as population size and iteration count, and optimal settings vary with data distribution. Feature subsets may also lack clear physical interpretation, reducing transparency and trust for operational staff. Current models rely on historical data and are not yet integrated with online monitoring for dynamic updates. Purely data-driven feature selection further limits the incorporation of domain knowledge, such as vibration modes or fluid dynamics. Future research should explore physics-guided bioinspired feature engineering.

4.2.3. Intelligent health diagnosis and performance trend prediction

As outlined in Section 2, conventional methodologies exhibit significant limitations in terms of comprehensively leveraging data for PHM. These approaches inherently suffer from temporal latency in data processing, which often leads to undetected systemic vulnerabilities and the subsequent emergence of unexpected critical events. In contrast, neural network architectures, through extensive training on large datasets coupled with iterative weight adjustments, exhibit enhanced capabilities in structural optimization when integrated with intelligent optimization algorithms. This synergistic combination effectively overcomes the fundamental constraints that are inherent to conventional machine learning approaches.

Hydroelectric units operate under dynamic environmental conditions that are characterized by variable load conditions, complex startup and shutdown sequences, and diverse abnormal operating regimes. This methodology accumulates comprehensive lifecycle operational data, and when coupled with neural network analysis, it enables the development of dynamic health assessment models with multiscenario adaptability on the basis of structural refinement. This approach has been successfully implemented in equipment condition diagnosis and performance prediction applications. Notably, Long *et al.* developed a novel whale optimization algorithm, a deep belief network hybrid architecture, and achieved precise identification of anomalous states in power generation equipment^[93]. Similarly, Liu *et al.* employed a GA to optimize both synaptic weights and activation thresholds in backpropagation neural networks and reported a 19% accuracy improvement over conventional BP implementations^[94]. In a complementary approach, Shao *et al.* utilized an artificial fish swarm algorithm for the parametric optimization of deep autoencoders, which exhibited significantly enhanced feature extraction capabilities^[92].

Performance prediction implements continuous monitoring ranging from incipient defect manifestation to impending complete failure, proactively generating maintenance alerts through the integrated analysis of current and prognostic equipment states to achieve informed maintenance decision-making^[104]. These predictive models generate equipment performance degradation curves through offline training and online computational processes, enabling RUL estimation on the basis of a health index threshold analysis. Fu *et al.* proposed an ensemble EMD-long-and short-term memory (LSTM) hybrid approach for hydroelectric unit degradation prediction, which demonstrated superior accuracy in capturing operational deterioration patterns^[96]. Luo *et al.* leveraged the time series processing capabilities of deep learning technologies and the adaptability of big data technology to develop an LSTM-deep belief network (DBN) fusion framework for hydroturbine fault prognosis^[97].

While the LSTM architecture effectively mitigates gradient vanishing and explosion issues inherent in RNNs, it results in computational bottlenecks^[105] when processing ultralong sequence data^[106]. To address these limitations, recent advancements have incorporated transformer models that utilize global self-attention mechanisms to capture long-range temporal dependencies or establish multi-sensor feature fusion architectures that integrate local and global characteristics for enhanced fault diagnosis^[107,108]. Furthermore, a former-based architecture has been implemented to optimize computational efficiency and extend processing capacity for ultralong sequence datasets^[98]. The transformer captures correlations between

nonadjacent anomalies in vibration signals and analyzes long-term data spanning startups, shutdowns, and operational transitions. By modeling long-term dynamic characteristics, it identifies incipient subtle faults in critical components such as bearings and runners and integrates multidimensional asynchronous signals, including temperature and power, to capture complex parameter couplings and operational regime transitions.

Graph neural networks effectively address the limitations of CNNs and RNNs in processing graph-structured data from sensor networks in non-Euclidean spaces. By aggregating node neighborhood information and explicitly capturing the interdependencies between data points, this method accurately models equipment interactions, rendering it particularly suitable for condition monitoring in systems with complex component interdependencies. This approach provides innovative solutions for health diagnosis and prognosis in complex electromechanical systems^[109].

Although the integration of neural networks and bioinspired optimization has improved diagnostic and predictive accuracy, its application remains contentious. Existing studies show highly inconsistent performance improvements across different network architectures via the same optimization algorithm and sometimes even erratic performance across different fault types, highlighting its limited generalizability. Newer models such as transformers and graph neural networks (GNNs), while capable of capturing long-range dependencies and non-Euclidean data relationships, have high computational complexity and rely heavily on large amounts of labeled data for training. This fundamentally conflicts with the reality of hydropower operations, where annotated samples are scarce and labeling rates are low.

4.2.4. Modeling for the optimization of maintenance decision-making

Maintenance decision-making serves as the subsequent phase of diagnostics and prognostics. Current studies in PHM have focused on improving diagnostic or assessment accuracy, resulting in outdated maintenance decision-making methods. However, for managers, formulating flexible, reliable, and cost-effective maintenance plans is crucial for maintenance personnel. As complex systems with limited service life, unit equipment follows the lifecycle curve shown in Figure 8. When defects are minor, no repairs are needed; however, when health alerts are imminent, maintenance plans should be developed through scientific decision-making.

Maintenance decision-making aims to address the issues of over-maintenance or under-maintenance arising due to improper scheduling and the misalignment between equipment reliability and maintenance economics. The final phase of a unit's health management must balance safety, reliability, and cost effectiveness. The decision parameters include multi-objective factors such as unit identification, maintenance timing, and intervention severity, and external considerations such as production schedules and resource allocation must also be integrated^[110]. As shown in the technical framework, this strategy combines component-level maintenance protocols, inherently forming a multi-objective network optimization problem. Thus, the process results in a complex decision-making system with multiple objects, constraints, and variables, as illustrated in Figure 11. The solid lines in the diagram indicate the factors related to maintenance decision-making for hydroelectric units.

Bioinspired intelligence optimizations for achieving maintenance decision-making discard traditional experience-driven and statistical approaches. It leverages data-driven methods to predict equipment performance, evaluate degradation states, and calculate RULs, thereby enabling condition-opportunity maintenance. Specifically, when a component reaches the minimum health threshold and requires intervention, other components nearing their end-of-life thresholds gain prioritized maintenance

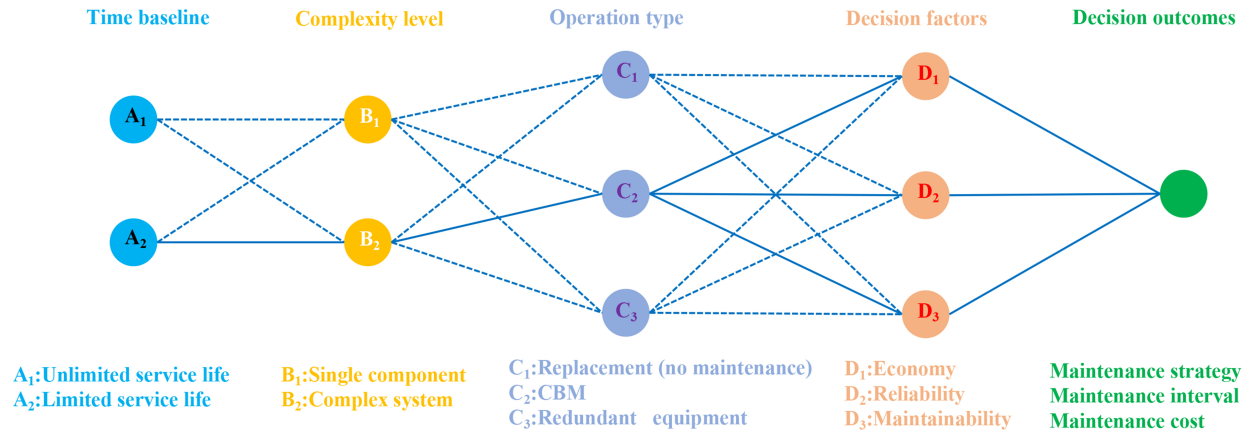


Figure 11. Maintenance decision-making flowchart.

opportunities. This approach reduces the maintenance frequency and extends the overall operational availability. The economic feasibility, maintainability, and other decision factors are subsequently integrated to formulate the final optimized maintenance decision model, as depicted in Figure 12.

The maintenance decision optimization model defines the minimum cost and the number of opportunistic maintenance components as objective functions, while safety and maintainability are used as constraints. Bioinspired intelligence optimization resolves these multi-objective functions to derive Pareto optimal solutions. A fundamental trade-off exists between opportunistic maintenance component count and system availability, i.e., increased availability reduces the number of components eligible for opportunistic maintenance as both parameters strive for maximization. Ayoobian *et al.* employed GA optimization to generate Pareto frontiers, determining optimal nuclear plant maintenance strategies through a sensitivity index analysis^[99]. Additionally, ant pheromone mechanisms can be simulated, in which individual maintenance tasks are treated as nodes to optimize execution sequences on the basis of task criticality. The methodology was subsequently extended from single-unit optimization to hydroelectric unit clusters, achieving fleet-level optimization rather than individual unit prioritization.

While Pareto optimal solutions are mathematically sound, they often fail to account for real-time disruptions such as unexpected field failures, dynamic resource constraints, and grid dispatch commands. Consequently, optimized plans frequently prove ineffective during actual execution. Current models assume stable parameters and deterministic conditions. Future efforts should focus on developing robust optimization algorithms capable of responding to uncertainty and dynamically adjusting strategies. Another promising yet underexplored direction is human-AI collaborative decision-making, which seeks to integrate bioinspired intelligence outcomes effectively with human expert experience rather than completely replacing them.

4.2.5. New generation intelligent O&M system

Current hydromechanical-electrical couplings in complex systems resist comprehensive capture through purely data-driven approaches. Integrating data-driven methods with physics-based models enables theoretical-empirical fusion for precise unit state monitoring. A physics-informed neural network (PINN) embeds physical law constraints into neural network loss functions, and the available clear application cases of the PINN for industrialization enhance the reliability and interpretability of the PHM for hydroelectric generators, which have complex mechanisms and multiple physical field couplings^[111].

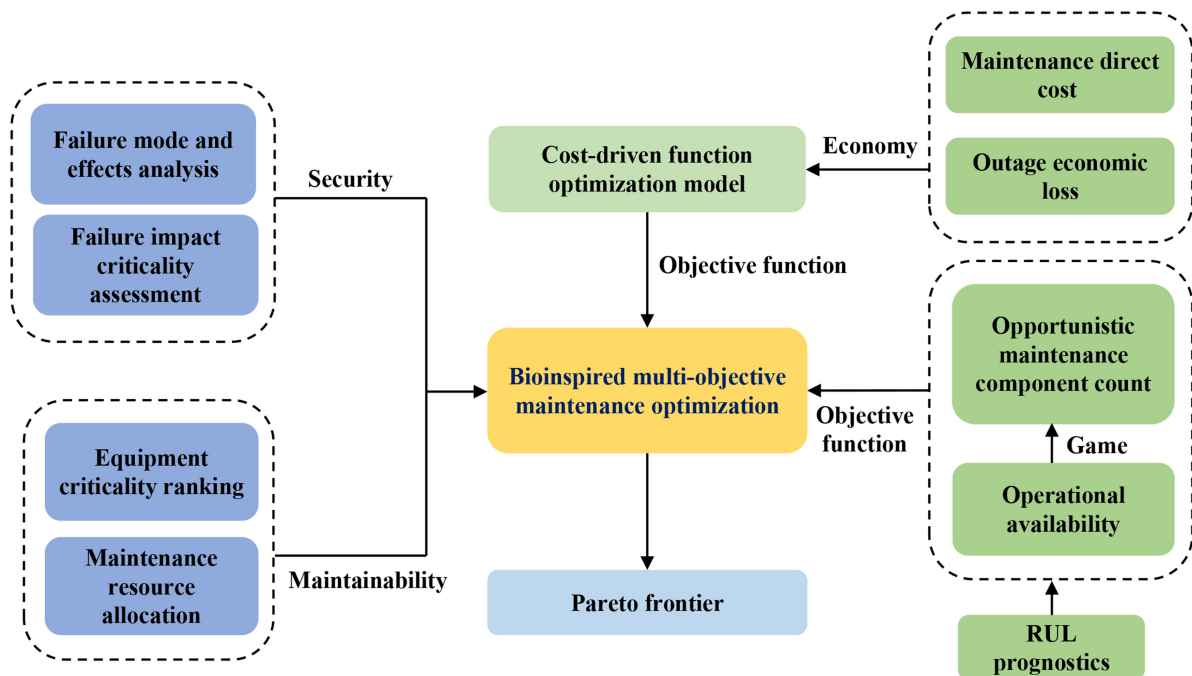


Figure 12. Optimization model for maintenance decision-making.

Heterogeneities in equipment configurations and operating contexts require parameter tuning or retraining, limiting model transferability under domain shifts. Addressing this challenge calls for improved transfer learning, optimized resource allocation, and integration of physics-based priors with data-driven adaptation. PHM also faces the issue of limited labeled data. Self-supervised learning uses abundant unlabeled operational data to learn effective representations through methods such as contrastive learning, masked autoencoding, and predictive tasks. By forecasting future data segments or attributes, models capture dynamic patterns and causal links, with deviations serving as indicators for online monitoring and early warnings.

Advances in large language models (LLMs) enable maintenance systems to process complex, unstructured, multimodal data with strong analytical capabilities^[112]. Maintenance logs, fault records, and inspection reports contain valuable but underused insights into equipment health. LLMs can extract degradation patterns and latent risks, improving prognostic accuracy. Combining domain knowledge - such as turbine structures and component degradation mechanisms - with knowledge graph reasoning supports explainable health assessments. Fine-tuned LLMs, adapted with minimal plant-specific data, allow transfer learning for deeper degradation analysis across historical operations, environmental impacts, and control modes, ultimately enhancing long-term performance and stability. At present, there are few studies using deep reinforcement learning and transfer learning for fault diagnosis of hydroelectric or wind units^[113,114]. Moreover, in the power generation field, there are almost no studies taking adaptive temporal-topological graph convolutional networks^[115].

Future health management of hydroelectric units should focus on real-time monitoring, precision, and personalized strategies. Digital twin (DT) technology enables virtual mapping of unit states, simulating performance under diverse conditions, synchronizing health data in real time, and optimizing strategies through simulations. With bioinspired intelligence for parameter adjustments, DTs improve operational

efficiency and energy utilization^[116,117].

To strengthen autonomous systems, robots can be deployed in inaccessible areas for monitoring and maintenance. Running lightweight bioinspired models on robotic edge computing platforms enables on-site processing, reducing data transmission and latency for faster responses and autonomous decisions. Integrating bioinspired intelligence with robotics establishes a closed-loop, data-driven O&M framework, as illustrated in [Figure 13](#), representing a key pathway toward reduced or fully unmanned hydropower station operation^[118].

The differences between bioinspired intelligence and existing predictive maintenance methods for hydroelectric units are shown in [Table 4](#). The system deployment will be jointly implemented with the existing situation awareness, analysis, and fault diagnosis system for hydroelectric units at a large hydropower station. Building upon traditional AI-based monitoring and diagnostics will further optimize the state perception subsystem and expand the health management module, achieving comprehensive functionality from evaluating the overall unit health status to predicting subsystem or component faults, pinpointing locations, and generating maintenance strategies. The O&M of hydroelectric units will also progress from the stage of data-driven and algorithm optimization to the stage of intelligent integrated maintenance with intelligent PHM^[119-121].

The system's global and closed-loop automation architecture compensates for operational personnel's limitations in professional expertise and empirical knowledge during unit maintenance, effectively mitigating subjective judgment discrepancies. Concurrently, the pyramid-shaped human-machine interaction mechanism spanning from monitoring to decision-making will be hierarchically presented to maintenance technicians, operational staff, and management personnel, maintaining precise alignment with the power plant's organizational structure. To address the critical question of whether AI-recommended maintenance strategies should entirely supersede human expertise, the implementation framework adopts a bidirectional approach: system-generated recommendations ascend through hierarchical levels, whereas human directives descend through command channels, coupled with peer-level comparative analysis to guide field operations. This methodology ensures synergistic integration of algorithmic precision and human experiential knowledge within the maintenance ecosystem.

5. CONCLUSION AND DISCUSSION

5.1. Conclusion

This study focuses on the RCM to explore the application potential, key technical frameworks, and developmental directions of bioinspired intelligence in the monitoring and health management of hydroelectric units. Given the limitations of traditional maintenance models, integrating bioinspired intelligence with engineering requirements provides innovative approaches for intelligent O&M.

This study defines the core objectives of unit situation awareness and health management.

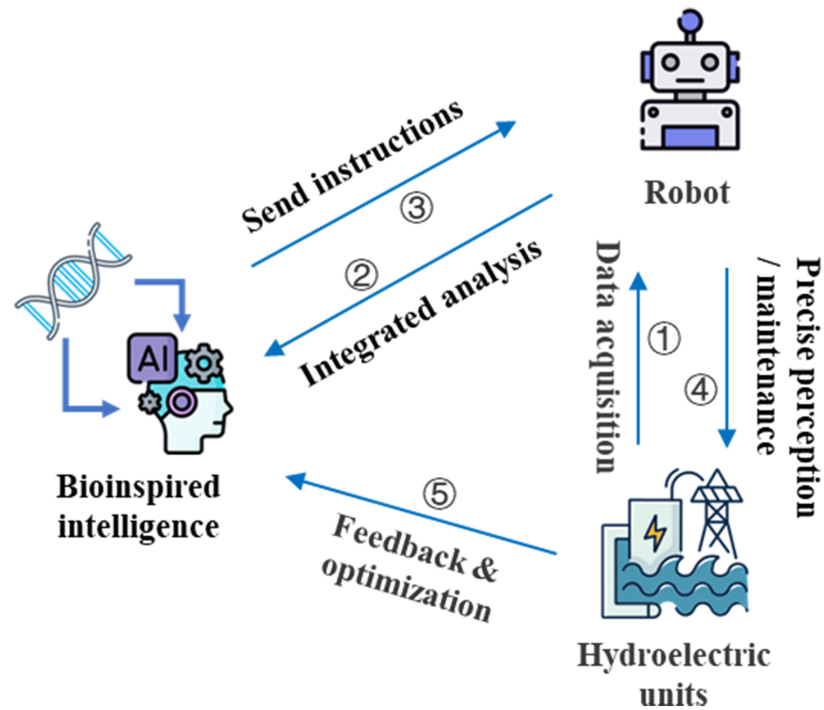
(1) By leveraging bioinspired intelligence techniques that integrate real-time monitoring, multi-source data fusion, feature mining, health assessment, equipment degradation prediction, and multi-objective maintenance optimization, proactive fault warnings prior to failure, dynamic prediction of performance, and globally optimized maintenance strategies under multi-constraint conditions can be achieved.

(2) The structural consistency, swarm collaboration, dynamic adaptability, and global optimization capabilities of bioinspired intelligence enhance the rationality of sensor layouts, the robustness of multi-

Table 4. Comparison of bioinspired intelligence with existing predictive maintenance methods for hydroelectric units

Category	Traditional predictive maintenance ^[6,7,43]	Bioinspired intelligence ^[47,63]
Data acquisition	Fixed sensors and manual periodic inspections	Robotic active multimodal perception
Algorithmic logic	Statistics based or shallow ML models	Bioinspired mechanism driven computation
Decision mechanism	Rule-based systems and empirical formulas	Self-learning, adaptive and self-organizing decisions
System architecture	Centralized data processing and passive response	Edge-cloud collaborative intelligence
Diagnostic capability	Known fault pattern recognition	Unknown anomaly detection

ML: Machine Learning.

**Figure 13.** The collaborative working process of bioinspired intelligence and robots. Icon made by Good Ware, bsd, Iconic Artisan , Freepik from Flaticon.

source heterogeneous data fusion, the precision of feature extraction, the generalizability of health assessment and prediction models, and the cost-effectiveness of maintenance decisions.

5.2. discussion

Bioinspired intelligence for smart hydroelectric maintenance faces certain technical challenges. The existing algorithms exhibit weak adaptability and rely on limited data sources, warranting enhanced model generalizability through transfer learning and incremental training. The current maintenance decision strategies remain insufficient, as multi-objective decision-making must balance safety, economic efficiency, and reliability, with considerations for future environmental and additional concerns. The development of intelligent O&M systems is also constrained by hardware costs, computational power, and cross-domain collaboration capabilities.

The deep integration of data-driven approaches and the PINN enhances model interpretability. Cross-modal knowledge fusion, which combines knowledge graphs with large-scale model technologies, enables the extraction of multimodal data associations. The DT of unit behavior under diverse operational

scenarios, integrated with bioinspired intelligent optimization strategies, further improves long-term system stability. Edge-AI deployment and robots offer innovative solutions for the situation awareness and health management of hydroelectric units. Future developments will drive the hydropower industry toward intelligent and refined O&M, providing support for ensuring efficient, secure, reliable, and sustainable clean energy systems.

DECLARATIONS

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Authors' contributions

Made substantial contributions to conception and design of the study and performed data analysis and interpretation: Zhang, L.; Qin, S.; Li, J.; Yang, S. X.

Performed data acquisition and provided administrative, technical, and material support: Li, X.; Sun, H.; Wang, J.; Liu, X.; Yang, K.

Availability of data and materials

Not applicable.

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Conflicts of interest

Yang, S. X. serves as the Editor-in-Chief of the journal *Intelligence & Robotics*. He was not involved in any steps of editorial processing, notably including reviewers' selection, manuscript handling and decision making. Li, X. is affiliated with CHN ENERGY Dadu River Repair & Installation Co., Ltd.; Sun, H. is affiliated with CHN ENERGY Dadu River Production Command Center; Wang, J. is affiliated with Dadu River Pubugou Hydropower General Plant, CHN ENERGY Investment Group Co., Ltd.; Yang, K. is affiliated with China Petroleum Engineering & Construction Corporation Southwest Company. The other authors have declared no conflicts of interest.

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

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REFERENCES

1. Ji, C.; Zhou, T.; Huang, H. Operating rules derivation of Jinsha Reservoirs system with parameter calibrated support vector regression. *Water. Resour. Manage.* **2014**, 28, 2435-51. DOI
2. Sun, L.; Niu, D.; Wang, K.; Xu, X. Sustainable development pathways of hydropower in China: interdisciplinary qualitative analysis and scenario-based system dynamics quantitative modeling. *J. Clean. Prod.* **2021**, 287, 125528. DOI
3. Wu, H.; Han, C.; Zhao, L.; Xu, J.; Fu, Y.; Ren, X. Research on 3D modeling digital twin technology based on Kraftwerk-

- Kennzeichen-System coding for hydropower stations. In *2024 5th International Conference on Clean Energy and Electric Power Engineering (ICCEPE)*, Yangzhou, China. IEEE; 2024. pp. 358–64. DOI
4. Wang, P.; Guo, Y.; Xu, Z.; Wang, W.; Chen, D. A novel approach of full state tendency measurement for complex systems based on information causality and PageRank: a case study of a hydropower generation system. *Mech. Syst. Signal. Process.* **2023**, *187*, 109956. DOI
 5. He, Y. L.; Ma, Z. G.; Li, Q. A.; Huang, Z. Y. Research and application of maintenance decision-making for hydropower units based on reliability-centered maintenance. *Mech. Electr. Technol. Hydropower. Stn.* **2024**, *47*, 29–31,35. (in Chinese). DOI
 6. Kumar, K.; Saini, R. A review on operation and maintenance of hydropower plants. *Sustain. Energy. Technol. Assess.* **2022**, *49*, 101704. DOI
 7. de Santis, R. B.; Gontijo, T. S.; Costa, M. A. Condition-based maintenance in hydroelectric plants: a systematic literature review. *Proc. Inst. Mech. Eng. O. J. Risk. Reliab.* **2022**, *236*, 631–46. DOI
 8. Zheng, R.; Chen, B.; Gu, L. Condition-based maintenance with dynamic thresholds for a system using the proportional hazards model. *Reliab. Eng. Syst. Saf.* **2020**, *204*, 107123. DOI
 9. Lee, J.; Wu, F.; Zhao, W.; Ghaffari, M.; Liao, L.; Siegel, D. Prognostics and health management design for rotary machinery systems - reviews, methodology and applications. *Mech. Syst. Signal. Process.* **2014**, *42*, 314–34. DOI
 10. Luczak, A. Neurons as autonomous agents: a biologically inspired framework for cognitive architectures in artificial intelligence. *Cogn. Syst. Res.* **2025**, *90*, 101338. DOI
 11. Cui, Y.; Luo, H.; Yang, T.; Qin, W.; Jing, X. Bio-inspired structures for energy harvesting self-powered sensing and smart monitoring. *Mech. Syst. Signal. Process.* **2025**, *228*, 112459. DOI
 12. Jiang, Q.; Li, X.; Yang, L.; Ma, Y.; Li, H. Innovation and application of reliability-centered maintenance technology for pumped storage power plant. *J. Phys. Conf. Ser.* **2024**, *2694*, 012014. DOI
 13. Pourahmadi, F.; Fotuhi-Firuzabad, M.; Dehghanian, P. Application of game theory in reliability-centered maintenance of electric power systems. *IEEE. Trans. Ind. Appl.* **2017**, *53*, 936–46. DOI
 14. Alagöz, İ.; Bulut, M.; Geylani, V.; Yıldırım, A. Importance of real-time hydro power plant condition monitoring systems and contribution to electricity production. *TEPES.* **2020**, *1*, 1–11. DOI
 15. Guilan, W.; Hongshan, Z.; Shuangwei, G.; Zengqiang, M. Numeric optimal sensor configuration solutions for wind turbine gearbox based on structure analysis. *IET. Renew. Power. Gener.* **2017**, *11*, 1597–602. DOI
 16. Kamm, S.; Jazdi, N.; Weyrich, M. Knowledge discovery in heterogeneous and unstructured data of Industry 4.0 Systems: challenges and approaches. *Procedia. CIRP.* **2021**, *104*, 975–80. DOI
 17. Wang, M.; Wang, X.; Yang, L. T.; Deng, X.; Yi, L. Multi-sensor fusion based intelligent sensor relocation for health and safety monitoring in BSNs. *Inf. Fusion.* **2020**, *54*, 61–71. DOI
 18. Hartigan, J. A.; Wong, M. A. Algorithm AS 136: a K-means clustering algorithm. *J. R. Stat. Soc. C. Appl. Stat.* **1979**, *28*, 100–8. DOI
 19. Medeiros, A.; Cardoso, R.; Oliveira Júnior, J.; Alves, S. Failure analysis of gear using continuous wavelet transform applied in the context of wind turbines. *Proc. Inst. Mech. Eng. J. J. Eng. Tribol.* **2024**, *238*, 860–8. DOI
 20. Ghods, M.; Tabarniarami, Z.; Faiz, J.; Bazrafshan, M. A. Turn-to-turn and phase-to-phase short circuit fault detection of wind turbine permanent magnet generator based on equivalent magnetic network modelling by wavelet transform approach. *IET. Electric. Power. Appl.* **2024**, *18*, 1005–20. DOI
 21. Tian, H.; Yang, L.; Ji, P. Intelligent analysis of vibration faults in hydroelectric generating units based on empirical mode decomposition. *Processes* **2023**, *11*, 2040. DOI
 22. An, X.; Pan, L. Characteristic parameter degradation prediction of hydropower unit based on radial basis function surface and empirical mode decomposition. *J. Vib. Control.* **2015**, *21*, 2200–11. DOI
 23. Liu, T.; Kong, F.; Yang, L.; Guo, Z. Operational risk assessment of hydropower units based on PSSCA-VMD-CNN-GBiLSTM and multi-feature fusion. *Comput. Electr. Eng.* **2024**, *118*, 109412. DOI
 24. Fang, M.; Zhang, F.; Yang, Y.; Tao, R.; Xiao, R.; Zhu, D. The influence of optimization algorithm on the signal prediction accuracy of VMD-LSTM for the pumped storage hydropower unit. *J. Energy. Storage.* **2024**, *78*, 110187. DOI
 25. Zhang, F.; Guo, J.; Yuan, F.; Shi, Y.; Li, Z. Research on denoising method for hydroelectric unit vibration signal based on ICEEMDAN-PE-SVD. *Sensors* **2023**, *23*, 6368. DOI PubMed PMC
 26. Ren, Y.; Liu, P.; Hu, L.; et al. Research on noise reduction method of pressure pulsation signal of draft tube of hydropower unit based on ALIF-SVD. *Shock. Vib.* **2021**, *2021*, 5580319. DOI
 27. Lu, Z.; Tao, R.; Xiao, R.; Li, P. Forecasting the hydropower unit vibration based on adaptive variational mode decomposition and neural network. *Appl. Soft. Comput.* **2024**, *150*, 111040. DOI
 28. Szymański, J.; Operlejn, M.; Weichbroth, P. Enhancing word embeddings for improved semantic alignment. *Appl. Sci.* **2024**, *14*, 11519. DOI
 29. Yang, Z. Fault diagnosis of wind turbine bearing based on CNN-XGBoost. *J. Phys. Conf. Ser.* **2021**, *2033*, 012200. DOI
 30. Łuczak, D. Data-driven rotary machine fault diagnosis using multisensor vibration data with bandpass filtering and convolutional neural network for signal-to-image recognition. *Electronics* **2024**, *13*, 2940. DOI
 31. Valentín, D.; Presas, A.; Valero, C.; Egusquiza, M.; Egusquiza, E. Selection and optimization of sensors for monitoring of francis turbines. *IOP. Conf. Ser. Earth. Environ. Sci.* **2021**, *774*, 012028. DOI
 32. Li, J.; Pang, J.; Qin, M.; et al. Study on sand wear testing and numerical simulation of a 500 MW class pelton turbine. *Water* **2025**,

- 17, 317. DOI
33. Shrestha, R.; Gurung, P.; Chitrakar, S.; et al. Review on experimental investigation of sediment erosion in hydraulic turbines. *Front. Mech. Eng.* **2024**, *10*, 1526120. DOI
34. Mazaheri-Tehrani, E.; Faiz, J. Airgap and stray magnetic flux monitoring techniques for fault diagnosis of electrical machines: an overview. *IET. Electric. Power. Appl.* **2022**, *16*, 277-99. DOI
35. Li, Y.; Li, Z. Application of a novel wavelet shrinkage scheme to partial discharge signal denoising of large generators. *Appl. Sci.* **2020**, *10*, 2162. DOI
36. Lucena, E. S. D.; Oliveira, T. F. D.; Maciel, M. C.; et al. Hydrological cycle and humidity on the behavior of partial discharges in hydrogenerator. *Int. J. Power. Energy. Syst.* **2020**, *40*, 203-0178. DOI
37. Zio, E. Reliability engineering: old problems and new challenges. *Reliab. Eng. Syst. Saf.* **2009**, *94*, 125-41. DOI
38. Wu, J.; Kang, R.; Li, X. Uncertain accelerated degradation modeling and analysis considering epistemic uncertainties in time and unit dimension. *Reliab. Eng. Syst. Saf.* **2020**, *201*, 106967. DOI
39. Wang, P.; Xu, Z.; Chen, D. An integrated framework for reliability prediction and condition-based maintenance policy for a hydropower generation unit using GPHM and SMDP. *Reliab. Eng. Syst. Saf.* **2023**, *238*, 109419. DOI
40. Liu, Y.; Xu, Y.; Liu, J.; Shi, Y.; Li, S.; Zhou, J. Real-time comprehensive health status assessment of hydropower units based on multi-source heterogeneous uncertainty information. *Measurement* **2023**, *216*, 112979. DOI
41. O'Connor, P. D. T. Commentary: reliability-past, present, and future. *IEEE. Trans. Rel.* **2000**, *49*, 335-41. DOI
42. Guo, L.; Li, N.; Jia, F.; Lei, Y.; Lin, J. A recurrent neural network based health indicator for remaining useful life prediction of bearings. *Neurocomputing* **2017**, *240*, 98-109. DOI
43. Cao, X.; Li, P.; Ming, S. Remaining useful life prediction-based maintenance decision model for stochastic deterioration equipment under data-driven. *Sustainability* **2021**, *13*, 8548. DOI
44. Backlund, F.; Akersten, P. RCM introduction: process and requirements management aspects. *J. Qual. Maint. Eng.* **2003**, *9*, 250-64. DOI
45. Gupta, G.; Mishra, R. P. A SWOT analysis of reliability centered maintenance framework. *J. Qual. Maint. Eng.* **2016**, *22*, 130-45. DOI
46. Zhu, H.; Liu, S.; Qu, Y.; Han, X.; He, W.; Cao, Y. A new risk assessment method based on belief rule base and fault tree analysis. *Proc. Inst. Mech. Eng. O. J. Risk. Reliab.* **2022**, *236*, 420-38. https://www.researchgate.net/publication/350977628_A_new_risk_assessment_method_based_on_belief_rule_base_and_fault_tree_analysis. (accessed 15 Sep 2025)
47. Zhu, Y. L.; Chen, H. N.; Shen, H. Bio-inspired computing: individual, swarm and community evolution models and methods. Tsinghua University Press; 2013. <https://xueshu.baidu.com/ndscholar/browse/detail?paperid=770483c21984702b7aad97ff3256b530>. (accessed 15 Sep 2025).
48. McCulloch, W. S.; Pitts, W. A logical calculus of the ideas immanent in nervous activity. *Bull. Math. Biophys.* **1943**, *5*, 115-33. DOI
49. Hebb, D. O. The organization of behavior: a neuropsychological theory. 1st edition. Psychology Press; 2005. DOI
50. Rosenblatt, F. The perceptron: a probabilistic model for information storage and organization in the brain. *Psychol. Rev.* **1958**, *65*, 386-408. DOI PubMed
51. Holland, J. H. Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence. MIT Press; 1992. DOI
52. Minsky, M.; Papert, S. A. Perceptrons: an introduction to computational geometry. MIT press; 1988. DOI
53. Hopfield, J. J. Neural networks and physical systems with emergent collective computational abilities. *Proc. Natl. Acad. Sci. U. S. A.* **1982**, *79*, 2554-8. DOI PubMed PMC
54. Rumelhart, D. E.; Hinton, G. E.; Williams, R. J. Learning representations by back-propagating errors. *Nature* **1986**, *323*, 533-6. DOI
55. Dorigo, M.; Maniezzo, V.; Colomi, A. Ant system: optimization by a colony of cooperating agents. *IEEE. Trans. Syst. Man. Cybern. B. Cybern.* **1996**, *26*, 29-41. DOI PubMed
56. Kennedy, J.; Eberhart, R. Particle swarm optimization. In *Proceedings of ICNN'95 - International Conference on Neural Networks*, Perth, Australia. November 27 - December 01, 1995. IEEE; 1995. pp. 1942-8. DOI
57. Hinton, G. E.; Osindero, S.; Teh, Y. W. A fast learning algorithm for deep belief nets. *Neural. Comput.* **2006**, *18*, 1527-54. DOI PubMed
58. Hinton, G. E.; Salakhutdinov, R. R. Reducing the dimensionality of data with neural networks. *Science* **2006**, *313*, 504-7. DOI PubMed
59. Gandolfi, D.; Mapelli, J.; Puglisi, F. M. Editorial: brain-inspired computing: from neuroscience to neuromorphic electronics for new forms of artificial intelligence. *Front. Neurosci.* **2025**, *19*, 1565811. DOI PubMed PMC
60. Zhang, G.; Zhang, P.; Zhou, F.; et al. Multi-scale spatio-temporal data modelling and brain-like intelligent optimisation strategies in power equipment operation and inspection. *Appl. Math. Nonlinear. Sci.* **2025**, *10*, 20250022. DOI
61. Zhang, P.; Zhang, G.; Zhou, F.; et al. Research on power dynamic data sample generation technology based on brain-like computation and its efficient computation methods. *Appl. Math. Nonlinear. Sci.* **2025**, *10*, 20250023. DOI
62. Tozer, L. 'Biocomputer' combines lab-grown brain tissue with electronic hardware. *Nature* **2023**, *624*, 481. DOI PubMed
63. Kar, A. K. Bio inspired computing - a review of algorithms and scope of applications. *Expert. Syst. Appl.* **2016**, *59*, 20-32. DOI
64. Li, J.; Hu, Y.; Yang, S. X. A novel knowledge-based genetic algorithm for robot path planning in complex environments. *IEEE. Trans. Evol. Comput.* **2025**, *29*, 375-89. DOI

65. Binitha, S.; Sathya, S. S. A survey of bio inspired optimization algorithms. *Int. J. Soft. Comput. Eng.* **2012**, *2*, 137–50. <https://www.ijscce.org/wp-content/uploads/papers/v2i2/B0523032212.pdf>. (accessed 15 Sep 2025)
66. Fister, I. Jr.; Yang, X. S.; Fister, I.; Brest, J.; Fister, D. A brief review of nature-inspired algorithms for optimization. *arXiv* **2013**, arXiv:1307.4186. <https://doi.org/10.48550/arXiv.1307.4186>. (accessed 2025-09-15)
67. Li, J.; Yang, S. X. Intelligent collective escape of swarm robots based on a novel fish-inspired self-adaptive approach with neurodynamic models. *IEEE. Trans. Ind. Electron.* **2024**, *71*, 14460–9. DOI
68. Samigulina, G.; Samigulina, Z. Diagnostics of industrial equipment and faults prediction based on modified algorithms of artificial immune systems. *J. Intell. Manuf.* **2022**, *33*, 1433–50. DOI
69. Li, J.; Yang, S. X. A novel feature learning-based bio-inspired neural network for real-time collision-free rescue of multirobot systems. *IEEE. Trans. Ind. Electron.* **2024**, *71*, 14420–9. DOI
70. Ma, L.; Chen, S.; Wei, D.; Zhang, Y.; Guo, Y. A comprehensive hybrid deep learning approach for accurate status predicting of hydropower units. *Appl. Sci.* **2024**, *14*, 9323. DOI
71. Dao, F.; Zeng, Y.; Zou, Y.; Qian, J. Fault diagnosis method for hydropower unit via the incorporation of chaotic quadratic interpolation optimized deep learning model. *Measurement* **2024**, *237*, 115199. DOI
72. Li, X.; Zhang, J.; Xiao, B.; et al. Fault diagnosis of hydropower units based on Gramian angular summation field and parallel CNN. *Energies* **2024**, *17*, 3084. DOI
73. Wang, Y.; Xiao, Z.; Liu, D.; Chen, J.; Liu, D.; Hu, X. Degradation trend prediction of hydropower units based on a comprehensive deterioration index and LSTM. *Energies* **2022**, *15*, 6273. DOI
74. Zhang, J.; Liu, L.; Wang, L.; Xi, W. Fault detection of key parts of wind turbine based on BP neural network combination prediction model. *Energy. Inform.* **2024**, *7*, 436. DOI
75. Gao, Y.; Miyata, S.; Akashi, Y. Automated fault detection and diagnosis of chiller water plants based on convolutional neural network and knowledge distillation. *Build. Environ.* **2023**, *245*, 110885. DOI
76. Cacace, J.; Scognamiglio, V.; Ruggiero, F.; Lippello, V. Motor fault detection and isolation for multi-rotor UAVs based on external wrench estimation and recurrent deep neural network. *J. Intell. Robot. Syst.* **2024**, *110*, 2176. DOI
77. Torres-Cabrera, J.; Maldonado-Correa, J.; Valdiviezo-Condolo, M.; Artigao, E.; Martín-Martínez, S.; Gómez-Lázaro, E. A novel data-driven approach with a long short-term memory autoencoder model with a multihead self-attention deep learning model for wind turbine converter fault detection. *Appl. Sci.* **2024**, *14*, 7458. DOI
78. Perez-Sanjines, F.; Peeters, C.; Verstraeten, T.; Antoni, J.; Nowé, A.; Helsen, J. Fleet-based early fault detection of wind turbine gearboxes using physics-informed deep learning based on cyclic spectral coherence. *Mech. Syst. Signal. Process.* **2023**, *185*, 109760. DOI
79. Yan, K.; Chong, A.; Mo, Y. Generative adversarial network for fault detection diagnosis of chillers. *Build. Environ.* **2020**, *172*, 106698. DOI
80. Yang, S.; Zhou, Y.; Chen, X.; Li, C.; Song, H. Fault diagnosis for wind turbines with graph neural network model based on one-shot learning. *R. Soc. Open. Sci.* **2023**, *10*, 230706. DOI PubMed PMC
81. Li, P.; Anduv, B.; Zhu, X.; Jin, X.; Du, Z. Diagnosis for the refrigerant undercharge fault of chiller using deep belief network enhanced extreme learning machine. *Sustain. Energy. Technol. Assess.* **2023**, *55*, 102977. DOI
82. Cherng, A. Optimal sensor placement for modal parameter identification using signal subspace correlation techniques. *Mech. Syst. Signal. Process.* **2003**, *17*, 361–78. DOI
83. Zhang, X. H.; Wu, S. B.; Fang, S. E.; Chen, L. X. Multi-objective optimization of sensor placement for structural health monitoring using pareto artificial fish swarm algorithm. *J. Vib. Eng.* **2022**, *35*, 351–8. (in Chinese). <http://zdgcxb.csve.org.cn/cn/article/pdf/preview/202202010.pdf>. (accessed 15 Sep 2025)
84. Yue, H. Y.; Lv, M.; Li, H. W.; Liu, Z. Z.; Zhong, Y. F. Arrangement of pressure monitoring points in water supply network based on swarm intelligence optimization algorithm. *China. Water. Wastewater.* **2020**, *36*, 66–70. (in Chinese). DOI
85. Shmelev, N. G.; Gorbatshevich, M. I.; Kryukov, I. I.; Kovalev, A. G. Inspection of rotor disks of HPT and LPT of TK-10-4 gas-compressor units by the ultrasonic flaw detection method. *Russ. J. Nondestruct. Test.* **2012**, *48*, 15–22. DOI
86. Rafajlowicz, E. Optimal experiment design for identification of linear distributed-parameter systems: frequency domain approach. *IEEE. Trans. Autom. Control.* **1983**, *28*, 806–8. DOI
87. Niknam, T.; Olamaei, J.; Amiri, B. A hybrid evolutionary algorithm based on ACO and SA for cluster analysis. *J. Appl. Sci.* **2008**, *8*, 2695–702. DOI
88. Zhang, W. S.; Wang, Z. G. Missing data prediction based on improved sparrow algorithm optimized deep extreme learning machine. *Electr. Meas. Technol.* **2024**, *45*, 63–7. (in Chinese). DOI
89. Tyagi, S.; Panigrahi, S. An improved envelope detection method using particle swarm optimisation for rolling element bearing fault diagnosis. *J. Comput. Des. Eng.* **2017**, *4*, 305–17. DOI
90. Cerrada, M.; Zurita, G.; Cabrera, D.; Sánchez, R.; Artés, M.; Li, C. Fault diagnosis in spur gears based on genetic algorithm and random forest. *Mech. Syst. Signal. Process.* **2016**, *70–1*, 87–103. DOI
91. Cao, C.; Li, M.; Jiang, S.; Zhang, G.; Li, Z.; Lu, N. Fault warning method of a hydropower unit based on IMSGP-WEDI. *J. Vib. Shock.* **2024**, *43*, 52–60. <https://jvs.sjtu.edu.cn/EN/Y2024/V43/I8/52>. (accessed 15 Sep 2025)
92. Shao, H.; Jiang, H.; Zhao, H.; Wang, F. A novel deep autoencoder feature learning method for rotating machinery fault diagnosis. *Mech. Syst. Signal. Process.* **2017**, *95*, 187–204. DOI

93. Long, X.; Li, S.; Wu, X.; Jin, Z.; Salcedo, J. V. Wind turbine anomaly identification based on improved deep belief network with SCADA data. *Math. Probl. Eng.* **2021**, *2021*, 1–15. DOI
94. Liu, P.; Zhang, W. A fault diagnosis intelligent algorithm based on improved BP neural network. *Int. J. Patt. Recogn. Artif. Intell.* **2019**, *33*, 1959028. DOI
95. Li, Q.; Zhuo, Z.; Gao, R.; et al. A pig behavior-tracking method based on a multi-channel high-efficiency attention mechanism. *Agric. Commun.* **2024**, *2*, 100062. DOI
96. Fu, Z. X.; Yin, G.; Zhu, J. P.; Yuan, Y. Research on deterioration degree prediction method for hydropower units based on EEMD and LSTM. *Acta. Energaiae. Solaris. Sin.* **2022**, *43*, 75–81. (in Chinese). DOI
97. Luo, Y.; Wu, B. X. Water turbine vibration fault prediction method based on deep learning LSTM-DBN. *J. Vib. Meas. Diagn.* **2022**, *42*, 1233–8+51. (in Chinese). DOI
98. Lan, Q.; Zhu, Y.; Lin, B.; Zuo, Y.; Lai, Y. Fault prediction for rotating mechanism of satellite based on SSA and improved informer. *Appl. Sci.* **2024**, *14*, 9412. DOI
99. Ayoobian, N.; Mohsendokht, M. Multi-objective optimization of maintenance programs in nuclear power plants using genetic algorithm and sensitivity index decision making. *Ann. Nucl. Energy.* **2016**, *88*, 95–9. DOI
100. Al-Majali, B. H.; Zobaa, A. F. Analyzing bi-objective optimization Pareto fronts using square shape slope index and NSGA-II: a multi-criteria decision-making approach. *Expert. Syst. Appl.* **2025**, *272*, 126765. DOI
101. Tripathi, A.; Gupta, P.; Trivedi, A.; Kala, R. Wireless sensor node placement using hybrid genetic programming and genetic algorithms. *Int. J. Intell. Inf. Technol.* **2011**, *7*, 63–83. DOI
102. Xu, X.; Deng, J.; Lin, H.; Li, Z.; Wen, H. Lightweight anomalous detection of hydro turbine operation sound using fusion network enhanced by load information. *IEEE. Trans. Instrum. Meas.* **2025**, *74*, 1–13. DOI
103. Kumar, N.; Kumar, H. A fuzzy clustering technique for enhancing the convergence performance by using improved fuzzy c-means and particle swarm optimization algorithms. *Data. Knowl. Eng.* **2022**, *140*, 102050. DOI
104. Wang, Y.; Xu, W. A novel decision optimization for thermal power unit based on condition-based predictive maintenance and equilibrium optimizer. *Phys. Commun.* **2024**, *65*, 102372. DOI
105. Bai, M.; Liu, J.; Ma, Y.; Zhao, X.; Long, Z.; Yu, D. Long short-term memory network-based normal pattern group for fault detection of three-shaft marine gas turbine. *Energies* **2021**, *14*, 13. DOI
106. Han, S.; Shao, H.; Huo, Z.; Yang, X.; Cheng, J. End-to-end chiller fault diagnosis using fused attention mechanism and dynamic cross-entropy under imbalanced datasets. *Build. Environ.* **2022**, *212*, 108821. DOI
107. Wu, Z.; He, L.; Wang, W.; Ju, Y.; Guo, Q. A fault prediction method for CNC machine tools based on SE-ResNet-Transformer. *Machines* **2024**, *12*, 418. DOI
108. Yang, Z.; Li, G.; Xue, G.; He, B.; Song, Y.; Li, X. A novel multi-sensor local and global feature fusion architecture based on multi-sensor sparse Transformer for intelligent fault diagnosis. *Mech. Syst. Signal. Process.* **2025**, *224*, 112188. DOI
109. Li, T.; Zhou, Z.; Li, S.; Sun, C.; Yan, R.; Chen, X. The emerging graph neural networks for intelligent fault diagnostics and prognostics: a guideline and a benchmark study. *Mech. Syst. Signal. Process.* **2022**, *168*, 108653. DOI
110. Nguyen, V.; Do, P.; Vosin, A.; Lung, B. Artificial-intelligence-based maintenance decision-making and optimization for multi-state component systems. *Reliab. Eng. Syst. Saf.* **2022**, *228*, 108757. DOI
111. Liao, W.; Long, X.; Jiang, C. A physics-informed neural network method for identifying parameters and predicting remaining life of fatigue crack growth. *Int. J. Fatigue.* **2025**, *191*, 108678. DOI
112. Jiang, X. C.; Zang, Y. M.; Liu, Y. D.; Sheng, G. H.; Xu, Y. P.; Qian, Q. L. ChatGPT-like models and key technologies for power equipment. *High. Volt. Eng.* **2023**, *49*, 4033–45. (in Chinese). DOI
113. Li, T.; Yang, J.; Ioannou, A. Data-driven control of wind turbine under online power strategy via deep learning and reinforcement learning. *Renew. Energy.* **2024**, *234*, 121265. DOI
114. Li, Y.; Jiang, W.; Zhang, G.; Shu, L. Wind turbine fault diagnosis based on transfer learning and convolutional autoencoder with small-scale data. *Renew. Energy.* **2021**, *171*, 103–15. DOI
115. Mei, X.; Yuan, X.; Jin, J.; et al. ATGCN: an adaptive temporal-topological graph convolution network with nodal attention for robot fault diagnosis. *IEEE/ASME. Trans. Mechatron.* **2025**, 1–11. DOI
116. Grieves, M.; Vickers, J. Digital twin: mitigating unpredictable, undesirable emergent behavior in complex systems. In: Kahlen F, Flumerfelt S, Alves A, editors. Transdisciplinary perspectives on complex systems. Cham: Springer International Publishing; 2017. pp. 85–113. DOI
117. Wang, Y. H.; Cao, T.; Gao, S. L.; et al. Conceptualization and application prospects of a digital twin system for hydropower unit. *Proc CSEE* **2025**;45:4526–42. (in Chinese) https://cstj.cqvip.com/Qikan/Article/Detail?id=7201259657&from=Qikan_Search_Index. (accessed 15 Sep 2025)
118. Li, J.; Xu, Z.; Zhu, D.; et al. Bio-inspired intelligence with applications to robotics: a survey. *Intell. Robot.* **2021**, *1*, 58–83. DOI
119. Liu, Z.; Zheng, J.; Zhang, Q.; Xu, R. Advances and trends in intelligent maintenance for wind turbine systems. *Sustain. Energy. Technol. Assess.* **2025**, *80*, 104398. DOI
120. Dhinakaran, D.; Edwin Raja, S.; Velselvi, R.; Purushotham, N. Intelligent IoT-driven advanced predictive maintenance system for industrial applications. *SN. Comput. Sci.* **2025**, *6*, 151. DOI
121. Hulwan, D. B.; Shitra, C.; Chokkalingan, A.; et al. AI-based fault detection and predictive maintenance in wind power conversion systems. *E3S. Web. Conf.* **2024**, *591*, 02003. DOI