International Journal for Housing Science and Its Applications
Publish August 10, 2025. Volume 46, Issue 4 Pages 1732-1744

https://doi.org/10.70517/ijhsa464151

Development and Application of a Health Management System for Electrical Equipment in Corrosive Environments Based on Multi-Objective Optimization Algorithms

Ziran Chen[1], Xiaoyi Shi[2,*], Yong Tu[1], Ganxin Jie[2], Qijun Zhang[1] and Zhanfeng Chang[1]
[1] Yibin Xiangjiaba Power Plant, The Three Gorges Jinsha River Sichuan-Yunnan Hydropower Development Co., Ltd, Yibin, Sichuan, 644000, China
[2] State Key Laboratory of Environmental Adaptability for Industrial Products, China National Electric Apparatus Research Institute Co., Ltd Guangzhou, Guangdong, 510000, China
Corresponding authors: (e-mail: shixy@cei1958.com).

Abstract Electrical equipment in China's hot and humid coastal region has been in the harsh environment of high temperature, high humidity and salt spray for a long time, which accelerates the corrosion of equipment contamination, shortens the life span, and decreases the insulation performance, and seriously threatens the safe operation of the equipment and the safety of people. This paper proposes a health management system for electrical equipment based on multi-objective optimization algorithm for the problem of rapid corrosion decay of electrical equipment in the harsh environment of hot and humid coastal regions. Based on the OSA-CBM architecture, a hierarchical health management system integrating data acquisition, condition detection, health assessment, predictive assessment and decision generation is constructed, and a complete solution including hardware platform and software platform is designed. By establishing a multi-objective dynamic maintenance decision model considering corrosive environmental factors, a balanced optimization of equipment availability and maintenance cost is achieved. Simulation results show that when the optimal reliability threshold is 0.65, the maintenance cost rate is as low as 1.663; the maintenance time interval under the multi-objective dynamic decision-making model decreases from 3320 to 2252 with the growth of the service age cycle, reflecting the accelerated deterioration trend of the health state of electrical equipment. System performance tests show that the response time of the login module is as expected in the range of 250-400 concurrent users, and the transaction success rate is maintained at 100%. This study provides an effective solution for the health management of electrical equipment in corrosive environments, optimizes preventive maintenance strategies, and improves equipment reliability and economy.

Index Terms Electrical equipment, Health management system, Multi-objective optimization, Corrosive environment, Preventive maintenance, Fault prediction

I. Introduction

China's hot and humid coastal region mainly refers to the southeastern coastal waters, because it is located in the subtropics, the monsoon year-round, so it has abundant wind energy resources, but also suffers from high temperature, high humidity, salt spray, typhoons and other harsh environmental impacts [1], [2]. Electrical equipment in this harsh atmospheric environment for a long time, if the protective measures are not in place will cause rapid contamination and corrosion of the internal components of electrical equipment, which will lead to a rapid decline in the quality of these components, greatly shorten their service life, and seriously threaten the safe operation of electrical facilities [3]-[5]. At the same time the components are contaminated and corroded, it also often means a serious decline in electrical insulation performance, which seriously threatens the safety of people and facilities [6], [7]. At the same time, electrical equipment is relatively sophisticated, once a failure occurs, it is difficult to repair, and in serious cases, even need to be completely refurbished, and its environmental failure maintenance costs are usually high [8], [9]. Therefore, it is very necessary to take effective health management measures for electrical equipment.

Traditional power equipment operation and maintenance management often relies on manual experience, which is inefficient and prone to omissions [10]. However, the development of digital technology and the exponential increase in computing power of computer hardware have provided the possibility of training and applying large-scale intelligent models [11]. Accordingly, health management of electrical equipment has experienced a shift from a knowledge-driven form to a data-driven form. Digital technology plays an important role in the business of inspection image recognition, state volume sensing, fault diagnosis, condition assessment and operation and maintenance decision-making in the health management of electric primary equipment by constructing intelligent models based on specific objectives for training and application [12]-[14]. These intelligent models fully demonstrate the advantages of the data-driven approach to be accurate, real-time and efficient in high-volume data processing work [15], [16].

China's hot and humid coastal region mainly refers to the southeast coastal waters, because it is located in the subtropics, the monsoon year-round, so it has abundant wind energy resources, but also suffers from high temperature, high humidity, salt spray, typhoons and other harsh environmental impacts. Electrical equipment in this harsh atmospheric environment for a long time, if the protective measures are not in place will cause rapid contamination of electrical equipment internal components, corrosion, and then make the quality of these components decline rapidly, greatly shortening its service life, a serious threat to the safe operation of electrical facilities. In the components are contaminated and corroded at the same time, often means that the electrical insulation performance of a serious decline, and then seriously threaten the safety of people and facilities. At the same time, electrical equipment is relatively sophisticated, once the failure, it is difficult to repair, and in serious cases, even need to be completely renovated, its environmental failure maintenance costs are usually higher. Therefore, it is very necessary to take effective health management measures for electrical equipment. The traditional operation and maintenance management of electrical equipment often relies on manual experience, which is inefficient and prone to omissions. However, the development of digital technology and the exponential increase in computing power of computer hardware have made it possible to train and apply large-scale intelligent models. Accordingly, health management of electrical equipment has experienced a shift from knowledge-driven to data-driven forms. Digital technology plays an important role in the inspection image recognition, state volume perception, fault diagnosis, condition assessment and operation and maintenance decision-making in the health management of electric power primary equipment by constructing intelligent models based on specific objectives for training and application. These intelligent models fully demonstrate the advantages of the data-driven approach in large-volume data processing work in an accurate, real-time and efficient manner.

In this study, the health management system of electrical equipment is constructed through a multi-objective optimization algorithm to address the corrosion problem of electrical equipment in harsh environments in hot and humid coastal regions. Firstly, the overall architecture of the system is designed based on the OSA-CBM framework to ensure its openness, standardization and scalability; secondly, the hardware and software platforms are developed, including sensor selection, data acquisition and processing, to realize the comprehensive monitoring of the equipment status; then, the multi-objective dynamic maintenance decision-making model is established considering the corrosive environmental factors, and the reliability, availability and maintenance cost are incorporated into the unified framework for optimization; finally, the multi-objective optimization algorithm is simulated and analyzed for optimization; lastly, the multi-objective optimization algorithm is used for optimization. Finally, the effectiveness of the system is verified through simulation analysis and practical testing. This study not only makes up for the shortcomings of the traditional maintenance strategy for the corrosive environment, but also provides a new way of thinking for the health management of electrical equipment that takes into account the reliability and economy, which is of great significance for improving the operation safety and service life of electrical equipment in the hot and humid coastal environment.

II. Electrical equipment health management system development

System Health Management (SHM) is a new technology used to improve the autonomy and reliability of complex systems such as spacecraft, effectively reducing the operating costs and extending the lifetime of electrical equipment. The electrical equipment health management system is based on networked distributed intelligence using an open architecture that automatically and autonomously collects information from sensors and actuators and processes this information using an embedded knowledge system. It then relies on a combination of a priori knowledge and newly collected information to detect the health of electrical equipment. Faults are forecasted and handled before actual failures occur, avoiding serious consequences.

II. A. System framework

II. A. 1) OSA-CBM architecture

(1) Definition of CBM

The purpose of system monitoring and maintenance is to make timely and accurate diagnosis, prevention or elimination of faults for various abnormal states or faults, to provide necessary guidance for system operation, to improve the reliability, safety and effectiveness of system operation, to prolong the service life of the system, and to reduce the loss of faults. The development of system maintenance methods has gone through three stages, namely, early after-the-fact maintenance, regular preventive maintenance and condition-based maintenance (CBM).

CBM is to diagnose, predict and rationalize the future maintenance scheduling time of the system by real-time monitoring of the working status of the equipment and the working environment, with the help of artificial intelligence and other advanced technologies.CBM methodology is based on the actual operating status of the system and determining the optimal maintenance of the system in reality, to reduce the whole life cycle cost of the system, and to increase the stability of the system.

(2) OSA-CBM System

The Open System Architecture for Condition Based Maintenance (OSA-CBM), is a set of standardized structures and frameworks for facilitating the flow of information in condition based maintenance systems [17]. OSA-CBM describes the six functional blocks for building a condition based maintenance system, the specific architecture of which is shown in Fig. 1, as well as the interfaces between these blocks. The standard provides methods for integrating many different software components and simplifies the process by specifying the inputs and outputs between components. In short, it describes a standardized messaging system for condition maintenance.

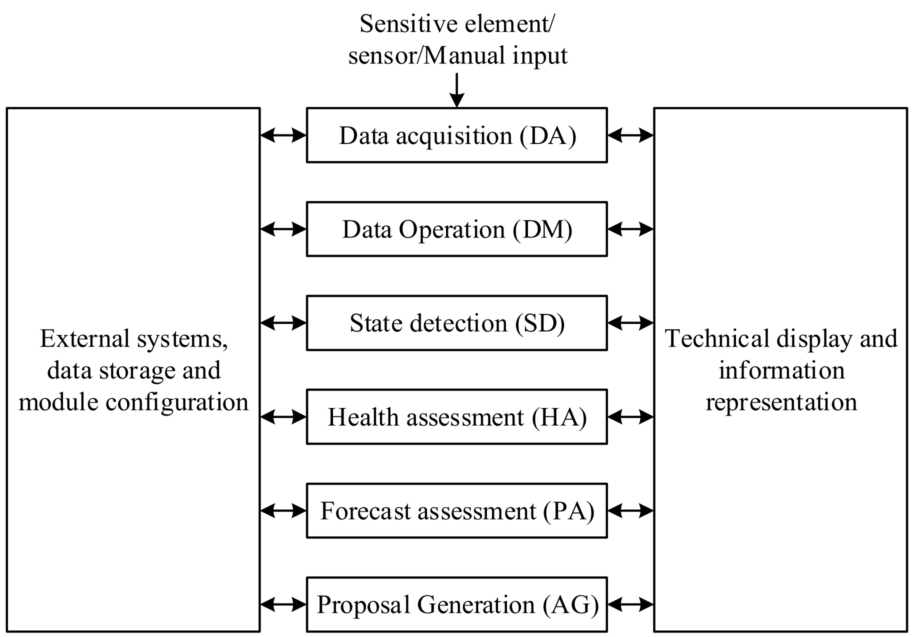

Figure 1: OSA-CBM Hierarchical architecture expansion

(1) Data Acquisition Layer. The data acquisition layer has calibrated digital sensors connected to the field for data acquisition, and this layer provides an interface for the condition maintenance system to access the digital sensor data.

(2) Data operation layer. The output of the data operation layer includes filtered sensor data, spectra, and other characteristic quantities. This layer accepts signals and data from the data acquisition layer or other signal processing modules, and uses specialized feature extraction algorithms to perform signal conversion for single or multiple channels.

(3) State detection layer. The status detection layer accepts data from the data acquisition layer, the data operation layer and other status monitoring layers, and its main function is to compare the feature values with the desired values or operational thresholds and output them to the status indicator, or it can issue alarms based on the pre-specified thresholds.

(4) Health assessment layer. The health assessment layer accepts data from different status detectors or other health assessment modules, determines whether the monitored systems, subsystems, or equipment components are healthy or not when they deteriorate, and makes recommendations with a certain level of confidence about the failure state.

(5) Predictive Assessment Layer. The prediction and assessment layer predicts the future health state of the equipment based on the current health state of the equipment, or estimates the remaining useful life of the equipment under a given planned utilization profile.

(6) Recommendation generation layer. The recommendation generation layer accepts data from the health assessment layer and the predictive assessment layer and gives activity recommendations and program choices, including associated maintenance activity schedules.

II. A. 2) Basic system architecture

The architecture is the top-level design of the system, and the system's wholeness, correctness and consistency are ensured through the architecture design. In order to make the hardware and software unit components from different vendors interchangeable, enhance the integration capability of the electrical equipment health management system, and effectively reduce the maintenance cost of electrical equipment health management. In this paper, based on the OSA-CBM system framework, an open, standardized, componentized and hierarchical electrical equipment health management system architecture is constructed [18]. The whole system architecture consists of three parts, i.e., distributed arrangement of electronic equipment, management server and mobile maintenance terminal. The health management functions are accomplished through nine functional domains, including data storage, data acquisition, data sending and receiving and processing, condition monitoring, database management service, fault diagnosis service, fault prediction service, health management service, and out-of-band management.

Electronic equipment mainly realizes the functions of data acquisition, recent storage, local status monitoring and fault alarm, and obtains health assessment and maintenance decision support by requesting services from the management server.

The management server mainly provides services such as fault diagnosis, fault prediction, health assessment and maintenance decision-making for equipment through various models and algorithms, and provides system-level real-time status monitoring and analysis, as well as remote out-of-band management functions.

The mobile maintenance terminal is mainly used for the management and maintenance of the equipment, such as power management, software upgrade, log management and status monitoring, and also has the database management function for the equipment and the management server.

II. B.Hardware and software design

II. B. 1) System Hardware Design

Hardware design is the basis for the operation of the entire electrical equipment health management system, the choice of sensor measurement point location, sensor device accuracy, the accuracy of the data acquisition equipment, etc. will affect the accuracy of the data, and have an impact on the results of the subsequent data processing, data storage, fault diagnosis, fault prediction, so the design of the hardware should be considered for the selection of the device, the reliability of the device, maintainability, security, testability, environmental Adaptability, security and other factors.

The hardware platform is located in the sensor layer and data acquisition layer in the system architecture, which mainly includes hardware devices such as sensors, data acquisition devices and data transmission devices. Sensors are installed on the measurement equipment, and their main function is to convert physical quantities of the equipment into electrical signals. According to the requirements of measurement, the corresponding sensors are selected for different physical quantities, such as pressure sensors for pressure measurements, temperature sensors for temperature measurements, and rotational speed sensors for rotational speed measurements, etc. The installation location and installation process of the sensors are also important. The installation position of the sensor, installation process, etc. will directly affect the value of the signal obtained by the sensor, and the selection of the sensor device will affect the accuracy of the signal obtained, so the sensor is the basis for the output results of the entire electrical equipment health management system. Data acquisition equipment is generally acquisition card or collector, etc., to achieve the conversion of analog electrical signals to digital electrical signals and signal pre-processing and other functions.

Sensors, data acquisition equipment is generally based on the demand to choose the appropriate finished product to build hardware platform, so the manufacturer, equipment compliance, equipment quality, equipment accuracy, etc. are factors to consider, in addition to the transmission interface of the device is also a very important factor, a professional unified data transmission interface in order to make the data stable and reliable transmission, easy to interact.

II. B. 2) System software design

For more accurate reporting, electrical equipment health management systems must rely on large amounts of monitoring data collected and transmitted by hardware and software platforms. The software platform usually runs in a network environment, and the software development platform is based on the level of distributed logic and object-oriented architecture. The business logic of the system can be divided into data layer and business layer. The business layer and the display layer are bottom-up, and the management and security functions are realized by running each layer, providing security for the whole system and coordinating the operation and management of each layer.

The software of the system mainly includes data acquisition, transmission, processing, storage and display parts.

Specifically, the software design uses C language and Keil μVision development tools to realize the following functions:

(1) Data acquisition. The temperature and voltage of the on-board electronic equipment as well as the module self-test results, version information and other data are collected through sensors and processed by the MCU microcontroller.

(2) Data transmission. Transmit the collected data through the communication bus or Ethernet to facilitate the computer module or PC to obtain the desired data.

(3) Data processing: The MCU can process the received data and report the abnormal information obtained to the computer module or PC to realize data analysis, diagnosis and other functions.

(4) Data storage. Store the processed data into Flash for subsequent inquiry and analysis.

(5) Data display. Display the acquired data through the serial interface, including the collected data, module information and abnormal alarms.

III. Multi-objective dynamic decision-making model for electrical equipment

Whole Life Quality and Health Management (WHQHM) is the effective and healthy management of a product throughout its entire life cycle (requirements analysis phase, solution demonstration phase, engineering development phase, testing and finalization phase, delivery phase, decommissioning and disposal phase).SHM integrates the system itself and maintenance assurance, and considers SHM as a design feature from the very beginning of the system design (i.e., the requirements analysis phase), instead of designing it as an add-on system after the fact, aiming to maximize the benefits of this new concept. The aim is to maximize the benefits of this new concept.

III. A. Modeling Dynamic Preventive Maintenance Decisions

III. A. 1) Basic notation and problem description

According to the actual situation of the production process of electrical equipment, in order to illustrate the modeling process of the maintenance decision optimization model and at the same time describe the research problem more clearly, this paper assumes:

(1) A single piece of equipment is modeled without considering other equipment associated with it.

(2) Two types of maintenance (unscheduled and scheduled) are considered together, with scheduled maintenance occurring when the equipment health index reaches a threshold, pre-planned decisions are made, and maintenance costs are relatively low. Unplanned maintenance (i.e., minor repairs with negligible time) is used for sudden failures that occur when the health threshold is not reached, resulting in higher maintenance costs due to randomness.

(3) Both types of maintenance can only result in the repair of non-new equipment, where unplanned maintenance does not change the health index of the equipment (the health index is the same as before the failure).

(4) Maintenance costs consist of three components, namely, the cost of maintenance itself, the cost of work-in-process losses due to downtime, and the cost of operational delays due to the duration of maintenance.

(5) After several maintenance cycles, if the maintenance operation is too frequent, the equipment needs to be renewed, resulting in additional renewal costs.

Assume i is the maintenance cycle, T_i is the time interval between the i rd and $(i-1)$ th maintenance of the equipment, $f_i(t)$ is the failure rate function between the i th and $(i-1)$ th maintenance of the equipment, H_0 is the health index threshold of the equipment, C_{sp} is the maintenance cost of planned maintenance, and C_{sb} is the downtime cost of planned maintenance. C_{up} is the maintenance cost of unscheduled maintenance, C_{ub} is the downtime cost of unscheduled maintenance, C_{od} is the cost rate of job delays caused by maintenance activities, C_{qp} is the cost rate of interruptions of job q at location p, and the cost of additional equipment renewal is C_{rs}. t_{pm} is the time for scheduled maintenance of equipment, t_q is the processing time of job q, d_q is the delivery time of job q, and the optimal value of each under a single objective is MT* (Minimum Maximum Desired Time of Delay), TT* (Minimum Total Desired Time of Delay) and IC* (Minimum Job Interruption Cost).

III. A. 2) Repairing non-new model construction

According to the established maintenance strategy, preventive maintenance occurs when the reliability of equipment j reaches its threshold value of R_j. The reliability equation is:

$$\exp[-\int_0^{T_{1j}} h_{1j}(t)dt] = \exp[-\int_0^{T_{2j}} h_{2j}(t)dt] = \\ ... = \exp[-\int_0^{T_{ij}} h_{ij}(t)dt] = R_j \tag{1}$$

It can be rewritten as:

$$\int_0^{T_{1j}} h_{1j}(t)dt = \int_0^{T_{2j}} h_{2j}(t)dt = ... \\ = \int_0^{T_{ij}} h_{ij}(t)dt = -\ln R_j \tag{2}$$

The above equation shows that in each preventive maintenance cycle, the probability of failure of the equipment is equal and is $-\ln R_j$. Considering the repair-non-new effect of preventive maintenance, the relationship between the distribution function of failure rate of the equipment in each maintenance cycle in the above equation can be expressed as:

$$h_{(i+1)j}(t) = b_{ij} h_{ij}(t + a_{ij} T_{ij}) \\ t \in (0, T_{(i+1)j}) \tag{3}$$

where $0 < a_i < 1$ is a decreasing age factor that prevents the failure rate of the equipment from returning to zero after preventive maintenance, and $b_i > 1$ is an increasing failure rate factor that causes the failure rate of the equipment to change more rapidly after preventive maintenance. In fact, as equipment with the increase in service age will occur material fatigue, aging and rust, and maintenance can not completely change these conditions, so maintenance itself can not make the equipment back to the initial state, at the same time, equipment aging and other aggravation is bound to accelerate the occurrence of equipment failure. As can be seen, the integration of the decreasing service age factor and the increasing failure rate factor is consistent with the actual situation of equipment maintenance.

Considering the preventive maintenance cost rate c_{pj}, the downtime cost rate c_{dj}, the required maintenance time τ_{pj}, and the cost of a single minor repair C_{mj}, the maintenance cost rate of equipment j during the task time [0,T] is defined as:

$$c_j = \frac{NC_{mj}(-\ln R_j) + N(c_{pj} + c_{dj})\tau_{pj}}{\sum_{i=1}^{N}(T_{ij} + \tau_{pj})} \tag{4}$$

In the formula, N is the frequency of preventive maintenance, satisfying $\sum_{i=1}^{N-1}(T_i + \tau_{pj}) < T < \sum_{i=1}^{N}(T_{ij} + \tau_{pj})$. The reason for using the above form in the denominator instead of T is that the last preventive maintenance of the equipment within the optimization range may not necessarily occur at the time T. By optimizing the objective function $\min c_j$, the reliability threshold of equipment j and the corresponding maintenance cost rate within [0, T] can be obtained.

III. A. 3) Multi-objective preventive maintenance decision modeling

Unscheduled maintenance is performed assuming that the equipment fails during the i st maintenance cycle. Preventive maintenance is performed after determining the optimal preventive maintenance interval, during which the number of failures can be expressed as $\int_0^{T_i} \lambda_i(t)dt$. Many preventive maintenance models focus only on minimizing the cost rate, which in the i rd maintenance cycle is:

$$c_{ri} = \frac{C_p + C_f \int_0^{T_{ci}} \lambda_i(t)dt}{T} \tag{5}$$

Among them:

$$T = T_{ci} + T_p + T_f \int_0^{T_{ci}} \lambda_i(t)dt \quad (6)$$

In some cases, however, losses due to electrical equipment failure or malfunction include not only a reduction in revenue, but can also result in work not being completed as well as default and time issues. In such cases, electrical equipment availability is the focus of attention. During the i st maintenance cycle, the equipment availability was:

$$A_i = \frac{MUT}{MUT + MDT} = \frac{T_{ai}}{T_{ai} + T_p + T_f \int_0^{T_{ai}} \lambda_i(t)dt} \quad (7)$$

In real production, preventive maintenance has to cope with multiple requirement indicators, which is the multi-objective decision-making problem. In this paper, a multi-objective preventive maintenance decision model is proposed to integrate and optimize the repair cost rate and equipment availability. By unifying the magnitudes of c_{ri} and A_i and introducing the weighting factors w_1 and $w_2(w_1 + w_2 = 1)$, the optimal preventive maintenance interval T_{oi}^* is determined in the i th maintenance cycle, which minimizes the objective function, and the objective function of its multi-objective preventive maintenance decision-making model is:

$$v = -w_1 \frac{A_i}{A_i^*} + w_2 \frac{c_{ri}}{c_{ri}^*} \quad (8)$$

Once the objective function is determined, the optimal T_{oi}^* can be determined by minimizing V in Eq. and $\min(T_{ai}^*, T_{ci}^*) \le T_{oi}^* \le \max(T_{ai}^*, T_{ci}^*)$.

III. B. Optimization of multi-objective dynamic decision-making model

III. B. 1) Linear weighting method for solving optimization models

The linear weighted sum method is one of the most basic evaluation function methods, and its core idea is based on the importance of each objective in the problem [19]. It is given a weighting coefficient, the weighting coefficient is a set of numbers $w_1, w_2, ...w_m$ given corresponding to m objective such that $\sum_{i=1}^{m} w_i = 1, w_i \ge 0, i = 1, ...m$, and then the sum function of the sum of the individual objective functions with weighting coefficients is used as a new evaluation function.

The calculation steps of linear weighting method are as follows:

Step1 Give a set of weight coefficients according to the importance of each objective in the problem.

Step2 Find the linear weighting kernel function, i.e.:

$$\min_{x \in D} \sum_{i=1}^{m} w_i f_i(x) \quad (9)$$

In order to solve the multi-objective planning model correctly and reasonably, the objective function of each component should be unified.

In order to solve the multi-objective planning model correctly and reasonably, it is generally necessary to do a unified scale for each component objective function, which is mainly to avoid the influence of the final result due to the different orders of magnitude or large differences in the values of each objective function. The unified magnitude can generally be divided into 2 steps, namely:

Step1 Each component objective function is added with the same appropriately large positive number, so that the changed objective function can be expressed as:

$$f_i(x) > 0, \quad \forall x \in D, \quad i = 1, 2...m \quad (10)$$

Step2 Find the minimal value of each objective function on D after the change, i.e.:

$$f_i^* = \min_{x \in D} f_i(x) \quad (11)$$

The function $f_i(x) / f_i^*, i = 1, 2, ...m$ is used as the objective function for each component of the solution. The weight factor w_1, w_2 is assigned after the unification of the measures for A_k and c_{rk} .

The relative size of the weight coefficients indicates the relative importance of each objective, and the important objectives should be multiplied by larger weight coefficients, while the relatively unimportant objectives are multiplied by smaller weight coefficients, so the determination of the weight coefficients becomes the key to find a reasonable and satisfactory solution of the linear weighting and function method. And there are many methods to determine the weight coefficients, such as α-method, expert evaluation method, judgment matrix method, etc. In this paper, the size of the weight coefficients is determined by judgment matrix method.

In order to solve the problem of optimization direction, combined with the unity of scale and power coefficients to determine the relevant knowledge, the introduction of $\frac{A_x}{A_x^*}$ and $\frac{c_{rk}}{c_{rx}^*}$, so that the multi-objective model is unified for the optimization of the minimization, the introduction of $-\frac{A_k}{A_k^*}$ in the objective function, by the nature of the steady state availability of $\min -\frac{A_k}{A_k^*} \Leftrightarrow \max \frac{A_k}{A_k^*}$, so that we get:

$$\begin{cases} \max w_1 \frac{A_k}{A_k^*} \\ \min w_2 \frac{c_{rk}}{c_{rk}^*} \end{cases} \overset{\text{Unify to minimize}}{\Rightarrow} \begin{cases} \min - w_1 \frac{A_k}{A_k^*} \\ \min w_2 \frac{c_{rk}}{c_{rk}^*} \end{cases} \tag{12}$$

III. B. 2) Multi-objective optimal preventive maintenance strategy

At present, based on the loss pattern of the internal components of electrical equipment and the time distribution of failure, a reasonable preventive maintenance strategy has become a hot spot in academic research. However, most of the traditional preventive maintenance strategies are based on the failure rate curve modeling of the equipment's own historical failure data, so the optimal preventive maintenance strategy for electrical equipment considering the impact of corrosive environments is particularly important.

Based on this, this paper combines the Weibull reliability distribution model to establish a comprehensive recession evolution rule for electrical equipment based on the corrosive environment. Namely:

$$\lambda_{(k+1)}(t) = \varepsilon_k b_k \lambda_k (t + a_k T_k) \tag{13}$$

where ε_k is the environmental factor, a_k is the service age residual factor, and b_k is the failure rate acceleration factor. The range of values of the three factors meets $(0 < a_k < 1, b_k > 1, \varepsilon_k > 1)$, and their values can be fitted by cycle fitting method, failure rate fitting method and empirical method when combined with the actual maintenance requirements. In this example, the environmental factor $\varepsilon_k = 1.5$, for the gradual deterioration of the environment, $a_k = 0.7$, $b_{k=3}$.

Then the environmental factors are added into the failure rate function, and the preventive maintenance strategy under the influence of different corrosive environmental factors is established with the objectives of maximum steady-state availability of equipment and minimum average cost rate of maintenance.

After unifying the quantitative outline, determining the weight coefficients, unifying the optimization direction, and adopting the method of linear weighted sum function, the maintenance decision objective of the equipment in the k st maintenance cycle for both the integrated steady state availability and the average cost rate is v_k, which can be expressed as:

$$V_k = -w_1 \frac{A_k}{A_k^*} + w_2 \frac{c_{rk}}{c_{rk}^*} \tag{14}$$

where w_i and $w_2 (w_1, w_2 \geq 0, w_1 + w_2 = 1)$ are the weighting coefficients of the steady-state availability and the average cost rate, respectively. Since the steady-state availability takes the opposite number, the optimal preventive maintenance interval τ_k^* can be obtained by minimizing the global maintenance decision objective. The steps to solve for the optimal preventive maintenance interval T_k^* over the working life cycle when considering the multi-objectives of steady state availability and average cost rate are as follows:

Step1 Initialize the model parameters and input the assumed values of equipment working life parameter T_d, failure rate distribution function parameter η, β, and maintenance decision model parameter $\alpha_p, \alpha_f, c_p, c_f, a_k, b_k, \varepsilon_k$.

Step2 Solve the optimal preventive maintenance interval τ_k^* according to the linear weighted sum function method.

Step3 Judge whether the equipment reaches the working life T_d, if not T_d, then make $\lambda_{(k+1)}(t) = \varepsilon_k b_k \lambda_k (t + a_k T_k)$, $k = k + 1$, jump to Step2, calculate the time interval of the next maintenance cycle.

Step4 If the working life T_d is reached, assign the value to the last preventive maintenance cycle and end the calculation.

IV. Electrical equipment health management system application validation

The health management system of electrical equipment focuses on predicting, monitoring and managing the health status of the system by utilizing the integration of advanced sensors (e.g., eddy current sensors, low-power wireless integrated microsensors, wireless MEMS, etc.) and with the help of a variety of algorithms (e.g., Gabor transform, Fast Fourier Transform, Discrete Fourier Transform) and intelligent models (e.g., expert systems, neural networks, fuzzy logic, etc.). This paper establishes a health management system for electrical equipment by drawing on and absorbing advanced experience, studying key technologies in depth, and combining the specific characteristics of general complex systems. This chapter mainly focuses on the data analysis of its effectiveness, in order to further enhance the health management effect of electrical equipment in corrosive environments.

IV. A. Multi-objective dynamic maintenance decision simulation

IV. A. 1) Simulation results of equipment maintenance costs

Failure rate distribution functions of electrical equipment are varied, and this paper selects the more typical Weibull distribution as an example. The Weibull distribution is a more extensive form of failure rate distribution, which is widely used in the failure rate description of mechanical and electrical equipment products. In the Weibull distribution model, the shape parameter (m) and the life characteristic parameter (n) of the electrical equipment are generally obtained by analyzing the historical failure data of the electrical equipment and using mathematical statistics. For the simulation analysis in this section, it is assumed that m=2 and n=120.

In order to obtain the optimal maintenance schedule for electrical equipment, it is also necessary to determine the parameters such as adjustment factor, cost factor and maintenance period. In this paper, it is assumed that the adjustment factor is 0.6, the additional cost in addition to the cost required for normal preventive maintenance when the equipment is renewed, the maintenance cost rate of the equipment in its life cycle and the preventive maintenance cost rate are 90, 180 and 30, respectively, and the maintenance period is set to 2. Since the form of the cost optimization function is more complex, and its calculation process is more cumbersome when optimized by using the traditional mathematical method, therefore, this paper Monte Carlo simulation method is used to optimize it. The Monte Carlo simulation method is especially useful for mathematical modeling problems in engineering technology (such as calculating high-dimensional integrals, solving systems of algebraic equations, and calculating inverse matrices, etc.) when general analytical or numerical methods encounter difficulties in solving them. The optimization range of reliability (R) for preventive maintenance of decision variables is set to be [0.5,1.0] and the number of maintenance (N) is between [1,6], and the simulation operation is implemented using MATLAB software. The optimization results obtained for different reliability are shown in Table 1.

From the simulation results, it can be seen that in the life cycle of electrical equipment health management, its minimum maintenance cost rate is 1.663, the corresponding optimal reliability threshold is 0.65, and the optimal number of preventive maintenance is 5 times. That is, the electrical equipment is updated at the 5thi preventive maintenance, when the lowest maintenance cost of electrical equipment health management is spent. In addition, the reliability-based preventive maintenance strategy makes the maintenance cycle of electrical equipment show a certain decreasing trend, which is very consistent with the actual maintenance situation of electrical equipment health management.

Table 1: The simulation result

R	Min maintenance cost					
	N=1	N=2	N=3	N=4	N=5	N=6
0.82	3.812	2.355	1.935	1.752	1.751	1.692
0.76	3.584	2.268	1.857	1.717	1.672	1.669
0.71	3.513	2.243	1.834	1.715	1.665	1.671
0.68	3.467	2.232	1.812	1.711	1.664	1.671
0.65	3.436	2.219	1.808	1.698	**1.663**	1.672
0.61	3.375	2.181	1.789	1.696	1.665	1.674

0.56	3.319	2.146	1.765	1.694	1.668	1.683
0.50	3.152	2.084	1.751	1.712	1.686	1.715

As the reliability threshold increases, the health management maintenance intervals of electrical equipment are gradually reduced, which indicates that more frequent preventive maintenance is required to ensure that the high reliability of electrical equipment is maintained. And the reliability threshold increases with the increase in the cost of minor repairs, which means that the electrical equipment is down due to failures, which may result in the loss of various costs. If the costs of unscheduled downtime, risk of order delays, etc. are high, more frequent preventive maintenance is needed to reduce the number of breakdowns in the maintenance cycle and thus reduce the potential loss of downtime.

IV. A. 2) Dynamic preventive maintenance cycles for equipment

In this section, the proposed multi-objective dynamic cyclic preventive maintenance strategy is practically applied to a lathe machine in a series-parallel manufacturing system producing hydraulic transmissions, and the effectiveness of the strategy for improving equipment performance is verified. Therefore, under the consideration of corrosive environments, global optimal maintenance intervals need to be dynamically planned to trade-off various local objectives to meet the comprehensive performance needs of equipment maintenance value and equipment productivity. The main objective of the arithmetic study and analysis of the dynamic multi-objective preventive maintenance strategy planning model for maintenance decision making at the equipment level is to obtain the optimal predictive maintenance intervals of the equipment in real time in a dynamic loop using the proposed optimization and improvement planning strategy, and to compute the equipment availability and the maintenance value rate in each maintenance cycle.

Based on the previously designed multi-objective dynamic preventive maintenance model for electrical equipment considering corrosive environmental factors, the optimal time interval for each maintenance cycle (K) is dynamically decided, and the specific results are shown in Table 2. In the table, T and M denote the optimal maintenance time interval and maximum equipment availability, respectively, and MV denotes the maintenance value rate of equipment j in the kth maintenance cycle.

Based on the results in the table, with the maximum number of maintenance N=10 as the maintenance planning interval of electrical equipment, the following conclusions can be found intuitively in the preventive maintenance planning results of electrical equipment in the table:

(1) The optimal maintenance interval under the multi-objective dynamic decision-making model is gradually shortened with the growth of the service life cycle, and its value is reduced from 3320 when the maintenance cycle is 1 to 2252 when the maintenance cycle is 8. The reduction of the optimal maintenance cycle implies the increase of the frequency of preventive maintenance, and the same tendency is also reflected in the model of the value of the maintenance of the equipment and the model of the availability of the equipment. The above results show that with the increase of service age and maintenance frequency, the health state of electrical equipment shows an accelerated deterioration trend, and more frequent preventive maintenance operations are needed to ensure the normal operation of electrical equipment.

(2) Whether in the equipment maintenance value model, the equipment availability model, or the multi-objective maintenance model, the availability and maintenance value rate of each maintenance cycle are decreasing. Along with the growing failure rate of the equipment, the increasing probability of failure downtime triggers the increase of maintenance cost, while the accelerated deterioration of the equipment leads to less recovery of the maintenance value, thus leading to the decline of the maintenance value rate of the electrical equipment and the availability of the equipment.

(3) In the same preventive maintenance cycle, the maximum equipment availability of the equipment availability model outperforms the equipment availability of the equipment maintenance value model and the multi-objective model in terms of efficiency metrics, due to the decision function's commitment to maximizing equipment availability. Similarly, the maintenance value of the equipment maintenance value model is optimal among the three when considering the economic metrics. The above results show that the analysis of the multi-objective model in this paper is meaningful, along with different management objectives, equipment managers can construct decision objectives matching their own needs and manufacturing scenarios according to the multi-objective dynamic maintainability decision model, so as to plan the required multi-objective preventive maintenance cycle for electrical equipment.

Table 2: The dynamic preventive maintenance cycle of the equipment

K	Equipment availability			Equipment maintenance value			Multi-objective model		
	T	M	MV	T	M	MV	T	M	MV
1	3875	0.945	0.171	3297	0.948	0.195	3320	0.948	0.181
2	3716	0.942	0.143	3126	0.943	0.166	3153	0.946	0.182
3	3496	0.938	0.131	2943	0.940	0.153	2968	0.941	0.138
4	3284	0.934	0.122	2775	0.937	0.142	2803	0.939	0.126
5	3116	0.931	0.116	2621	0.934	0.131	2645	0.936	0.114
6	2953	0.928	0.108	2481	0.930	0.123	2507	0.933	0.107
7	2716	0.996	0.105	2345	0.927	0.116	2374	0.929	0.098
8	1628	0.998	0.086	2223	0.923	0.111	2252	0.924	0.095

IV. B. Electrical Equipment Health Management System Performance

IV. B. 1) Statistics on test results of electrical equipment

In order to verify the feasibility of the electrical equipment health management system designed in this paper in analyzing the health status of electrical equipment, the engine of a factory's machinery and equipment is selected as the object of study, and the data related to motor speed is collected by setting up sensors to analyze the display test results of engine speed data after data acquisition and processing. In the test process of engine speed, this paper has set up a total of 360 use cases, and the execution of the test cases is 360 cases, and Table 3 shows the results of the display test of the engine speed data processing of electrical equipment. In the table, Passed, Failed and Blocked respectively indicate the number of test cases that passed the test, the number of test cases with errors and the number of test cases that could not be tested due to various reasons, and Newly added refers to the number of new test cases that have been executed due to the addition of new features in this version.

As can be seen from the table, in the engine speed use case test of the electrical equipment, the total number of successfully executed test cases is 356, and 4 test cases failed the test, and among the 4 test cases that failed the test, there are 2 cases belonging to the problem of functional description of the test requirements, 1 case belonging to the problem of boundary value change, and 1 case belonging to the problem of real-time performance of the test software. After getting the test results of electrical equipment, according to the corresponding statistical results, the tester can submit the software defect analysis problem report form to the software developer for correction.

Table 3: Statistics of electrical equipment test results

Test	Use cases	Newly added	Passed	Failed	Blocked
Function	196	0	194	2	0
Boundary value	42	0	41	1	0
Performance	53	0	53	0	0
Real-time	69	0	68	1	0
Total	360	0	356	4	0

The software problem analysis and report provided the developers with directions for modifying the problems. There are four types of problems identified during the testing of the electrical equipment health management system. The first type of problem is that the software does not fulfill the functional requirements of the requirements, and the possible causes of this type of problem are the design errors of the developers or the software version. The second type of problem is that the software has features that are not required by the requirements. This type of problem can be caused by imperfections in the requirements or redundancies in the implementation. The third type of problem is that the software does not fulfill a goal that is not required by the requirements, but should be fulfilled, which may be due to inadequate requirements. The fourth type of problem is that the software is difficult to understand, not easy to use, and runs slowly. The cause of this type of problem may be a problem in the hardware design or software implementation.

Waiting for the developer to revise the problem and then resubmit it, the tester will also need to perform regression testing on that part. The test case will not be closed until the problem is resolved.

IV. B. 2) Health management system performance testing

According to the test case described, in the performance testing of the system login module, the test objects that need special attention are the response time of the login operation and the concurrent success rate of the login operation, so the overall script of the login operation is written in Action() in VuGen and recorded in HTML mode. In order to facilitate the concurrent load test of the login operation, all the test usernames and passwords are listed into a login information matrix for VuGen to call. Insert transactions before and after the login operation to get the response time of the login operation. Add a checkpoint at the home page loading to check whether the display data appears on the home page, if it appears, it means the login is successful, if it does not appear, it means the login fails. Each virtual user logs out of the system after logging in for a preset Think time.

For the performance test analysis of the login module of the electrical equipment health management system, a single business load scenario model is used. The number of concurrent users for each module is set to every 50 in the range of 0 to 500, and the concurrent user loading strategy for each scenario is to load 20 users every 2 seconds into the collection point to standby, and run the scenario when the number of users in the collection point reaches the specified number, and the running time is set to 4 minutes. When exiting, the parallel strategy is to exit 20 users every 30 seconds. The characteristic data of the login module of the electrical equipment health management system at the number of users from 0 to 500 are taken and analyzed to derive the performance test results and bottleneck analysis. Table 4 shows the performance test results of the login module of the electrical equipment health management system, where X1~X5 denote the average transaction response time, transaction success rate, throughput rate, CPU utilization and hit rate, respectively.

From the data in the table, when the number of concurrent users increases from 50 to 300, the throughput rate and click rate change significantly, the CPU utilization rate also fluctuates within a normal range, the average response time of the transaction is controlled between 1.792s~2.538s, and the success rate of the transaction is maintained at 100%. It indicates that at this time, the login module of the electrical equipment health management system has less pressure and works in a normal state. However, when the number of concurrent users increases to 450, with the rapid increase in the click rate, the throughput rate increases little, indicating that at this time the system service pressure is greater, and the average response time reaches 4.112s, which has exceeded the expectations of the system login response time. When the number of concurrent users reaches 500, the transaction success rate decreases from 100% to 77.48%, the response time is too high, and it can be considered that the electrical equipment health management system is on the verge of collapse. After analyzing the data of the average corresponding time of the transaction, it is found that the number of concurrent users that meet the expectation of the system login response time is between 250-400 people, which can basically meet the requirements of the login module of the electrical equipment health management system.

Table 4: System login module performance test results

Users	X1 (s)	X2 (%)	X3 (MB/s)	X4 (%)	X5 (a/s)
50	1.792	100.00	18.72	55.37	548.35
100	1.935	100.00	21.34	60.51	716.42
150	2.241	100.00	24.65	68.45	942.51
200	2.304	100.00	30.18	72.63	1496.66
250	2.419	100.00	40.57	78.96	2184.73
300	2.538	100.00	52.14	82.91	2865.69
350	3.075	100.00	56.36	84.35	3483.92
400	3.684	100.00	58.75	88.76	4542.81
450	4.112	100.00	60.88	92.38	5616.47
500	-	77.48	-	100.00	-

V. Conclusion

In this paper, an electrical equipment health management system based on multi-objective optimization algorithm is developed for the problem of electrical equipment health management in corrosive environment, and the following main conclusions are achieved:

The electrical equipment health management system constructed based on OSA-CBM architecture realizes the whole process management of data collection, condition monitoring, health assessment, predictive maintenance and decision support, and the system login module operates stably under 250-400 concurrent users, and the response time meets the system requirements;

The results of electrical equipment failure rate modeling using Weibull distribution show that when the reliability threshold is 0.65 and the number of preventive maintenance is 5 times, the lowest maintenance cost rate is 1.663, which verifies the economy of reliability-based preventive maintenance strategy;

The multi-objective dynamic maintenance decision model introducing the corrosive environment factor shows that the optimal maintenance interval decreases from 3320 to 2252 and the equipment availability decreases from 0.948

to 0.924 with the growth of the service age cycle, reflecting the accelerated deterioration law of the health state of electrical equipment under the corrosive environment;

The proposed multi-objective optimization method can better balance the equipment availability and maintenance cost compared with the single-objective model, which provides an effective tool for scientific decision-making of electrical equipment in corrosive environments. The study has important practical value for improving the safety, reliability and economy of electrical equipment in hot and humid coastal areas.

Funding

Research Project of Three Gorges Jinsha River Chuanyun Hydropower Development Co., Ltd (Z422202010).

References

[1] Wilkie, D., & Galasso, C. (2020). Impact of climate-change scenarios on offshore wind turbine structural performance. Renewable and Sustainable Energy Reviews, 134, 110323.
[2] Bailey, H., Brookes, K. L., & Thompson, P. M. (2014). Assessing environmental impacts of offshore wind farms: lessons learned and recommendations for the future. Aquatic biosystems, 10, 1-13.
[3] Rathish, R. J., Prabha, S. S., Dorothy, R., Jancyrani, S., Rajendran, S., Singh, G., & Kumaran, S. S. (2019). Corrosion issues in electronic equipments—An overview. Int. J. Corros. Scale Inhib, 8(4), 799-815.
[4] Shi, X., Ke, Q., Lei, J., & Yuan, Z. (2020, July). Corrosion Failure Analysis of Electrical Equipment in Distribution Power System under High Temperature and High Humidity Environment. In Journal of Physics: Conference Series (Vol. 1578, No. 1, p. 012204). IOP Publishing.
[5] Chen, X., Zhang, Z., Zhang, H., Yan, H., Liu, F., & Tu, S. (2022). Influence of air pollution factors on corrosion of metal equipment in transmission and transformation power stations. Atmosphere, 13(7), 1041.
[6] Price, S. J., & Figueira, R. B. (2017). Corrosion protection systems and fatigue corrosion in offshore wind structures: current status and future perspectives. Coatings, 7(2), 25.
[7] Shamir, M., Braithwaite, J., & Mehmanparast, A. (2023). Fatigue life assessment of offshore wind support structures in the presence of corrosion pits. Marine Structures, 92, 103505.
[8] Kirchgeorg, T., Weinberg, I., Hörnig, M., Baier, R., Schmid, M. J., & Brockmeyer, B. (2018). Emissions from corrosion protection systems of offshore wind farms: Evaluation of the potential impact on the marine environment. Marine pollution bulletin, 136, 257-268.
[9] López-Ortega, A., Bayón, R., & Arana, J. L. (2018). Evaluation of protective coatings for offshore applications. Corrosion and tribocorrosion behavior in synthetic seawater. Surface and Coatings Technology, 349, 1083-1097.
[10] Li, S., & Li, J. (2017). Condition monitoring and diagnosis of power equipment: review and prospective. High Voltage, 2(2), 82-91.
[11] Xubin, L. I., Fuqiang, T. I. A. N., & Yike, G. U. O. (2023). Key Technologies for Health Management and Intelligent Operation and Maintenance of Power Equipment in New Power Systems. Power System Technology, 47(9), 3710-3726.
[12] Peng, C., Tang, Z., Gui, W., Chen, Q., Zhang, L., Yuan, X., & Deng, X. (2020). Review of key technologies and progress in industrial equipment health management. IEEE Access, 8, 151764-151776.
[13] Kou, L., Li, Y., Zhang, F., Gong, X., Hu, Y., Yuan, Q., & Ke, W. (2022). Review on monitoring, operation and maintenance of smart offshore wind farms. Sensors, 22(8), 2822.
[14] Li, M., Kefal, A., Oterkus, E., & Oterkus, S. (2020). Structural health monitoring of an offshore wind turbine tower using iFEM methodology. Ocean Engineering, 204, 107291.
[15] Shaaban, M. F., Osman, A. H., & Aseeri, F. M. (2019). A multi-objective allocation approach for power quality monitoring devices. IEEE Access, 7, 40866-40877.
[16] Yang, C. (2021). An adaptive sensor placement algorithm for structural health monitoring based on multi-objective iterative optimization using weight factor updating. Mechanical Systems and Signal Processing, 151, 107363.
[17] Yudao Sun & Juan Yin. (2025). Dynamic condition-based maintenance for shock systems based on damage evolutions using deep reinforcement learning. Reliability Engineering and System Safety,261,111095-111095.
[18] Jinshuo Zhang. (2024). Research on Fault Prediction and Health Management System of Railway Tunnel Drilling and Blasting Construction Machinery Based on Machine Learning. International Journal of New Developments in Engineering and Society,8(5).
[19] Wang Liyong,Huang Xiaozan,Wu Jianpeng,Zhang Jinle & Yang Chengbing. (2025).Multi-objective optimization shift strategy for vehicle based on adaptive linear weighted sum method. Proceedings of the Institution of Mechanical Engineers,239(5),1798-1811.