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A Transformer Maintenance Interval Optimization Method Considering Imperfect Maintenance and Dynamic Maintenance Costs

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Abstract: As one of the most critical components of the power grid system, transformer maintenance strategy planning significantly influences the safe, economical, and sustainable operation of the power system. Periodic imperfect maintenance strategies have become a research focus in preventive maintenance strategies for large power equipment due to their ease of implementation and better alignment with engineering realities. However, power transformers are characterized by long lifespans, high reliability, and limited defect samples. Existing maintenance methods have not accounted for the dynamic changes in maintenance costs over a transformer's operational lifetime. Therefore, we propose a maintenance interval optimization method that considers imperfect maintenance and dynamic maintenance costs. Utilizing defect and maintenance cost data from 400 220 KV oil-immersed transformers in northern China, we employed Bayesian estimation for the first time to address the distribution fitting of defect data under small sample conditions. Subsequently, we introduced imperfect maintenance improvement factors to influence the number of defects occurring in each maintenance cycle, resulting in more realistic maintenance cost estimations. Finally, we established an optimization model for transformer maintenance cycles, aiming to minimize maintenance costs throughout the transformer's entire lifespan while maintaining reliability constraints. Taking a transformer's strong oil circulation cooling system as an example, our method demonstrates that while meeting the reliability threshold recognized by the power grid company, the system's maintenance cost can be reduced by 41.443% over the transformer's entire life cycle. Through parameter analysis of the optimization model, we conclude that as the maintenance cycle increases, the factors dominating maintenance costs shift from corrective maintenance to preventive maintenance.

Keywords: imperfect maintenance; maintenance interval optimization; improvement factors

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1. Introduction

Power transformers are critical and high-value equipment in the power system, accounting for 60% of the total power investment [1]. Any faults or hidden defects in power transformers can lead to operational issues and system shutdowns, resulting in significant economic and resource losses. Therefore, effective maintenance methods are crucial to ensure the normal and safe operation of power transformers.

In terms of maintenance timing, the power system employs various maintenance methods, including corrective maintenance (CM), preventive maintenance (PM), and predictive maintenance (PdM). For power transformers, the main maintenance strategies are corrective maintenance and preventive maintenance. Due to the high cost associated with corrective maintenance, which can be comparable to the cost of replacing the entire unit, many power transformers currently adopt a preventive maintenance strategy.

Maintenance can be categorized into minimal maintenance, imperfect maintenance, and complete maintenance/replacement based on the extent of repair. Due to the technical complexity and high cost of major repairs/replacements, power transformers often undergo imperfect maintenance as their primary maintenance approach [2].

Imperfect maintenance can be further divided into sequential maintenance, fault control maintenance, maintenance restriction strategies, and periodic maintenance with fixed intervals. Due to the high cost and complexity of organizing maintenance inspections, periodic imperfect maintenance strategies are widely adopted for power transformers [3].

Compared to other maintenance strategies, periodic imperfect maintenance is closer to engineering practice and offers simplicity in operation and maintenance management, making it a popular choice in both research and practical applications [4]. Consequently, scholars and industry professionals have focused on the research of periodic imperfect maintenance strategies. In the context of wind turbine units under periodic maintenance, Wang proposed a multi-objective fixed-cycle dynamic imperfect maintenance decision to address the issues of over-maintenance and under-maintenance [5]. Moghadam et al. introduced an extended mixed-integer linear programming model that utilized information gap decision theory to optimize power grid maintenance costs and enhance network reliability. They applied this model to an actual distribution network in Iran [6]. Li et al. developed a more accurate meta-action unit periodic preventive maintenance strategy using the generalized geometric process method [7]. Zhao et al. established a transformer condition-based maintenance strategy by incorporating the proportional intensity model, which considered both operating time and maintenance activities [8]. Lin et al. proposed a preventive opportunity maintenance method based on the Weibull distribution to minimize power outage time in railway traction power supply systems [9]. Balushi et al. employed Markov processes to analyze the maintenance parameters of power transformers, taking into account various component combinations and multiple maintenance personnel [10].

To address the optimization of periodic imperfect maintenance for power transformers, previous studies have identified common issues [2]:

1. Limited research on power transformers: The current research on periodic imperfect maintenance for power systems primarily focuses on hydropower stations and wind power, with limited studies on the optimization of periodic imperfect maintenance strategies for power transformers.
2. Limited maintenance history data: Data on power transformers is often scarce, and the same fault mode rarely repeats in the same equipment. This limitation makes it challenging to develop complex periodic maintenance strategies. Additionally, optimized maintenance strategies usually apply to more common and simple maintenance tasks. For example, there is an abundance of data available for common defects such as indicator lights not working or minor oil leakage, while severe defects like fan motor failures have limited or no data.
3. Static maintenance costs and benefits: Previous studies often assume constant costs for maintenance tasks and pay less attention to how these costs change over time.

To address these issues, this paper considers the dynamic changes in maintenance costs over time and introduces an imperfect maintenance improvement factor that accounts for these changes with operating time. A maintenance interval optimization model is established with reliability as a constraint. The sequential least squares programming method is employed to solve the model. This paper proposes a transformer maintenance interval optimization method that considers imperfect maintenance and dynamic costs. It dynamically considers the maintenance cycle cost with limited maintenance data and optimizes the maintenance interval for power transformers under different defect patterns. This method, along with the findings of this paper, can be applied to the optimization of maintenance strategies for power transformers owned by power companies of different scales.

The structure of this paper is as follows: Section 2 discusses the relevant work on periodic maintenance and imperfect maintenance. Section 3 introduces the dataset used in this research. Section 4 presents the theoretical framework and steps of the transformer maintenance interval optimization method based on imperfect maintenance factors and considering reliability. Section 5 verifies the effectiveness of the method through a comparison of maintenance cases in a power grid in Inner Mongolia and draws relevant conclusions based on the case results.

2. Related Works

Periodic imperfect maintenance is a widely adopted maintenance method that involves performing imperfect maintenance at fixed time intervals. It can be categorized into two main approaches: maximizing availability and minimizing maintenance costs.

2.1. Periodic Imperfect Maintenance to Maximize Availability

In the context of maximizing availability, Moghadam et al. proposed an extended mixed-integer linear programming model that utilized information gap decision theory (IGDT) to optimize the annual cost of power grid maintenance, reduce interruptions, and improve network reliability. They applied this model to an actual distribution network in Markazi Province, Iran [6].

Li et al. developed a more accurate meta-action unit periodic preventive maintenance strategy using the generalized geometric process (GGP) method [7].

Zhao et al. incorporated imperfect maintenance issues into transformer condition-based maintenance strategies and established a maintenance strategy based on the proportional intensity model (PIM), considering both operating time and maintenance activities [8].

Lin et al. proposed a preventive opportunity maintenance (POM) method based on the Weibull distribution to minimize power outage time in railway traction power supply systems [9].

Balushi et al. analyzed the mean time between failures (MTBFs), availability index, and expected busy cycle of maintenance personnel for power transformers using Markov processes, considering various component combinations and multiple maintenance personnel [10].

Pereira et al. introduced an innovative preventive maintenance optimization approach that considered the intervention level of maintenance activities as an independent variable, aiming to minimize the total maintenance cost over a user-defined planning horizon [11].

2.2. Periodic Imperfect Maintenance to Minimize Maintenance Costs

With an increasing number of power transformers being put into use, periodic imperfect maintenance, aiming to minimize maintenance costs while ensuring the availability specified by the industry, has become the main direction for optimizing maintenance strategies for power transformers [12].

In the context of minimizing maintenance costs, Tsai et al. established and optimized a periodic preventive maintenance model for critical components in electromechanical systems using genetic algorithms (GAs) to maximize the unit cost life of the system while maintaining its availability and avoiding unexpected failures [13].

Liu et al. proposed an optimal replacement strategy for multi-state systems under periodic imperfect maintenance, using a non-homogeneous continuous-time Markov model and a general generating function method to determine the optimal number of failures to maximize long-term expected profit [14].

Melcher-Hernández et al. developed a fault occupancy rate (ROCOF) function based on a two-parameter Weibull distribution to evaluate the impact of inadequate maintenance measures on equipment reliability and determine the optimal maintenance interval and frequency by minimizing the cost function [15].

Zhang et al. developed a maintenance decision-making model based on life cycle cost analysis for power transformers, aiming to select the best maintenance strategy that balances reliability and economy [16].

Murugan et al. conducted a failure analysis of power transformers to identify root causes and propose effective maintenance planning in electric utilities, using statistical analysis and root cause analysis (RCA) [17].

Trappey et al. developed an intelligent engineering asset management system for power transformer maintenance using principal component analysis (PCA) and a back-propagation artificial neural network (BP-ANN) for real-time monitoring and fault prediction [18].

Soodbakhsh et al. presented a robust reliability-based maintenance planning method for power systems, prioritizing distribution network components using a weighted reliability index and optimizing maintenance using an optimal bat algorithm method [19].

Xu et al. investigated the impact of imperfect repair on short-term power system maintenance scheduling and proposed a condition-based maintenance optimization model focusing on equipment deterioration failure [20].

Murugan et al. evaluated the health condition of in-service power transformers using a Health Index (HI) approach, incorporating three key stages: input for health index assessment, health index estimation, and output health index for the maintenance decision process [21].

Kim et al. proposed a method based on a weighted reliability index for prioritizing distribution network components and developed a lifetime efficiency index model and an optimal bat algorithm method for power transformers, aiming to balance reliability and maintenance costs [22].

Liang et al. optimized the periodic inspection of power transformers using a continuous time Markov chain (CTMC) model, considering different types of failure rates [23].

Wei et al. proposed a preventive maintenance and replacement strategy for photovoltaic power systems based on reliability constraints, using an off-cycle incomplete replacement maintenance model to minimize maintenance costs [24].

Wang et al. developed a dynamic imperfect preventive maintenance decision model based on a general updating process, aiming to minimize maintenance costs while ensuring the availability of wind turbines [25].

Dong et al. optimized maintenance strategies by maximizing expected profit within each updating period, considering variable user demands and realistic component lifetimes and repair times [26].

Wang et al. proposed an opportunistic conditional maintenance strategy for electrical distribution systems (EDSs) based on the structural dependency problem of power equipment, aiming to maximize the reliability of EDSs while reducing maintenance and troubleshooting costs [27].

Li et al. optimized power system maintenance strategies through a genetic algorithm, solving the trade-off problem between system maintenance risk and potential system fault risk [28].

Yu et al. designed an optimal preventive maintenance algorithm based on the update reward theorem, optimizing the maintenance plan of wind turbines and reducing maintenance costs [29].

Bian et al. introduced variable weights based on lifecycle cost and retirement age to select the optimal maintenance strategy for power transformers [30].

Wang et al. proposed a dynamic group maintenance strategy based on imperfect maintenance models, considering the economic dependence between wind turbines in wind farms [31].

Murugan et al. proposed a transformer maintenance method based on health index assessment, helping maintenance personnel conduct early fault diagnosis and reduce maintenance costs [32].

Wang et al. introduced a two-stage framework for alternative planning, optimizing asset intervention planning using a Monte Carlo program based on the probabilistic health index (HI) method [33].

Zcan et al. developed an optimization model of maintenance strategy for large-scale hydropower stations, considering multi-objective and multi-standard structures of complex equipment [34].

Gong et al. proposed a dynamic preventive maintenance strategy for subway vehicle traction systems, incorporating service age-decreasing factors and failure rate-increasing factors into a new dynamic reliability model [35].

Our comprehensive analysis of recent literature on periodic imperfect maintenance planning in the power industry reveals several trends and opportunities for improvement. We evaluated these studies based on three critical aspects: consideration of small sample scenarios, dynamic maintenance factors, and dynamic maintenance costs. The results of this analysis are presented in Table 1.

Table 1. The comparison between different methods over the past 3 years.

Item	Wei et al. [24]	Pereira et al. [11]	Murugan et al. [21]	Soodbakhsh et al. [21]	Kim et al. [22]
Case study object	Photovoltaic Power	heat exchangers	power transformer	power network	Substations
Small sample data	×	×	×	×	×
Incomplete maintenance factor	√	√	×	√	√
Dynamic maintenance cost	×	×	√	×	√
Calculation and optimization method	Mixed fault function	Maximum Likelihood Estimation Genetic Algorithm	Weighted Health Index	Optimal Bat Algorithm Particle Swarm Optimization	Cox Proportional Hazard Model Least Absolute Shrinkage Selection Operator Regression

As evidenced by Table 1, while current research in periodic imperfect maintenance often focuses on precise descriptions of effective age, there remain significant areas for enhancement. We have identified three key aspects that warrant further investigation:

1. Dynamic increase in maintenance costs: Most studies prioritize optimizing lifespan extension and maintenance intervals through factors like effective age, overlooking the temporal variability of maintenance costs. For power transformers, the escalating failure rates with each maintenance cycle inevitably lead to increased costs in subsequent maintenance periods. This dynamic cost structure is often neglected in current models.
2. Limited maintenance history data: The scarcity of defect samples in long-lifespan products like power transformers poses a significant challenge. Many studies fail to address the practical difficulties engineers face when planning maintenance for such equipment with limited high-quality historical data.
3. Variability of imperfect maintenance improvement factor: Current research often assumes a constant degree of imperfect maintenance or focuses on minimal maintenance scenarios. However, for power transformers, the efficacy of each maintenance task varies over the equipment's lifespan, a nuance that is frequently overlooked in existing models.

To address these gaps, we propose a novel approach that incorporates the dynamic nature of maintenance costs over time and introduces an imperfect maintenance improvement factor that accounts for varying maintenance effects. Our model aims to optimize maintenance intervals by minimizing costs while maintaining reliability constraints. We employ integer programming to solve this complex optimization problem.

In essence, we present a sophisticated transformer maintenance interval optimization method that integrates imperfect maintenance considerations with dynamic cost structures. This approach represents a significant advancement in maintenance planning for power transformers, offering a more realistic and adaptable framework for industry practitioners and researchers alike.

3. Data

Our study is based on an extensive dataset comprising defect records of 400 220 KV oil-immersed main transformers operating in northern China from 1994 to September 2023. This comprehensive dataset encompasses 86 distinct defect patterns, totaling 7202 records. It is crucial to note that these transformers have been consistently operating under low-load conditions, typically between 20% and 30% of their capacity, due to regulatory policies. Consequently, the recorded data predominantly reflect defects rather than operational failures.

Each defect record in our dataset is rich in detail, containing information such as the defective component, defect mode, defect number, converter number and model, defect discovery time, equipment debugging time, and defect severity. We consider the time of defect discovery as a close approximation of the actual defect occurrence time.

To complement this defect data, we have also compiled a comprehensive cost database. This includes various maintenance and replacement costs for the main components and their subcomponents, encompassing labor costs, material costs, mechanical costs, and spare parts costs for the main body, cooling system, and other major components. These costs have been adjusted for inflation to reflect current maintenance costs, allowing us to calculate accurate preventive maintenance, corrective maintenance, and overhaul costs.

In our analysis, we observed that for the same defective component, the cost of corrective maintenance remains relatively constant across different defect modes. To align with the actual maintenance policies and requirements of power grid companies, we have integrated different defect modes for each defective component. Furthermore, recognizing the significant impact of defect severity on maintenance costs, we have further categorized and statistically analyzed these integrated defect patterns based on the severity of each defective component. This severity classification follows a three-tier system: “normal”, “severe”, and “critical” [36]. This refined approach to data analysis and categorization allows for a more nuanced and practical application of our maintenance optimization model, taking into account both the technical aspects of defects and the economic realities of maintenance operations.

While our analysis is based on data from power transformers in northern China, it is important to emphasize that this approach serves primarily to validate the effectiveness of our method and provide a more intuitive description of the calculation steps. The data we have utilized represents the fundamental information typically collected by power companies of various scales across different countries. Therefore, the methods and findings presented in this paper have broad applicability for optimizing maintenance strategies of power transformers globally.

4. Methods

We present a maintenance interval optimization model that considers equipment reliability and imperfect maintenance. The overall framework of our method is illustrated in Figure 1 and consists of the following key steps:

1. Distribution selection and parameter estimation: Based on our investigation, we determined that the two-parameter Weibull distribution is most suitable for modeling transformer defects. Given that some defect patterns in the dataset have limited

samples, we employ small sample parameter estimation methods to fit the failure rate function accurately.

2. Imperfect maintenance modeling: We make necessary assumptions and design a time-varying imperfect maintenance improvement factor. This factor is incorporated into the maintenance cost calculation, allowing the cost to dynamically change as the maintenance cycle progresses. This approach forms the foundation for our periodic imperfect maintenance strategy.
3. Optimization model development: We establish an optimization model with the primary objective of minimizing maintenance costs while maintaining the failure rate within acceptable constraints. To solve this model, we utilize the SLSQP (Sequential Least Squares Programming) method, a robust optimization algorithm well-suited for this type of problem.
4. Results and analysis: Through this process, we obtain the optimal maintenance intervals for each defect pattern. We then conduct further analysis of these results to derive insights and recommendations for practical implementation.

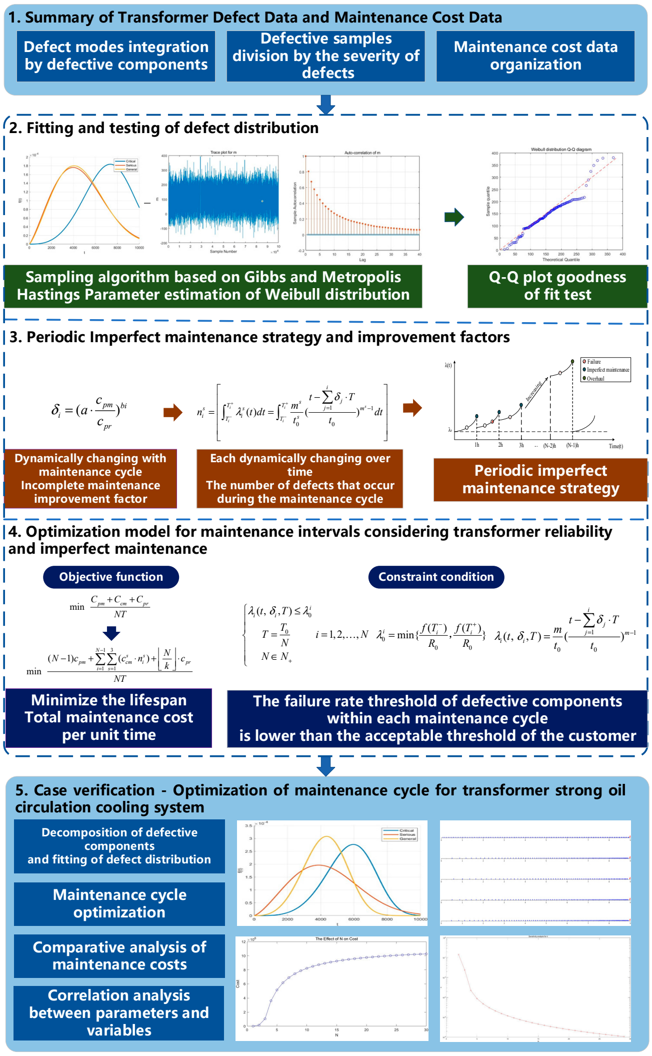


Figure 1. Overall framework.

This comprehensive approach allows for a more realistic and dynamic representation of maintenance processes, taking into account the complexities of equipment reliability and the imperfect nature of maintenance activities. By considering these factors, our model provides a more accurate and practical tool for optimizing maintenance intervals in transformer systems.

4.1. Modeling of Transformer Fault Distribution

In order to establish transformer reliability constraints in the maintenance interval optimization model, it is necessary to obtain the distribution of transformer faults. The first failure time t of the transformer is a random variable. According to the law of large numbers in statistics, the more samples there are, the closer the statistical measures (sample mean, sample variance, etc.) and empirical distribution function $F_n(t)$ of the sample are to the characteristic parameters (expected value, variance, etc.) and probability distribution function $F(t)$ of the random quantity t. Furthermore, to obtain the most intuitive probability distribution of the defect mode in the transformer, it is necessary to obtain the accurate characteristic parameters and probability distribution function of t through parameter estimation.

4.1.1. Determine the Type of Probability Distribution Function for Transformer Faults

In the analysis of the distribution pattern of power equipment failure rate and life, commonly used statistical probability distribution functions include two-parameter Weibull distribution, three-parameter Weibull distribution, Gamma distribution, normal distribution, lognormal distribution, etc. Among them, the Weibull distribution has a good fitting performance for modeling transformer fault time, and the Weibull function model has achieved good results in the cost analysis of transformers [37,38].

The cumulative fault probability distribution function of the dual parameter Weibull distribution is shown in Equation (1), the fault probability density distribution function is shown in Equation (2), and the fault rate function is shown in Equation (3).

$$F(t) = 1 - \exp(-(\frac{t}{t_0})^m) \tag{1}$$

$$f(t) = \frac{m}{t_0^m} t^{m-1} \exp(-(\frac{t}{t_0})^m) \tag{2}$$

$$\lambda(t) = \frac{f(t)}{1 - F(t)} = \frac{m}{t_0}(\frac{t}{t_0})^{m-1}, t \geq 0, m \geq 0, t_0 \geq 0 \tag{3}$$

In the formula, m is the shape parameter; t_0 is the scale parameter; t is the running time before the equipment malfunctions.

4.1.2. Distribution Fitting

In response to the problem of a small sample size of defects caused by the high reliability of transformers, the Bayesian estimation method is used to estimate the small sample parameters of the distribution function of the concerned defect modes, and Gibbs and Metropolis-Hastings sampling algorithms are used to estimate the parameter values [39–41]. Here, taking the cooling components of the strong oil circulation cooling system in power transformers as an example, the specific steps of distribution fitting calculation are given.

Step 1: Provide an initial parameter value $m^{(0)}$ and $t_0^{(0)}$

1. Based on the existing historical data shown in the table, provide an initial parameter value $m^{(0)}$ and $t_0^{(0)}$ using expert experience
2. Based on the existing historical data shown in Table 2, provide an initial parameter value using expert experience. Taking the oil leakage and leakage defect mode of the cooler components in the strong oil circulation cooling system of power transformers as an example, this type of fault is usually a general fault mode, and the total number of occurrences of this fault is 128 according to statistics. Based on expert experience, we can set $m^{(0)} = 50$ and $t_0^{(0)} = 200$.

Table 2. Fault times of the coolers in the forced oil circulation cooling system.

NO.	Fault Time (Days)									
01–10	86	193	587	674	871	907	908	949	962	1282
11–20	1483	1587	1624	1638	1650	1747	1793	2022	2609	2626
21–30	2663	2672	2689	2692	2735	2748	2748	2748	2799	2924
31–40	2926	2969	2971	3058	3124	3124	3174	3229	3283	3283
41–50	3363	3380	3401	3454	3470	3521	3528	3560	3645	3678
51–60	3747	3815	3836	3855	3864	3876	3890	3906	3911	3970
61–70	4013	4034	4165	4184	4192	4275	4378	4454	4458	4514
71–80	4562	4569	4605	4639	4680	4754	4873	4878	4928	4936
81–90	4971	4989	5082	5089	5105	5181	5250	5264	5265	5355
91–100	5389	5405	5430	5440	5445	5534	5609	5623	5643	5700
101–110	5708	5738	5813	5842	5870	5887	5957	5988	6036	6075
111–120	6193	6212	6235	6235	6244	6254	6281	6315	6378	6426
121–128	6500	7965	8653	9710	10,446	11,053	11,345	11,402		

Step 2: Sample parameter $m^{(0)}$ based on the given initial value of the parameter.

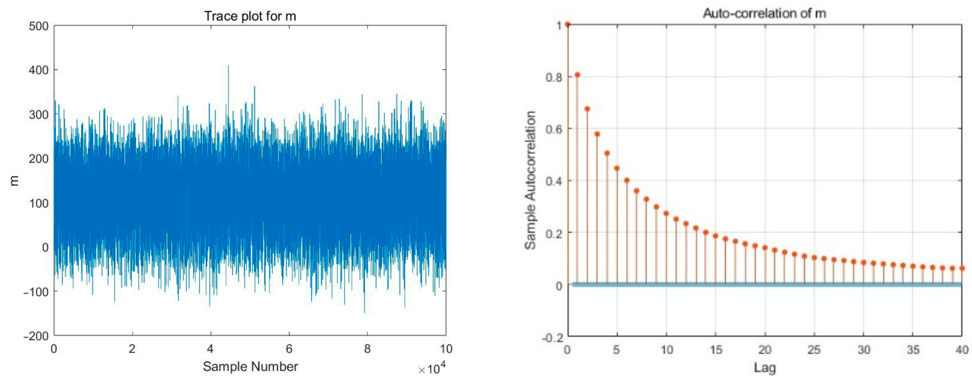
1. Based on the information of m, choose the recommended density function $m^{(1)} \sim N\left(\mu_1, \sigma_1^2\right)$
2. Calculate the acceptance probability r of the M-H algorithm based on a posterior distribution [42]:
$$r = \frac{p\left(m^{(1)} \mid x\right) J\left(m^{(0)} \mid m^{(1)}\right)}{J\left(m^{(1)} \mid m^{(0)}\right) p\left(m^{(0)} \mid x\right)} \tag{4}$$
where $p(\bullet \mid \bullet)$ is a posterior distribution, and $J(\bullet \mid \bullet)$ is the suggested density function.
3. Randomly select $u \sim unif(0,1)$, if $r > u$, accept $m^{(1)}$, otherwise $m^{(1)} = m^{(0)}$.

Step 3: Sample parameter t_0 based on the given initial value of the parameter $m^{(1)}, t_0^{(0)}$.

1. Based on the information of t_0, choose the recommended density function $t_0 \sim N\left(\mu_2, \sigma_2^2\right)$
2. Calculate the acceptance probability r of the M-H algorithm based on a posterior distribution:
$$r = \frac{p\left(t_0^{(1)} \mid x\right) J\left(t_0^{(0)} \mid t_0^{(1)}\right)}{J\left(t_0^{(1)} \mid t_0^{(0)}\right) p\left(t_0^{(0)} \mid x\right)} \tag{5}$$
3. Randomly select $u \sim unif(0,1)$, if $r > u$, accept $t_0^{(1)}$, otherwise $t_0^{(1)} = t_0^{(0)}$.

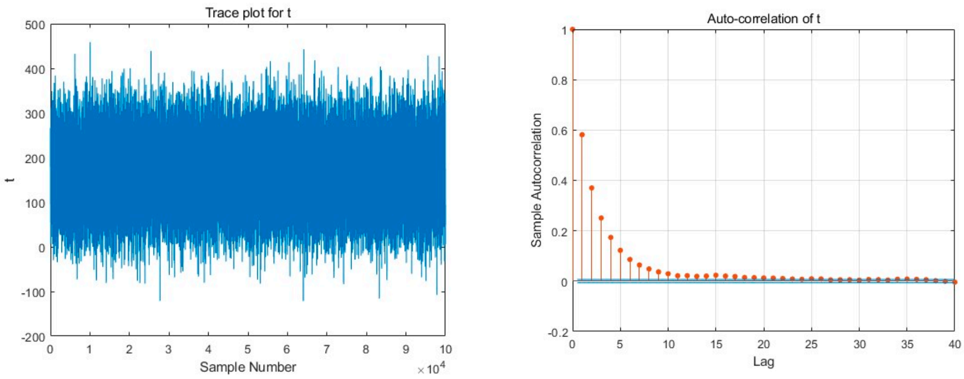
Step 4: Iteratively calculate parameter estimates.

1. Use the extracted parameter values as the new initial sampling values and repeat Step 2 and Step 3 for 10,000 times.
2. Taking the initial value of the cooling component situation in Step 1, in the calculation process of Steps 2 and Step 3, the acceptable probability $r > u$ of the scale parameter m appeared a total of 4667 times, while the acceptable probability $r > u$ of the shape parameter t_0 appeared a total of 4345 times. After iteration in Steps 2 and Step 3, the estimated parameters can be obtained, which are 2.2826 and 5227.6844, respectively. The trajectory map and autocorrelation map are shown in Figures 2 and 3.



(**a**) (**b**)

Figure 2. Trace and autocorrelation diagrams of parameter m: (**a**) trace diagram of shape parameter m; (**b**) autocorrelation diagrams of parameter m.



(**a**) (**b**)

Figure 3. Trace and autocorrelation diagrams of parameter t_0: (**a**) trace diagram of shape parameter t_0; (**b**) autocorrelation diagrams of parameter t_0.

Step 5: Goodness of fit test.

1. Perform goodness of fit tests on the estimated values m and t_0 of the fitted parameters and evaluate the fitting results using Q-Q plots [43].
2. Continuing the valuation obtained from the fourth case in step, the p-value of the goodness of fit test is 0.0539. At a confidence level of 0.05, the goodness of fit test did not reject the original hypothesis. As shown in Figure 4, except for a very small number of samples, the fitted Weibull distribution and sample distribution tend to fall on a straight line, indicating a good fit between the data and the Weibull distribution.

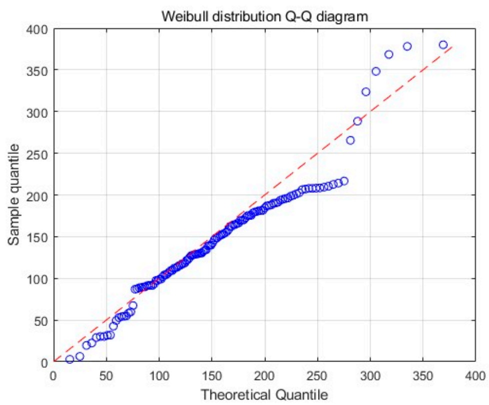


Figure 4. Weibull distribution Q-Q diagram.

4.2. Assumption of Maintenance Interval Optimization Model

Based on the actual work regulations and requirements of power grid maintenance, establish the following model assumptions.

1. Corrective maintenance is carried out at each maintenance node (i.e., between two maintenance cycles). Any defects/malfunctions that occur during the current maintenance cycle are repaired at the next maintenance node, but corrective maintenance does not change the failure rate and reliability;
2. Preventive maintenance is carried out at each maintenance node, and each preventive maintenance is an imperfect repair. After preventive maintenance, the performance of the equipment recovers to a younger time, but it is not the initial brand-new state when the equipment is put into use;
3. Perform a major overhaul after every k maintenance cycle, and repair as new after the overhaul;
4. The components have aging characteristics, and the failure rate increases with age, while the reliability decreases with age;
5. The total lifespan of the transformer $T_0 = N \cdot T$, N is the number of maintenance cycles within the lifespan, and T is the duration of each maintenance interval;
6. Because the shutdown caused by maintenance of the transformer does not affect the power supply, the shutdown cost is 0;
7. Customers have an acceptable minimum level of unreliability F_0^j under different failure modes, and each failure mode is independent of each other.

4.3. Imperfect Maintenance Improvement Factor

This article uses the imperfect maintenance improvement factor to measure the effectiveness of imperfect maintenance, and the effectiveness of each imperfect maintenance varies. Specifically, this article introduces different imperfect maintenance improvement factors in each maintenance cycle, thereby affecting the number of defect occurrences within each maintenance cycle. The dynamically changing number of defect occurrences affects the cost of corrective maintenance for each maintenance cycle, thereby dynamically affecting the total maintenance cost [44–46].

According to the theory of imperfect equipment maintenance, if the total number of s-level severity (s = 1 represents "average", s = 2 represents "severe", s = 3 represents "critical") defects that occur in a defective component of a transformer during the i-th maintenance cycle is n_i^s, which needs to be rounded up after calculation, Then the calculation formula is:

$$n_i^s = \left\lceil \int_{T_i^-}^{T_i^+} \lambda_i^s(t)dt = \int_{T_i^-}^{T_i^+} \frac{m^s}{t_0^s} \left(\frac{t - \sum\limits_{j=1}^{i} \delta_j \cdot T}{t_0} \right)^{m^s - 1} dt \right\rceil, \quad s = 1,2,3 \quad ; \quad i = 1,2,\ldots,N \quad (6)$$

Among them, $\lambda_i^s(t)$ represents the failure rate function of the s-level severe defect of the defective component in the i-th maintenance cycle, T_i^- is the start time of the i-th maintenance cycle, T_i^+ is the end time of the i-th maintenance cycle, δ_i is the imperfect maintenance improvement factor of the i-th maintenance cycle [47], and its expression is as follows:

$$\delta_i = (a \cdot \frac{c_{pm}}{c_{pr}})^{bi} \quad (7)$$

In the above equation, a is the maintenance cost adjustment coefficient, $1 \le a \le \frac{c_{pr}}{c_{pm}}$, c_{pr} is the cost of a single major overhaul, and c_{pm} is the cost of single preventive maintenance of the component; b is an adjustment parameter for the frequency of imperfect preventive maintenance, where $0 < b < 1$.

It should be noted that since a major overhaul after every k maintenance cycle can repair the components associated with the defect mode as new, the failure rate function $\lambda_i(t)$ and its integral for the severity of the defect need to be updated after every k maintenance cycle. If $h = \left\lfloor \frac{N}{k} \right\rfloor$, the following relationship exists during the calculation:

$$T_1^- = T_{k+1}^- = T_{2k+1}^- = \ldots = T_{hk+1}^- \tag{8}$$

$$T_1^+ = T_{k+1}^+ = T_{2k+1}^+ = \ldots = T_{hk+1}^+ \tag{9}$$

$$\delta_1 = \delta_{k+1} = \delta_{2k+1} = \ldots = \delta_{hk+1} \tag{10}$$

In summary, the schematic diagram of the imperfect maintenance strategy model established in this article is shown in Figure 5.

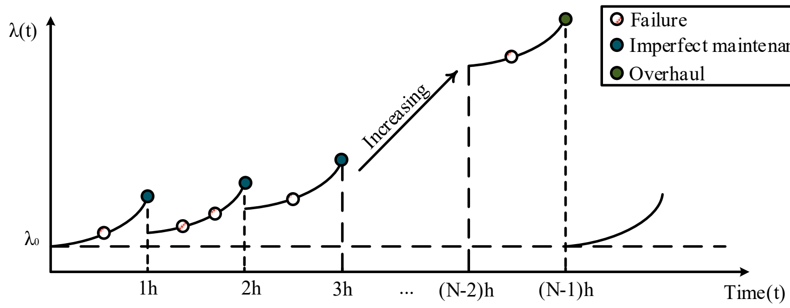


Figure 5. Schematic diagram of periodic incomplete maintenance strategy model.

4.4. Optimization Model for Maintenance Interval Considering Transformer Reliability and Imperfect Maintenance

4.4.1. The Total Maintenance Cost of a Transformer for a Defective Component

The total maintenance cost of a defective component in a transformer is composed of the following equation:

$$C_{total} = C_{pm} + C_{cm} + C_{pr} \tag{11}$$

Among them, C_{total} is the total maintenance cost of the transformer for the defective component, C_{pm} is the total preventive maintenance cost for the defective component, C_{cm} is the total corrective maintenance cost for the defective component, and C_{pr} is the total overhaul cost for the defective component.

4.4.2. Preventive Maintenance Costs

The total preventive maintenance cost for a defective component of a transformer is as follows:

$$C_{pm} = (N-1)c_{pm} \tag{12}$$

c_{pm} is the cost of a single preventive maintenance for the defective component.

4.4.3. Corrective Maintenance Costs

The total cost of corrective maintenance for a defective component of a transformer is as follows [48]:

$$C_{cm} = \sum_{i=1}^{N-1} \sum_{s=1}^{3} (c_{cm}^s \cdot n_i^s),\ i = 1, 2, \ldots, N-1\ ;\ \ s = 1, 2, 3 \tag{13}$$

Due to the significant difference in repair costs for transformer defects with different severity levels, the repair maintenance cost under this defect mode is divided into c_{cm}^1 ("general" defect single repair maintenance cost), c_{cm}^2 ("serious" defect single repair maintenance cost), and c_{cm}^3 ("critical" defect single repair maintenance cost);

4.4.4. Overhaul Cost

The total overhaul/replacement cost for a certain defect mode of the transformer is as follows:

$$C_{pr} = \left\lfloor \frac{N}{k} \right\rfloor \cdot c_{pr} \tag{14}$$

If a major overhaul/replacement is carried out after every k maintenance cycle, the number of major overhauls within the lifespan of the transformer is $\left\lfloor \frac{N}{k} \right\rfloor$.

4.4.5. Maintenance Interval Optimization Model

The objective function is to minimize the maintenance cost per unit of time within the lifespan of transformers, which is expressed in the following equation. The corrective maintenance cost in the total maintenance cost takes into account the imperfect maintenance improvement factor, which can provide a more accurate estimation of the number of occurrences of defects of each severity in each maintenance cycle, making the results of the optimization model more convincing [45].

$$\min \frac{C_{pm} + C_{cm} + C_{pr}}{NT} \tag{15}$$

and

$$\min \frac{(N-1)c_{pm} + \sum_{i=1}^{N-1} \sum_{s=1}^{3} (c_{cm}^{s} \cdot n_i^s) + \left\lfloor \frac{N}{k} \right\rfloor \cdot c_{pr}}{NT} \tag{16}$$

The main constraint is that the unreliability of the defective component of the transformer during each maintenance cycle should be lower than a certain threshold F_0.

Since the threshold provided by the power grid company is the unreliable threshold F_0^j for each defect mode of the transformer, it is assumed that each defect mode is independent of each other. By adding up the unreliable thresholds of all defect modes contained in the target defect component, the unreliable threshold F_0 for that defect component is obtained as follows:

$$F_0 = \sum_{j=1}^{n} F_0^j \tag{17}$$

where n is the number of all possible defect modes that may occur in the defective component. Also, due to $R_0 = 1 - F_0$ and the fact that the minimum value of the Weibull distribution fault probability density function in any interval can only appear at both ends of the interval, the constraint condition for $\lambda_0^i = \min\left\{ \frac{f(T_i^-)}{R_0}, \frac{f(T_i^+)}{R_0} \right\}$ is as follows:

$$\begin{cases} \lambda_i(t, \delta_i, T) \le \lambda_0^i \\ T = \frac{T_0}{N} \\ N \in N_+ \end{cases} \quad i = 1, 2, \ldots, N \tag{18}$$

Among them, $\lambda_i(t, \delta_i, T) = \frac{m}{t_0}\left(\frac{t - \sum_{j=1}^{i} \delta_j \cdot T}{t_0} \right)^{m-1}$ represents the failure rate function of the defective component in the i-th maintenance cycle.

5. Case Study

5.1. Case Calculation and Analysis

The forced oil circulation cooling system, a critical element of power transformers, comprises five main components: fan, control box, cooler, heat sink (tube), and submersible pump. Due to the negligible occurrence of defects in the heat sink (tube) over the nearly 30-year record period—with only one general defect that can be fully addressed during overhauls—we exclude this component from our analysis. Our optimization efforts focus on the maintenance intervals for the fan, control box, cooler, and submersible pump.

Based on the user-provided data for the forced oil circulation cooling system and its acceptable level of unreliability, we conducted a comprehensive analysis involving data collation and failure rate conversion. The results of this analysis are presented in Table 3. Currently, the system operates on a uniform maintenance interval of 720 h (equivalent to 30 days). Our analysis reveals significant discrepancies in component reliability under this maintenance regime:

1. Some components, such as the control box with serious defects, exhibit failure rates substantially below the acceptable threshold. This suggests potential over-maintenance, leading to unnecessary resource expenditure.
2. Conversely, other components, notably the fan with serious defects, demonstrate failure rates exceeding the acceptable limits. This indicates insufficient maintenance under the current interval, potentially compromising system reliability and failing to meet industry standards.

These findings highlight a critical imbalance in the current maintenance strategy. The 720-h uniform interval approach fails to account for the diverse reliability characteristics of individual components, resulting in both over-maintenance and under-maintenance scenarios within the same system.

Consequently, we conclude that there exists substantial room for optimization in the maintenance planning of the forced oil circulation cooling system. A more nuanced, component-specific approach to maintenance intervals could significantly enhance overall system reliability while potentially reducing unnecessary maintenance activities and associated costs. This optimization opportunity underscores the need for a more sophisticated, data-driven maintenance strategy that aligns more closely with the specific reliability profiles of each component within the system.

Utilizing the systematically organized data from the forced oil circulation cooling system, we first estimated the severity of defects for each component using Weibull distribution parameters. The results of this fitting and testing process are presented in Table 4, with the corresponding probability density distributions (PDFs) of faults illustrated in Figure 6. Analysis of the distributions in Figure 6 reveals several key insights:

1. Component similarity: The majority of components exhibit remarkably similar distributions across different severity levels. This similarity suggests that these components share comparable temporal failure characteristics, with a propensity for failures to occur in the early stages of operation. This finding has significant implications for maintenance cycle planning, as it allows for the potential coordination of maintenance activities across multiple components, thereby reducing unnecessary interventions and optimizing resource allocation.
2. Anomalous behavior: Despite the general trend, a small subset of components, notably the cooler (as depicted in Figure 6c), demonstrates significant deviations in their distribution patterns under critical conditions. These deviations are particularly pronounced when compared to the distributions observed for common and severe defects.
3. Cooler-specific insights: The distribution curve for critical defects in the cooler exhibits a distinct right-skew, approximating a normal distribution. This characteristic suggests that critical defects in the cooler tend to manifest later in the operational lifecycle. Consequently, maintenance strategies for the cooler should emphasize prevention and inspection protocols during the later stages of operation.

Table 3. Probability of component failures and maintenance costs during the original maintenance interval of a strong oil circulation cooling system.

Defective System	Defective Components	Total Number of Defects W	Severity j	First Failure Time (days)	Number of Defects w_j	Defect Probability Proportion P_j	Acceptable Failure Probability F_0	Acceptable Failure Rate λ_0^i	Actual Failure Rate λ	C_{pm}(¥)	C_{cm}(¥)
Cooling system (strong oil circulation)	Fan	711	serious	237	275	0.386779	0.0225	0.00075	0.004219	941.29	100,000
			commonly	292	436	0.613221	0.1725	0.00575	0.003425	20.32	50,000
	Control box	243	serious	2653	20	0.082305	0.2750	0.000917	0.000377	1877.22	100,000
			commonly	347	223	0.917695	0.2975	0.005333	0.002882	455.47	50,000
	cooler	183	critical	3063	1	0.005464	0.0125	0.000417	0.000326	3765.15	100,000
			serious	653	54	0.295082	0.025	0.000833	0.001531	3765.15	50,000
			commonly	86	128	0.699454	0.25	0.008333	0.011628	3765.15	30,000
	Submersible oil pump	278	critical	3918	6	0.021583	0.0075	0.00025	0.000255	100,000	200,000
			serious	822	22	0.079137	0.0425	0.001417	0.001217	638.38	100,000
			commonly	278	252	0.906475	0.08	0.002667	0.003597	13.7	50,000

Table 4. Parameter estimation table for the defect mode distribution of each component.

Defective System	Defective Components	Severity	Fit Value m	Fit Value t_0	Fit Value p
Cooling system (strong oil circulation)	Fan	serious	2.5015	3574.2238	0.0902
		commonly	2.6389	4967.3247	0.0613
	Control box	serious	2.4655	5485.2396	0.5002
		commonly	2.5912	5712.4332	0.1327
	cooler	critical	3.8266	7961.4850	0.7721
		serious	2.2119	5221.8332	0.1170
		commonly	2.2826	5227.6844	0.0539
	Submersible oil pump	critical	4.6117	6287.6012	0.3421
		serious	2.3529	4906.7916	0.5605
		commonly	3.8059	4717.6453	0.0801

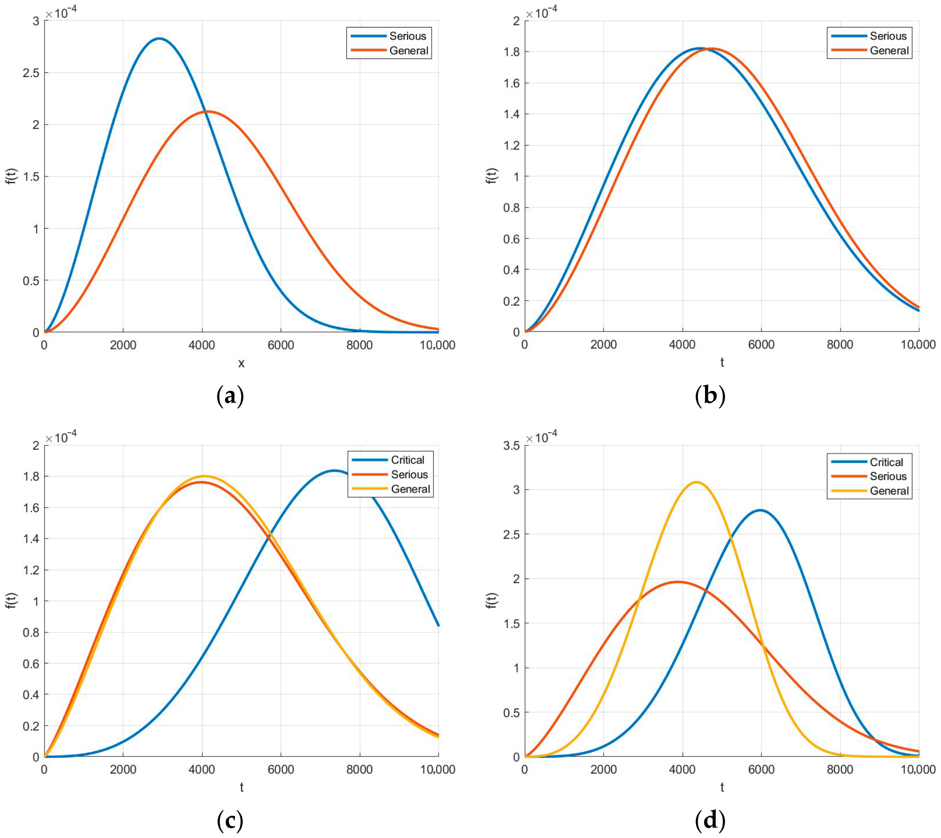


Figure 6. The probability density function of the failure of various components in a strong oil circulation cooling system: (**a**) PDF of the fan; (**b**) PDF of the control box; (**c**) PDF of the cooler; (**d**) PDF of the submersible oil pump.

These findings underscore the importance of a nuanced, component-specific approach to maintenance cycle planning. While the similarity in distribution patterns for most components allows for some degree of standardization in maintenance schedules, the unique behavior of components like the cooler necessitates tailored strategies. By incorporating these insights into maintenance planning, it becomes possible to optimize resource allocation, enhance system reliability, and potentially extend the operational lifespan of the cooling system as a whole.

Based on the parameters derived from the fitted Weibull distribution and taking into account the dynamic imperfect maintenance optimization factors, the aforementioned maintenance interval optimization model was formulated. Employing the Sequential Least Squares Programming (SLSQP) algorithm [49,50], and comparing it with the actual maintenance interval plan of 720 h, a maintenance schedule spanning 9 years after operation (within a single major overhaul cycle) was devised, as depicted in Figure 7. This schedule comprises a total of 5 preventive maintenance plans, which are categorized as follows: (a) actual scenario, (b) fan, (c) control box, (d) cooler, and (e) submersible pump. It is observed that, by incorporating the aspects of imperfect maintenance enhancement, the overall number of maintenance plans within a single overhaul cycle is reduced, and the frequency progressively increases over time, thereby aligning more effectively with the aging characteristics of long-life products such as power transformers. Furthermore, due to the shape parameter m and scale parameter t0 of the control box being virtually identical to those of the cooler under both normal and severe conditions, after applying the rounding-up procedure as per Formula 6, we found that the maintenance interval plans for (c) and (d) in Figure 7 are found to be the same.

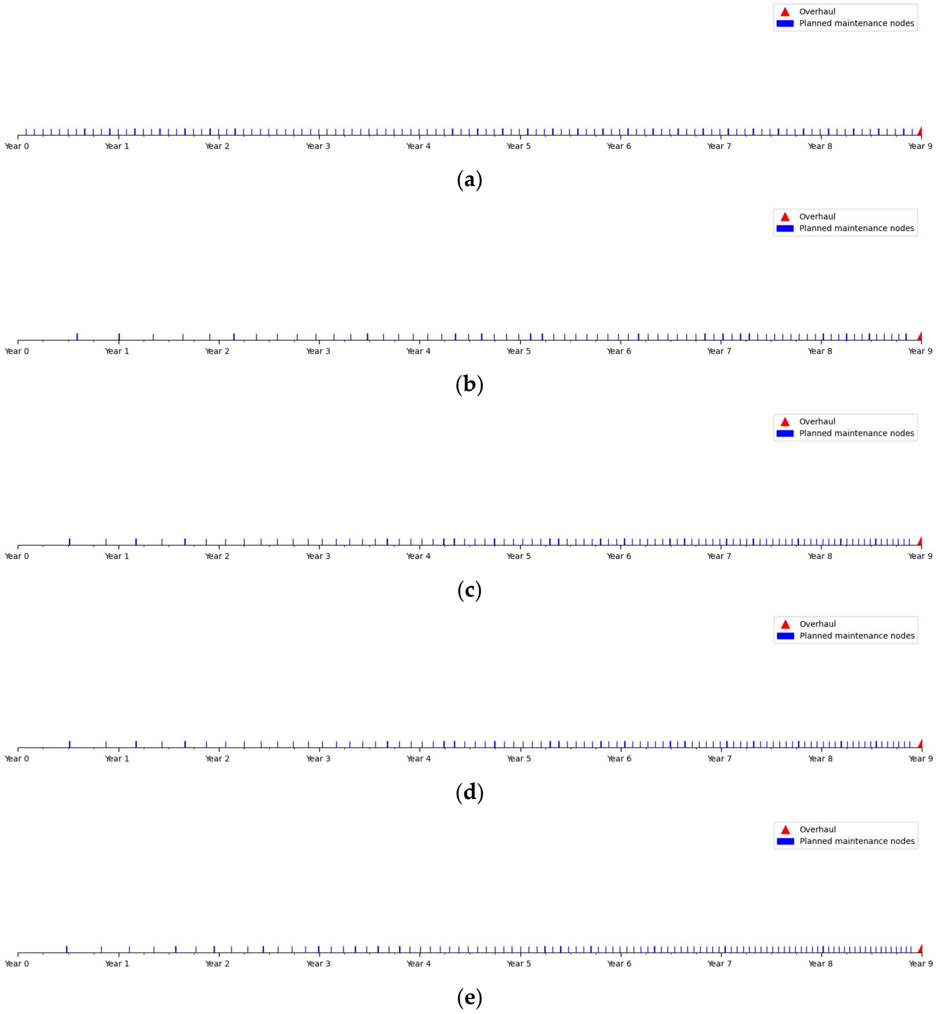


Figure 7. Comparison of maintenance interval planning for cooling system components under a single overhaul cycle: (**a**) actual cooling system maintenance interval under a single overhaul cycle; (**b**) maintenance interval of fan components under a single overhaul cycle; (**c**) maintenance interval of control box components under a single overhaul cycle; (**d**) maintenance interval of cooler components under a single overhaul cycle; (**e**) maintenance interval of submersible oil pump components under a single overhaul cycle.

The cost comparison before and after the optimization of the maintenance cycle is presented in Table 5. Compared to the actual maintenance plan cost under the 720-h cycle, it is evident that the maintenance cost for the strong oil circulation cooling system of a single power transformer has been reduced from the original CNY 1,980,689 to CNY 1,159,816 over one major overhaul cycle. This represents a significant reduction of 41.443%. Importantly, this cost reduction has been achieved while ensuring that the failure rates for defect modes across all severity levels remain within acceptable ranges.

Table 5. Comparison of maintenance costs before and after optimization of the maintenance cycle.

Defective System	Defective Components	Number of Maintenance Intervals	Average Interval Time (Days)	Maintenance Cost before Optimization (¥)		Optimized Maintenance Cost (¥)	
				Reparative Maintenance Costs	Preventive Maintenance Costs	Reparative Maintenance Costs	Preventive Maintenance Costs
Cooling system (strong oil circulation)	Fan	7	52.14	123,250	24,525	112,500	11,605
	Control box	9	40.56	32,875	299,751	28,750	18,312
	Cooler	9	40.56	16,600	519,385	15,400	228,049
	Submersible oil pump	10	36.5	40,000	410,385	32,875	198,407
Overhaul cost				513,918			
Total maintenance cost				1,980,689			

5.2. Parameter Analysis

We analyzed the relationships between maintenance cost and maintenance cycle, as well as between acceptable failure rate and maintenance cycle, in the maintenance interval optimization model. As illustrated in Figure 8, the initial growth rate of maintenance costs was relatively high. However, as the number of maintenance cycles increased, the growth rate of maintenance costs decelerated and began to increase uniformly with the maintenance cycle. Figure 9 demonstrates that as the number of maintenance cycles increased, the failure rate continuously decreased, with the rate of decrease gradually declining.

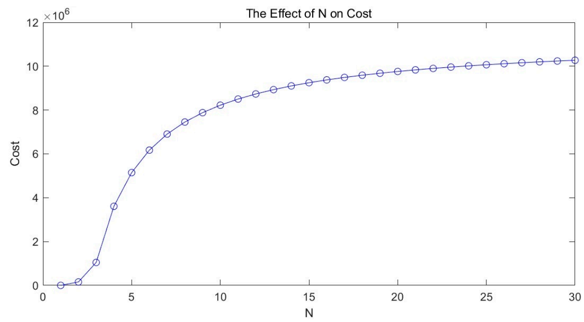


Figure 8. Curve of total maintenance costs over time.

By examining the cost changes in Figure 8 and correlating them with the failure efficiency curve in Figure 9, we can draw the following conclusions: Initially, the total maintenance cost increased rapidly due to a higher acceptable failure rate λ, longer intervals for imperfect maintenance, and a predominance of corrective maintenance. This resulted in faster growth of total maintenance costs. Subsequently, as the acceptable failure rate λ gradually decreased, the tolerance for product failure diminished. Consequently, imperfect maintenance intervals continued to shorten, and corrective maintenance decreased while preventive maintenance became dominant. This shift led to a slower and more constant growth rate in total maintenance costs.

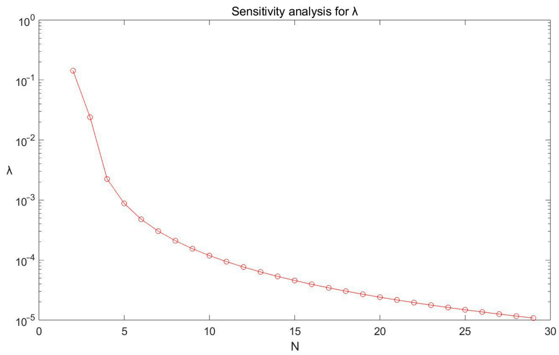


Figure 9. Failure rate curve with maintenance times.

6. Conclusions

We propose an optimization method for maintenance intervals constrained by failure rate, taking into account imperfect maintenance factors. This approach addresses the lack of maintenance historical data and non-dynamic maintenance costs in current power industry maintenance planning. The method begins by modeling the fault distribution of power transformers using a two-parameter Weibull distribution. Bayesian methods based on Gibbs and M-H sampling are employed to fit the distribution parameters of power transformers, largely solving the problem of Weibull distribution parameter estimation under small sample fault data of transformers. The estimated parameters are evaluated using Q-Q diagrams and other methods, with results indicating a good fitting effect suitable for calculating the number of failures in subsequent maintenance interval optimization.

In the maintenance interval optimization model, an imperfect maintenance improvement factor that dynamically changes as the maintenance cycle progresses is introduced. This allows for dynamic consideration of maintenance costs as the number of repairs increases, more accurately reflecting the maintenance interval of long-life products such as power transformers under imperfect maintenance conditions. The objective function aims to minimize the maintenance cost per unit time during the transformer's life cycle. When constructing the objective function, the change in the severity of defect modes on the cost of corrective maintenance is considered, and a maintenance interval optimization model is established with fault rate as a constraint.

The method was validated on the strong oil circulation cooling system of a 220 KV oil-immersed main transformer in the northern power grid of China. The maintenance cost of a single power transformer's strong oil circulation cooling system was reduced from CNY 1,980,689 to CNY 1,159,816.

As shown in Table 6, we compared our approach with selected publications from the past three years. This comparison demonstrates that our method not only integrates the relationship between dynamic maintenance costs and imperfect maintenance factors but also accounts for parameter identification in small sample sizes. This allows engineers to develop economically viable plans even with limited sample data.

Our method establishes a more scientific maintenance cycle for transformers at the subsystem level, significantly reducing maintenance labor and costs throughout the lifespan of transformers. The data required for this method is fundamental information that should be routinely recorded in the power industry's maintenance practices, including defect time, defect type, repair cost, and unreliability. Consequently, this approach applies to optimizing the maintenance cycle of power transformers in various countries and regions. The cases presented in studies [51,52] serve as examples of this applicability.

The method's effectiveness in reflecting the dynamic nature of maintenance costs is primarily based on the number of defects occurring during the maintenance cycle. However, it is important to note that additional factors, such as inflation of maintenance and replacement costs over time, should also be taken into consideration for a more comprehensive analysis.

Table 6. The comparison between different kinds of literature and ours.

Item	This Paper	Wei et al. [24]	Pereira et al. [11]	Murugan et al. [21]	Soodbakhsh et al. [19]	Kim et al. [22]
Case study object	Power transformer	Photovoltaic Power	heat exchangers	power transformer	power network	Substations
few-sample data	√	×	×	×	×	×
dynamic imperfect maintenance factions	√	√	√	×	√	√
dynamic maintenance cost	√	×	×	√	×	√
Calculation and optimization method	Bayes Metropolis-Hastings Improvement Factor SLSQP	Mixed fault function	Maximum Likelihood Estimation Genetic Algorithm	Weighted Health Index	Optimal Bat Algorithm Particle Swarm Optimization	Cox Proportional Hazard Model Least Absolute Shrinkage Selection Operator Regression

This approach can be particularly valuable for power utilities and maintenance planners worldwide, as it offers a robust framework for optimizing maintenance schedules while accounting for the specific operational conditions and economic factors of different regions. By implementing this method, organizations can potentially achieve substantial cost savings and improved reliability in their transformer maintenance programs.

Future research could focus on incorporating additional economic factors and refining the model to account for regional variations in maintenance practices and cost structures. This would further enhance the method's applicability and accuracy across diverse global contexts.

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