Reference-State-Based Circuit Breaker Reliability Analysis Method (Postprint)

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Abstract

Utilizing the concept of benchmark state, this paper proposes a comprehensive theoretical methodology for reliability analysis of high-voltage circuit breakers. First, based on the key state parameters selected during the benchmark state establishment process, key state parameter analysis techniques are implemented to thoroughly evaluate the performance quality of these parameters. Furthermore, by introducing performance across three dimensions—power grid strength, equipment strength, and equipment aging degree—the equipment performance condition is assessed to obtain the equipment benchmark state value. Subsequently, the benchmark state prediction process, as an extension of benchmark state analysis, employs classical statistical theory to develop a prediction model, providing reference for the development trend of equipment benchmark state. Finally, reliability analysis serves as the ultimate goal and final objective of benchmark state analysis; utilizing classical reliability theory, a reliability model is constructed and equipment reliability curves are plotted. From these curves, the equipment' s current and future reliability can be conveniently obtained, providing decision support for users' operation, maintenance, and inspection activities.

Full Text

Preamble

Reliability Analysis Method for Circuit Breakers Based on Benchmark State

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Abstract

This paper proposes a comprehensive theoretical framework for reliability analysis of high-voltage circuit breakers based on the benchmark state concept. The methodology comprises three core components: First, key state variables are selected and analyzed during benchmark establishment, incorporating three-dimensional performance metrics—grid strength, equipment strength, and equipment aging—to evaluate component performance and derive the equipment benchmark state value. Second, benchmark prediction extends this analysis by employing classical statistical theory to develop predictive models that forecast equipment benchmark state trends. Finally, reliability analysis serves as the ultimate objective, utilizing classical reliability theory to construct reliability models and generate equipment reliability curves. These curves enable straightforward determination of current and future reliability metrics, providing decision support for operation, maintenance, and overhaul planning.

Keywords: State variables, benchmark state, prediction, reliability

1 Introduction

The steady development of the national economy depends fundamentally on power system support, with all aspects of social life intimately connected to electricity supply. Under the guidance of China' s electric power industry "Twelfth Five-Year" development plan [?], grid voltage levels continue to increase and installed capacity grows steadily. Consequently, users demand higher power supply reliability, imposing more stringent requirements on power equipment operation and management.

High-voltage circuit breakers serve as critical protection and control devices in power grids, with their operating condition directly impacting overall system stability and supply reliability. Circuit breaker failures expose protected lines and equipment to severe damage risks, and delayed protective action can escalate grid incidents into widespread blackouts, causing substantial economic losses to production and daily life [?]. Traditional approaches to ensuring stable breaker operation rely on maintenance; however, frequent servicing not only escalates labor costs but also causes unnecessary outages and risks secondary damage from improper disassembly and reassembly. Therefore, equipment management entities urgently need methods to monitor breaker health status in real time while minimizing maintenance frequency, all under the premise of ensuring normal operation.

To conduct reliability analysis, the primary step involves assessing current equipment condition using the benchmark state concept. Figure 1 [Figure 1: see original paper] illustrates the benchmark state evaluation process.

2 Benchmark State Assessment

To better comprehend equipment operating conditions, an objective index is required to reflect whether current health status meets grid requirements. This paper, along with the literature "Research and Application of Intelligent Operation and Maintenance Systems for Power Transmission and Transformation Equipment" [?], represents research outcomes from Shenzhen Power Supply Bureau Co., Ltd. and State Grid Electric Power Research Institute Wuhan NARI Co., Ltd. under the project "Key Technologies for Full-Dimension Equipment Condition Monitoring Centers." As a continuation of previous research, this paper constructs a comprehensive, multi-angle evaluation system for in-service equipment based on the previously established "benchmark state" concept.

The benchmark state is defined as the condition where all specified equipment performance parameters remain within normal operating ranges under grid and self-strength requirements. This definition encompasses three key aspects: First, "strength requirements" include both grid strength and equipment strength, meaning equipment strength is assessed through design parameters, structural characteristics, and manufacturing processes, while grid strength is evaluated through adverse conditions such as overvoltage, overload, and short-circuit impacts. Second, "all specified performance maintained within normal operation" includes mechanical, electrical, insulation, and auxiliary component performance of high-voltage circuit breakers [?]. Third, while both conditions are essential and complementary for the benchmark state, the benchmark state itself is not static—it evolves when strength requirements increase significantly or when certain performance parameters can no longer maintain normal operation.

2.1 State Variable Analysis

Grid Strength. Grid strength refers to environmental and operating conditions at the equipment' s location in the power network. Environmental factors such as temperature and humidity affect breaker lifespan—excessive heat or moisture reduce operational life. Operating conditions include neutral grounding configurations at substations, which influence short-circuit current magnitude during ground faults and consequently impact breaker service life. The benchmark state-based reliability analysis aims to ensure equipment condition exceeds local grid strength requirements and to effectively regulate the relationship between equipment capability and grid strength. Table 1 presents the state variable indicators reflecting grid strength and their evaluation criteria.

Equipment Strength. Equipment strength comprehensively evaluates the risk resistance capability of in-service equipment from three perspectives: online monitoring device installation, defect and failure factors, and natural influences. Specific indicators and evaluation criteria are provided in Table 2 .

Equipment Aging Degree. Equipment aging assesses the main unit' s mechanical, electrical, and insulation performance, supplemented by auxiliary component evaluation, to determine overall aging condition. Specific indicators and evaluation criteria are listed in Table 3 .

In all tables, the score *s* represents the rating assigned to each state variable based on evaluation criteria, categorized into three levels (1, 2, 3), where 3 indicates optimal condition and 1 indicates poorest condition. The weight *k* represents the variable' s weighting factor, graded from 1 to 5 based on impact severity, where 5 signifies maximum impact and 1 signifies minimum impact. Specific values can be determined through statistical analysis of actual maintenance records and expert judgment. Consequently, the grid strength index *I*grid for a given device is defined as the weighted sum of individual state variable scores. Similarly, the equipment strength index *I*device and equipment aging index *I*age are calculated as weighted sums of their respective state variable scores.

2.2 Benchmark State Calculation

Strength Correction Factor. Equipment at identical aging levels requires different reliability assessments under varying grid and equipment strength conditions. To address this, a strength correction model is constructed based on grid strength and equipment strength evaluation results to obtain the strength correction factor *F*. This factor not only adjusts aging assessments but also enables prioritization of equipment with larger correction factors for focused attention.

As shown in Figure 2 [Figure 2: see original paper], the reference line *l*0 is defined by the equation $x + y = 0$. Let and represent normalized scores for grid strength and equipment strength (actual score divided by maximum possible score). The coordinates of circuit breaker *A* in the - coordinate system are (A, A), where 0 A 1 and 0 A 1. The strength correction factor *F* for breaker *A* is defined as its distance to the reference line:

$$F(A) = \frac{\delta_A + \gamma_A}{2}$$

The normalized value ranges from [0, 1]. When both grid strength and equipment strength scores are high, *F* approaches 1, exerting minimal influence on aging assessment results. Conversely, when these scores are low, the correction significantly reduces the adjusted aging assessment score.

Benchmark State Model. Before calculating the benchmark state, the equipment aging index must be mapped to a 100-point scale:

$$I_{\text{age}}^{100\%} = \frac{I_{\text{age}} - I_{\text{ageMin}}}{I_{\text{ageMax}} - I_{\text{ageMin}}} \times 100$$

where *I*ageMin and *I*ageMax represent the theoretical minimum and maximum aging indices, respectively.

The equipment benchmark state value BI is then obtained by multiplying the 100-point aging index by the strength correction factor:

$$BI = I_{\text{age}}^{100\%} \times F$$

BI is also a 100-point metric, where 100 represents excellent condition and 0 indicates equipment has reached end-of-life.

3 Benchmark State Prediction

Benchmark state analysis involves parameter classification and individual performance assessment, with comprehensive calculation of component benchmark values based on logical relationships between performance metrics to derive a single equipment benchmark state value BI that characterizes overall breaker condition. While BI effectively measures current operating status for maintenance decision-making, a time lag exists between data acquisition and benchmark calculation. By the time BI deviation is detected and corrective action taken, equipment may have already developed significant defects or experienced failure, impacting service life and posing potential hazards to the power system.

Predicting BI values across different life stages reveals condition trends throughout the equipment lifecycle, enabling preemptive measures before defects and failures occur. This not only extends service life but also significantly enhances overall power system reliability. Benchmark state prediction analyzes the relationship between BI and operational age to establish mathematical models describing equipment condition trajectories.

Statistical analysis indicates that benchmark state declines with service age, with optimal condition at commissioning and gradual deterioration over time, following an approximately exponential distribution. Referencing the health index calculation principle from UK EA Technology and incorporating a state decay coefficient, this paper proposes an empirical formula for equipment health level index variation over time:

$$BI_{t1} = BI_{t0} \times \left(1 - h \times e^{B(t1-t0)}\right)$$

where BIt1 is the predicted benchmark state at future time *t1*, BIt0 is the benchmark state at time *t0*, h is the state decay coefficient, B is the aging coefficient, and *t0* typically represents the commissioning year.

4 Reliability Analysis

4.1 Failure Rate Model

The benchmark state definition implies that lower BI values correspond to higher failure probabilities. Equipment failure probability directly reflects operational reliability, making failure rate determination the first step in reliability analysis.

Traditional failure rate analysis relies on long-term statistical tracking of in-service equipment to generate time-dependent failure rate curves, primarily using bathtub curves, Weibull distributions, and least squares methods [?]. However, operational data is often scarce, and such statistical analyses are fundamentally post-event assessments. Consequently, failure rate curves derived from incomplete data exhibit low credibility and limited value for maintenance guidance [?].

This paper references relevant literature suggesting that failure probability increases exponentially as equipment condition deteriorates [?], a trend consistent with field experience. The following probability model is proposed:

$$P = K \times e^{-C \times BI}$$

where BI is the equipment benchmark state value representing quantified condition status. The probability defined in this failure model represents "the probability of equipment failure within unit time Δt after time t due to condition deterioration," consistent with the classical definition of failure probability density. Thus, P denotes failure probability density (range 0–1). K and C are proportionality and curvature coefficients, respectively—constants related to equipment type, operating environment, and other factors without direct acquisition methods, typically obtained through inverse calculation.

Assuming a dataset of equipment with state and failure samples, where benchmark state categories BI range from 1 to N with corresponding equipment counts $M1$ to Mn, and failure counts Q during a historical assessment period, the following relationship must hold:

$$\sum_{i=1}^{N} Q_i = \sum_{i=1}^{N} M_i \times K \times e^{-C \times BI_i}$$

This yields an equation for K and C. With data spanning two or more years (providing multiple equation sets), least squares methods can solve for these coefficients.

4.2 Reliability Model

Having determined equipment failure rates, reliability calculation requires clear definitions of the reliability function $R(t)$ and cumulative failure distribution function $F(t)$ [?]: $R(t)$ represents the ratio of non-failed products to total products at time t, while $F(t)$ represents the ratio of failed products to total products at time t. By definition:

$$R(t) + F(t) = 1$$

Differentiating $F(t)$ yields the "probability of failure within unit time Δt after time t," defined as failure density $f(t)$:

$$f(t) = \frac{dF(t)}{dt}$$

The failure density $f(t)$ reflects failure probability density relative to total product quantity—equivalent to the failure probability density P from Section 4.1. Therefore, the relationship between reliability function and failure probability density is:

$$R(t) = 1 - \int f(t)\,dt$$

Substituting the reliability model from Section 4.1:

$$R(t) = 1 - \int K \times e^{-C \times BI(t)}\,dt$$

Based on this equation, equipment reliability curves can be plotted as shown in Figure 3 [Figure 3: see original paper]. These curves are generated in real time as equipment ages, enabling managers to clearly visualize current reliability and inform maintenance decisions. The three benchmark curves in Figure 3 [Figure 3: see original paper] represent:

1. **Blue reference curve**: Benchmark state variation pattern for equipment in this category. The difference between benchmark analysis results at any commissioning year and the lower limit of the acceptable benchmark range represents the equipment's safety margin. When this margin reaches zero, the intersection point (e.g., point Jn) indicates the major overhaul or replacement timing.
2. **Red curve**: Hypothetical mutation in benchmark state trajectory following a fault or defect from event point (time B), showing impacts on lifespan and overhaul timing.
3. **Green curve**: Hypothetical benchmark state improvement from maintenance at time C, with subsequent condition projection.

Points An, Bn, and Cn represent normal service life, post-fault/defect service life, and post-maintenance service life, respectively.

5 Method Application

Table 4 presents statistical data for a specific circuit breaker model, showing operational age versus benchmark state values *BI*. Fitting the data to the curve described in Equation (5) yields state decay coefficient $h = 0.04537$ and aging correction coefficient $B = 0.05363$. Defining the performance index for brand-new equipment (commissioned at $t0 = 0$) as 95 gives $BIt0 = 95$, resulting in the final benchmark state prediction model:

$$BI_{t1} = 95 \times (1 - 0.04537 \times e^{0.05363 \times t})$$

The equipment benchmark state trajectory is illustrated in Figure 4 [Figure 4: see original paper].

Table 5 shows the two-year distribution of *BI* values for this breaker model, divided into eight ranges with corresponding equipment counts from field statistics. Applying Equation (7) and using two-year statistical data, least squares calculation yields the proportionality and curvature coefficients for the failure rate model, presented in Table 6 .

The resulting failure rate model is:

$$P = 8530 \times e^{-0.161 \times BI}$$

Substituting this and the benchmark state model into Equation (11) produces the reliability model:

$$R(t) = 1 - \int 8530 \times e^{-0.161 \times 95 \times (1 - 0.04537 \times e^{0.05363 \times t})} \, dt$$

The corresponding equipment reliability curve is shown in Figure 5 [Figure 5: see original paper]. Equipment reliability declines with operational time, remaining relatively stable during early service life with a gradual downward trend, while degradation accelerates in later stages.

6 Conclusion

This paper proposes a comprehensive method for evaluating high-voltage circuit breaker operating conditions using grid strength, equipment strength, and equipment aging degree based on the benchmark state concept. Extending benchmark state analysis, the paper constructs a predictive model using mathematical statistics to forecast equipment condition trends. Finally, employing the proposed failure rate and reliability models, current and future reliability metrics are calculated and predicted to support user operation, maintenance, and overhaul decision-making.

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Note: Figure translations are in progress. See original paper for figures.