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Preface

The authors shared their work in writing this book.
It was a pleasure with Springer Associate Editor.

Hangzhou, China

Chengjin Ye
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Chapter 1
Risk Evaluation of Short-Circuit Fault in Power System

1.1 Descriptions of Power Systems and Their Risk Issues

Globally, on the one hand, with the expansion of the scale of the power system, the level of short-circuit current gradually increases. On the other hand, with the frequent occurrence of extreme weather, short-circuit faults occur more frequently. Taking China as an example, the power supply and load demand have obvious inconsistencies in spatial distribution. Constrained by resource endowments, the vast majority of China's coal, the hydro, wind, and solar resources are distributed in the western, southwestern, and northern regions. However, more than 70% of the energy demand is concentrated in the east-central region. The supply and demand centers of electricity are geographically thousands of kilometers apart. To ensure the efficient transmission and consumption of large energy bases, China has planned and built a large number of AC and DC ultra-high voltage transmission and transformation projects [1] and formed a "three vertical and three horizontal" ultra-high voltage backbone network. From a global perspective, driven by the demand for a wide area allocation of electric energy, several transnational power grids have been developed [2, 3]. For example, the U.S. and Canada power grids, the European power grid and the Russian-Baltic power grid, etc. In a significant speech delivered on September 22, 2020, at the 75th session of the United Nations General Assembly, General Secretary Xi Jinping noted that China would increase its national contribution, adopt more aggressive policies and measures, work to reach its peak CO_2 emissions by 2030, and work to achieve carbon neutrality by 2060 [4]. In the context of "carbon peaking and carbon neutral", the inverse distribution of resource endowment and energy demand in China determines that a "large power supply and huge grid" is still the inevitable trend of modern power grid development.

It is well known that excessive short-circuit current is one of the prominent problems of large grid operation. Short circuits are the most common type of fault in power systems and can be caused by insulation aging, lightning flashover, and bird and animal cross-connection. In recent years, various extreme weather events,

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including heavy rainfall, hurricanes, thunderstorms, and floods, are striking the world in an increasingly frequent and destructive manner [5]. Extreme weather hazards can exacerbate the probability and serious consequences of short-circuit faults in power systems, which is bound to bring great challenges to the safe and stable operation of power systems. For example, the major blackout that occurred in Brazil on November 10, 2009 [6] was mainly caused by a thunderstorm that triggered short-circuit faults in several lines of the power system one after another, resulting in a voltage collapse in the southeastern grid of Brazil, especially in the São Paulo area. The high-voltage DC transmission system of the Itaipu hydroelectric plant was bipolar blocked due to the activation of the minimum DC voltage protection on the inverter side. At the same time, the national interconnection system of Brazil was disconnected from Paraguay's 50 Hz AC grid. Ultimately, a massive blackout occurred in Brazil, resulting in a load loss of 24.436 GW, or approximately 40% of Brazil's total load. Similarly, when Super Typhoon Morathi struck Fujian on September 15, 2016, the mechanical load on line equipment in the horizontal direction against the wind increased significantly. As a result, there were up to 2830 short-circuit trips on lines above 10 kV, which increased the financial losses for power-using businesses and the pressure on grid companies to respond to emergencies and disasters. Numerous severe power outages both domestically and internationally have demonstrated that China's strategic energy security would be constrained by its inability to efficiently address short-circuit faults brought on by significant meteorological disasters.

At present, China's power grid has entered the post-development phase of the "new normal", and the average annual growth rate of electricity consumption during the 13th Five-Year Plan period has dropped from 8.8% in the 12th Five-Year Plan to 3.6–4.8%. In the context of the slowdown, the concept of precise investment in power grids has received increasing attention. Since the release of "No. 9", the rapid advancement of the power market construction further requires the power system to change the original relatively sloppy development mode and improve the operation economy [7]. Considering that the existing grid current-limiting measures are based on deterministic safety criteria without risk-awareness [8], and the short-circuit faults of power systems in the context of extreme meteorological disasters are mostly episodic in nature. If the existing decision method focuses only on the consequences of faults and ignores the probability of faults, it will easily lead to overly adventurous current-limiting schemes and affect the overall economy of grid planning and operation [8]. Therefore, the emphasis on accident risk is the overall current trend of the power system. The North American Electric Reliability Council (NERC) assists grid dispatch through risk assessment, empirical learning, and event root cause analysis. The PJM grid in the United States has introduced risk management methods into system and market operations [9]. In China, risk-based power system planning and operation has received increasingly widespread attention, e.g., the Regulations on Emergency Response and Investigation of Electricity Safety Accidents (Decree 599 of the State Council) has also directly proposed requirements for power system accident classification. In order to realize a comprehensive and optimal configuration of risk-based current-limiting measures and optimal control of short-circuit faults, it is urgent to take into account the binary attributes of the probability of occurrence of short-circuit faults and the consequences of faults in the context of growing attention to the economics of power systems. In addition to leading to faults that cannot be isolated by switchgear, oversized short-circuit currents also have the complex chain and derivative consequences. On the one hand, fault currents trigger significant temperature rise and electrodynamic forces within the transmission and substation equipment, which can easily damage the equipment under the influence of both thermal and dynamic stability, causing loss of load and affecting power supply reliability [8]. On the other hand, a short circuit is equivalent to an increase in branch circuits, and problems such as tripping due to short circuits can cause significant changes in the grid topology, which can lead to a shift in the stability boundary of the power system. If the operating point breaks through the stability boundary, serious consequences such as unit disconnection will occur. Numerous short-circuit-induced blackouts have happened all over the world, and these accidents share the following evolutionary characteristics: equipment short-circuit $\rightarrow$ faulty equipment decommissioning $\rightarrow$ normal equipment $N-1$ overload $\rightarrow$ stability problems $\rightarrow$ fault expansion. Existing short-circuit current limiting schemes generally consider only circuit breaker blocking capacity boundary conditions. Because of the complex secondary consequences of short-circuit faults such as disconnection and machine cutting, it is necessary to consider the reliability and stability problems caused by short-circuit faults in addition to the fault current magnitude when deciding on the short-circuit current limitation scheme and optimizing the control of short-circuit risks in large grids to ensure safe grid operation.

1.2 Evaluation Techniques of Short-Circuit Fault Probability

In this section, the intrinsic correlation between the service age and working condition of typical power equipment and the deterioration and aging of insulation is analyzed. A meteorological information-driven proportional risk model is established to assess the probability of short-circuit faults at grid nodes, taking into account internal factors such as equipment insulation aging and external factors such as meteorological statistics and equipment environmental conditions on the probability of short-circuit faults. To realize the probability assessment of short-circuit faults at grid nodes, the grid vulnerability analysis model is established for typhoon meteorological disaster scenarios.

1.2.1 Data-Driven Techniques

Many significant power outage situations, including the 2003 North American Blackout, evolved from short-circuit faults [10]. Because of their proximity to intricate environments, overhead lines are generally more likely to meet short-circuit faults. Therefore, this paper introduces a data-driven PHM to evaluate the short-circuit fault rate of overhead lines.

The framework of the data-driven PHM is illustrated in Fig. 1.1, which includes the reference short-circuit fault rate modeling and covariate connection function formulating. Specifically, the reference short-circuit fault rate is calculated based on the operation data of overhead lines. The covariate connection function considers the climate and surroundings data. The impact of covariates on the reference short-circuit fault rate is formulated utilizing techniques such as the Levenberg–Marquardt parameter estimator.

1.2.1.1 Basic Proportional Hazard Model

The PHM [11] was applied for the short-circuit fault rate modeling of electrical equipment in this paper, which is illustrated as:

$$h(t) = h_0(t)\psi(F(t)) \tag{1.1}$$

where $h_0(t)$ is the reference short-circuit fault rate function; $\psi(F(t))$ is a connection function used to quantify the effects of different factors on the short-circuit fault rate.

The reference short-circuit fault rate without consideration of extreme external conditions is mainly determined by insulation material damage caused by various

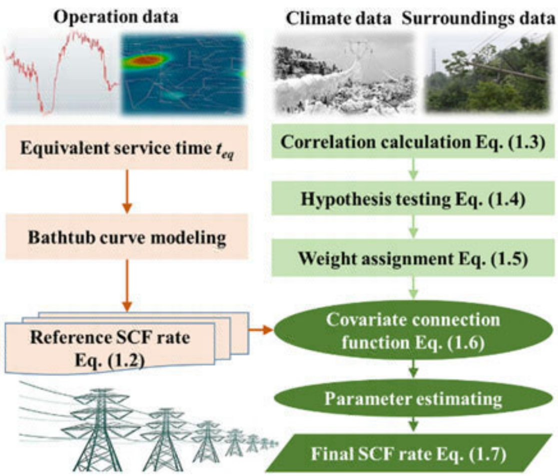

Fig. 1.1 Short-circuit failure rate modeling of overhead line

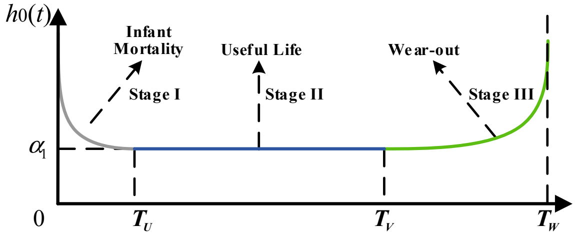

Fig. 1.2 Bathtub curve for reference SCF rate

defects, aging, or accidental factors [12], which can be well described with the Bathtub curve. The reference short-circuit fault rate typically goes through three stages [12], including infant mortality, useful life, and wear out, as shown in Fig. 1.2. Specifically, the short-circuit fault in Stage I is relatively frequent and is caused by defects in design, materials, and production process, or improper use. The short-circuit fault in stage II is caused by some random factors whose occurrence rates are relatively constant. Stage III is associated with the aging of insulation materials, where the SCF rate grows rapidly with the increasing accumulated service time. It is important to note that there is a long period of rigorous testing and quality checks prior to the deployment of certain types of electrical equipment. The real infant mortality stage is usually skipped or compressed to a very short duration. In this paper, stages II and III are considered in the reference SCF rate modeling.

For the reference SCF rate modeling, the Weibull distribution was selected because it is the most often used mathematical model to characterize the Bathtub curve [13].

$$h_0(t) = \begin{cases} \alpha_1; & T_U \le t < T_V \\ \alpha_2 e^{\beta_2 t}; & T_V \le t < T_W \end{cases} \tag{1.2}$$

1.2.1.2 Covariate Modeling

The climate and surrounding conditions are defined as covariates in connection function modeling. The detailed indices of each covariate are shown in Fig. 1.3. The indices of climate covariates include three climate conditions, i.e., rainstorm, hurricane, and wildfire. The values of the covariates were obtained by calculating the composite score of the correlation index.

In this paper, we aim to build a comprehensive evaluation framework to map from the considered indices to the required SCF rate while taking into account the various external circumstances. In particular, a data-driven approach is used that entails three steps: weight assignment, hypothesis testing, and correlation coefficient calculation.

First, the correlation between a particular influencing indicator and the SCF rate is measured using the Pearson product-moment correlation coefficient in Eq. (1.3).

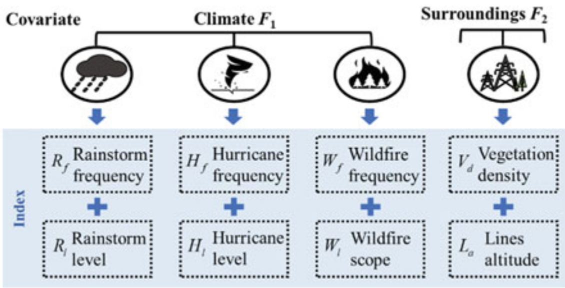

Fig. 1.3 Covariates and indices for short-circuit fault

$$r = \frac{\sum (x_a - \overline{x})(y_a - \overline{y})}{\sqrt{\sum (x_a - \overline{x})^2 \sum (y_a - \overline{y})^2}} \tag{1.3}$$

where x_a is the standardized value of the influencing factor obtained from statistic data and y_a is the statistic value of the SCF rate.

Second, the t-test is used for hypothesis testing to determine whether there is a link between the SCF rate and the relevant index. Assuming H_0: $\rho = 0$ (No correlation exists); H_1: $\rho \neq 0$ (Correlation does exist), the test statistics are as follows:

$$t = \frac{(\overline{r} - \rho)\sqrt{ND}}{\sigma_r} \sim t(ND - 1) \tag{1.4}$$

where σ_r is the standard deviation of the observed samples.

Thirdly, the probability of H_0 being rejected is determined by the testing probability p_{-a}. As shown in Fig. 1.4, p_{-a} can be calculated from the cumulative probability density under the corresponding t-distribution. When p_{-a} is small enough, the original hypothesis H_0 should be rejected. In other words, the correlation of interest is higher. Therefore, the weight of the influencing index ζ_a is calculated with Eq. (1.5) based on the obtained testing probability p_{-a}. The assigned principle also meets the requirement that the sum of weights is 1.

$$\zeta_a = \frac{1 - \mathrm{p}_{-a}}{\sum (1 - p_{-a})} \tag{1.5}$$

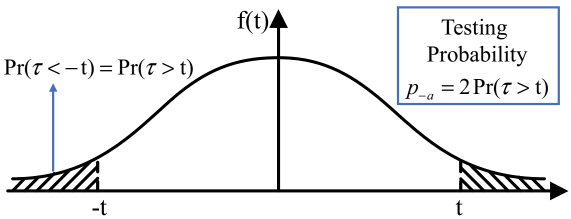

Fig. 1.4 t-distribution

Finally, the score of covariate F_{co} in a standard Hundred Score system with Na influencing indices can be obtained as:

$$F_{co} = 100\left(\sum_{a=1}^{Na} \zeta_a x_a\right) \tag{1.6}$$

1.2.1.3 Final Integrated PHM Model

Exponential function, as the most commonly used connection function, is applied to the covariate connection function modeling in this paper. The SCF rate function for overhead lines is developed by integrating the reference fault rate function and the covariate model:

$$h\left(t_{eq}, F; \gamma\right) = h_0\left(t_{eq}\right) \exp\left(\sum_{co=1}^{NZ} \gamma_{co} F_{co}\right) \tag{1.7}$$

where t_{eq} represents equivalent service time of lines; F_{co} represents the related covariates, here refers to the scores of climate and surrounding condition. γ_{co} can be estimated by the following parameter estimation method.

1.2.1.4 Model Parameter Estimation

The Levenberg–Marquardt method [14] is utilized to estimate the parameters, i.e., γ_1, γ_2 in this case. Specifically, a set of initial parameters are assigned as $\gamma^{(0)} = ({\gamma_1}^{(0)}, {\gamma_2}^{(0)})$. $\Omega_w = (t_{eq,w}, F_{1,w}, F_{2,w})$ represents the w-th observed historical data. Firstly, Ω_w is substituted into Eq. (1.8). Then, the Taylor expansion of Eq. (1.8) at $c^{(0)}$ is obtained and high order terms are omitted as:

$$TE\left(t_{eq}, F; \gamma\right) = h\left(\Omega_w; \gamma^{(0)}\right) + \sum_{v=1}^{2} \frac{\partial h(\Omega_w; \gamma)}{\partial \gamma_v}\left(\gamma_v - \gamma_v^{(0)}\right) \tag{1.8}$$

Finally, the overall variance is as follows based on the least squares principle:

$$\sigma = \sum_{w=1}^{ND} \{h_w - Th(\Omega_w; \gamma)\} + d \sum_{v=1}^{2} \left(\gamma_v - \gamma_v^{(0)}\right)^2 \tag{1.9}$$

where d is a damping coefficient used to prevent the occurrence of a singular matrix.

Set the first partial derivatives of Eq. (1.9) for all estimated parameters equal to zero. A set of two-parameter non-linear equations can be obtained, and then γ_v is repeatedly calculated using the Levenberg–Marquardt method until the difference between the two consecutive results can be ignored. Finally, a numerical solution of the connecting coefficients is obtained.

1.2.2 Analytical Techniques

This subsection introduces a fragile model that uses a hurricane instance to explain how to relate weather parameters to SCF rates of overhead lines. The determination of the overall SCF rate, weather-induced covariant SCF rate, and aging-based reference SCF rate are the three steps in the fragile model.

1.2.2.1 Aging-Based Reference SCF Rate Modeling

The reference SCF rate without consideration of extreme external conditions is mainly determined by insulation material damage caused by various defects, aging, or accidental factors [12], which can be well described with the Bathtub curve. Weibull distribution, as the most deployed mathematical model to describe the Bathtub curve [13], was used for the reference SCF rate modeling.

$$\lambda_A(t) = \begin{cases} \alpha_1; & T_U \le t < T_V \\ \alpha_2 e^{\beta_2 t}; & T_V \le t < T_W \end{cases} \tag{1.10}$$

The parameters in Eq. (1.10) can be fitted through long-term statistics of a large number of samples or obtained through modeling the physical aging mechanism of materials.

1.2.2.2 Covariant SCF Rate Modeling Under the Extreme Weather

Considering the extreme weather, the described SCF rates in Fig. 1.2 are greatly magnified. Under a hurricane, most short-circuit faults are caused by falling towers or trees, thus the SCF rate of overhead lines is mainly influenced by wind direction and speed. The wind load function L_W for a transmission line with coordinates (x, y) can be expressed as follows [15]:

$$L_W(x, y, t) = \varpi(t)\left[\varepsilon_1 \exp\left(-\frac{R^2}{2\gamma_1^2}\right) - \varepsilon_2 \exp\left(-\frac{R^2}{2\gamma_2^2}\right)\right] \tag{1.11}$$

$$R = \sqrt{[(x - \kappa_x(t)]^2 + [y - \kappa_y(t)]^2} \tag{1.12}$$

where ε_1 and ε_2 are hurricane intensity parameters; γ_1 and γ_2 denote influence scopes; R is the distance between hurricane center and transmission line; (x, y) and