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# Risk-Based Planning and Operation Strategy Towards Short Circuit Resilient Power Systems

 Springer

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ISBN 978-981-19-9724-2 ISBN 978-981-19-9725-9 (eBook)  
<https://doi.org/10.1007/978-981-19-9725-9>

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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  
Chao Guo  
Yi Ding

# Contents

<b>1</b>	<b>Risk Evaluation of Short-Circuit Fault in Power System</b>	<b>1</b>
1.1	Descriptions of Power Systems and Their Risk Issues	1
1.2	Evaluation Techniques of Short-Circuit Fault Probability	3
1.2.1	Data-Driven Techniques	4
1.2.2	Analytical Techniques	8
1.3	Evaluation Techniques of Short-Circuit Fault Consequences	11
1.4	Challenges of Short-Circuit Risk Prevention and Control	12
1.5	Organization of This Book for Resilience Enhancement in Power System Short-Circuit Faults	14
	References	14
<b>2</b>	<b>Risk-Based Optimal Configuration of Fault Current Limiter in Power System</b>	<b>17</b>
2.1	Introduction	17
2.2	Modeling of FCL and SCC Calculation	19
2.2.1	Dynamic Response Modeling of FCL	19
2.2.2	Modeling of SCC Calculation	20
2.3	Many-Objective FCL Configuration Modeling	21
2.3.1	Decision Variables	21
2.3.2	Objective Function	21
2.4	Solution Method	24
2.4.1	Coding Strategy	24
2.4.2	NSGA-III	24
2.5	Case Studies	26
2.5.1	Test System and Parameters	26
2.5.2	Pareto Solutions Analysis	27
2.5.3	Comparison Between the Proposed Risk-Based Method and the Traditional Deterministic Method	29
2.5.4	Solution Performance Analysis	31
2.6	Conclusion	32
	References	33

<b>3</b>	<b>5G-Based Optimal Configuration of Centralized Fault Current Limiter in Power System</b>	<b>35</b>
3.1	Introduction	35
3.2	Framework of the 5G-Based CSF for FCLs	37
3.2.1	Applying 5G for CSF of FCLs	37
3.2.2	Backup Strategy in Case of 5G Communication Failure	39
3.3	Formulation of the FD Model	40
3.3.1	Fault SCC Magnitude Constraint	41
3.3.2	Voltage Sag Constraint	42
3.3.3	Offline Fault Scanning Scheme for Online Decision	42
3.4	Description of the FCL Allocation Approach	43
3.4.1	Description of the FCL Allocation Approach	44
3.4.2	Formulation of the Bi-level FCL Allocation Model	45
3.4.3	Solution Method	46
3.4.4	Case Study	47
3.5	Conclusion	55
	References	55
<b>4</b>	<b>A Multi-state Model for Power System Resilience Enhancement Against Short-Circuit Faults</b>	<b>59</b>
4.1	Introduction	59
4.2	Extreme Weather Event Response Schema	60
4.2.1	Short-Circuit Current Limiting	61
4.2.2	Transient Stability Maintaining	63
4.2.3	Formulation of the MINLP in the Proposed Schema	65
4.3	Multi-state Modeling of Transmission System Resilience Enhancement	65
4.3.1	Multi-state Resilience Enhancement Against SCFs	66
4.3.2	State Generating Model	68
4.3.3	Traversal Procedure	69
4.4	Solution Method	70
4.4.1	Problem Reformulation	70
4.4.2	Searching Space Reduction	71
4.4.3	Heuristics Solution	72
4.5	Case Study	73
4.5.1	Scenario Generating	73
4.5.2	Sensitivity Analysis	74
4.5.3	Suggested Resilience Enhancement Scheme	76
4.5.4	Comparison Studies	77
4.6	Conclusions	79
	References	79

<b>5</b>	<b>Voltage Violations Assessment Considering Reactive Power Compensation Provided by Smart Inverters</b>	<b>83</b>
5.1	Introduction	83
5.2	Basic Models	84
5.2.1	Reactive Power Compensation Mechanism of Smart Inverters	84
5.2.2	Models of On-Load Tap Changers and Switching Capacitors	86
5.2.3	Comparisons of Different Compensation Strategies	87
5.2.4	Voltage Deviation Indexes	87
5.3	Simulation Methods for Voltage Violation Assessment	88
5.3.1	Kernel Density Estimation of Electric Vehicle Loads and Photovoltaics Outputs	88
5.3.2	Slice Sampling for Voltage Violation Assessment	89
5.3.3	Automated Step Width Selection for Slice Sampling	90
5.4	Risk Assessment for Voltage Violation	90
5.4.1	Voltage Regulation Modes	91
5.4.2	Voltage Regulation Constraints	92
5.4.3	Risk Assessment Process	93
5.5	Case Studies	94
5.5.1	Kernel Density Estimation Results	94
5.5.2	Performance of Slice Sampling	95
5.5.3	Sensitivity Analysis	95
5.6	Conclusion	96
	References	96
<b>6</b>	<b>A Distributed MPC to Exploit Reactive Power V2G for Real-time Voltage Regulation of Post-fault Power Systems</b>	<b>99</b>
6.1	Introduction	99
6.2	Basic Models of EV Chargers and the Grid	101
6.2.1	Operation Range of EV Chargers	101
6.2.2	Modeling of EV Chargers	102
6.2.3	Modeling of the Grid	104
6.3	The Framework of Proposed DMPC	105
6.4	DMPC Formulation	106
6.4.1	Prediction Models	106
6.4.2	Models Constraints	109
6.4.3	Objective Function	110
6.4.4	Mechanisms for DMPC	110
6.4.5	Pre-calculation and Communication Process	111
6.5	Case Study	113
6.5.1	Test System Description for Balanced DNs	113
6.5.2	Case 1: Effectiveness of DMPC Under Balanced DNs	114
6.5.3	Case 2: Impact of Communication Latency in Balanced DNs	115



6.5.4	Case 3: Effectiveness of DMPC Under Unbalanced DNs ...	117
6.6	Conclusion .....	119
	References .....	119
<b>7</b>	<b>A Stochastic Unit Commitment to Enhance Frequency Security of Post-fault Power Systems .....</b>	<b>123</b>
7.1	Introduction .....	123
7.2	The Proposed Integration-Based Frequency Security Criterion ....	125
7.2.1	Frequency Deviation During the PFR Process .....	126
7.2.2	Frequency Deviation During the SFR Process .....	127
7.3	Stochastic Frequency Security-Constrained Unit Commitment Model .....	129
7.3.1	First-Stage Problem: Coordination of Cost and Risk .....	129
7.3.2	Second Stage Problem: Risk Assessment .....	130
7.4	Solution Methodology .....	131
7.4.1	Problem Linearization .....	131
7.4.2	Regularized L-shape Algorithm .....	132
7.5	Case Study .....	133
7.5.1	Parameter Setting .....	133
7.5.2	Reserve Dispatch Under Different Security Requirements .....	134
7.5.3	Comparative Analysis Between the Proposed Frequency Security Criterion and the Conventional Criteria .....	135
7.5.4	Validation of the Proposed Frequency Security Criterion ...	139
7.5.5	Impacts of Operation Life and Hurricane Intensities on Operation Cost .....	140
7.6	Conclusion .....	140
	References .....	141
<b>8</b>	<b>A Data-Driven Reserve Allocation Method with Frequency Security Constraint of Post-fault Power System Considering Inverter Air Conditioners .....</b>	<b>145</b>
8.1	Introduction .....	145
8.2	Modeling of Power System Frequency Response Integrated with IACs .....	146
8.2.1	Power System Frequency Response Model .....	146
8.2.2	Equivalent Frequency Response Model of IACs .....	148
8.2.3	Power System Frequency Response Model with Aggregated IACs .....	150
8.3	Data-Driven Reserve Allocation with the Frequency Security Constraint .....	151
8.3.1	Problem Description .....	151
8.3.2	Data-Driven Approximation of Frequency Security Constraint .....	153
8.3.3	Suggest-and-Improve Method for QCQP .....	155

8.4	Case Studies .....	156
8.4.1	Aggregation of IACs .....	158
8.4.2	Reserve Allocation Results .....	159
8.5	Conclusion .....	162
	References .....	162
<b>9</b>	<b>Iterative Online Fault Identification Scheme for High Voltage Circuit Breaker .....</b>	<b>165</b>
9.1	Introduction .....	165
9.2	HVCB Condition Monitoring System .....	166
9.2.1	Current in the Coil .....	166
9.2.2	Vibration Signal .....	167
9.2.3	Framework of the HVCB Condition Monitoring System ...	169
9.3	Missing Data Repair Method .....	170
9.3.1	KNN-Based Clustering .....	171
9.3.2	ELM for Data Estimation .....	171
9.3.3	K-D Tree-Based Fast Scanning Technique .....	173
9.4	Softmax Classifier for HVCB Status Identification .....	174
9.5	Procedure of Iterative HVCB Diagnosis Utilizing Repaired Data .....	176
9.6	Realistic Case Studies .....	178
9.6.1	Case Description .....	178
9.6.2	Accuracy Validation .....	178
9.6.3	Searching Efficiency Validation .....	181
9.7	Conclusion .....	182
	References .....	182

# 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<sub>2</sub> 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,

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

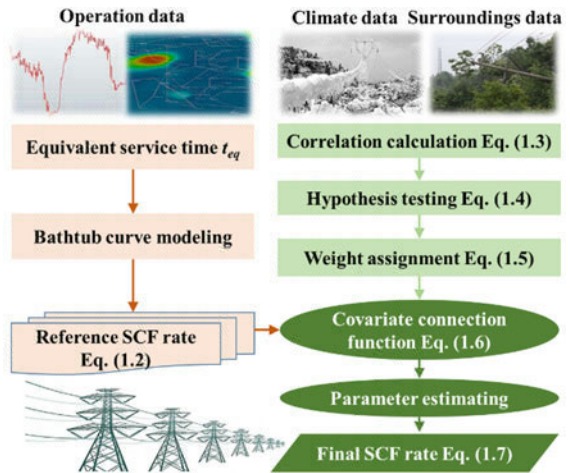
The PHM [11] was applied for the short-circuit fault rate modeling of electrical equipment in this paper, which is illustrated as:

$$h(t) = h_0(t)\psi(F(t)) \quad (1.1)$$

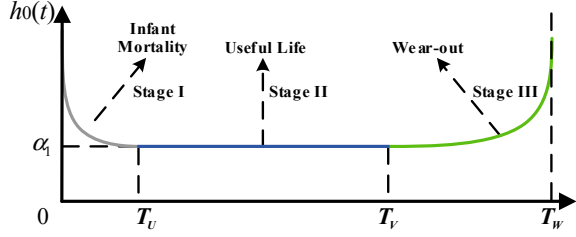
where  $h_0(t)$  is the reference short-circuit fault rate function;  $\psi(F(t))$  is a connection function used to quantify the effects of different factors on the short-circuit fault rate.

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].

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

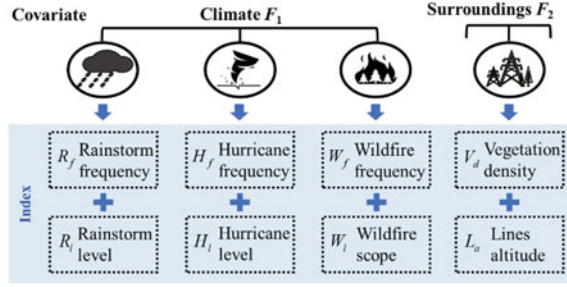
### 1.2.1.2 Covariate Modeling

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



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

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:

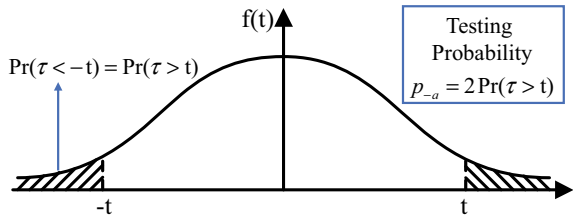
$$t = \frac{(\bar{r} - \rho)\sqrt{ND}}{\sigma_r} \sim t(ND - 1) \quad (1.4)$$

where  $\sigma_r$  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  $\zeta_a$  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.

$$\zeta_a = \frac{1 - p_{-a}}{\sum (1 - p_{-a})} \quad (1.5)$$

**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:

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

### 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:

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

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.  $\gamma_{co}$  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.,  $\gamma_1, \gamma_2$  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,  $\Omega_w$  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:

$$T E(t_{eq}, F; \gamma) = h(\Omega_w; \gamma^{(0)}) + \sum_{v=1}^2 \frac{\partial h(\Omega_w; \gamma)}{\partial \gamma_v} (\gamma_v - \gamma_v^{(0)}) \quad (1.8)$$

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

$$\sigma = \sum_{w=1}^{ND} \{h_w - T h(\Omega_w; \gamma)\} + d \sum_{v=1}^2 (\gamma_v - \gamma_v^{(0)})^2 \quad (1.9)$$

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  $\gamma_v$  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.

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

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]:

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

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

where  $\varepsilon_1$  and  $\varepsilon_2$  are hurricane intensity parameters;  $\gamma_1$  and  $\gamma_2$  denote influence scopes;  $R$  is the distance between hurricane center and transmission line;  $(x, y)$  and