

Review

Tree-Related High-Impedance Fault in Distribution Systems: Modeling, Detection, and Ignition Risk Assessment (Review)

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Abstract: Tree-related high-impedance faults (THIFs) in medium voltage distribution systems represent a typical fault, especially where an overhead line crosses a forested area. The arc caused by THIFs could ignite nearby combustibles, significantly increasing the risk of forest fires. THIF detection remains a significant challenge because this type of fault has weak characteristics, as the fault impedance can reach hundreds of $k\Omega$. Many previous studies have investigated reducing the risk of wildfires caused by THIFs. This paper reviews the existing literature on THIF modeling, detection, and ignition risk assessment. The modeling focuses on the distinctions and connections among electrical models of tree structures, traditional high-impedance fault (HIF) models, and THIF models. Detailed reviews and comparisons are conducted on THIF detection methods, encompassing fault analysis, fault feature extraction, and fault identification. The experiments and methods for assessing THIF ignition risk are also introduced and discussed. The review reveals critical research gaps. In modeling, there is a lack of frameworks that simultaneously elucidate underlying mechanisms and support detection algorithms. In detection algorithms, the existing methods have not been adequately validated under complex environmental conditions. In ignition risk assessment, current studies do not account for a comprehensive range of influencing variables. Finally, this paper proposes future research directions for THIF, aiming to provide a comprehensive reference for researchers and practitioners in this field.



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Keywords: tree-related high-impedance fault; distribution system; fault model; fault detection; ignition risk assessment

1. Introduction

Trees making contact with conductors is one of the main faults occurring in distribution systems. The grid is prone to failures caused by leaning trees in Nordic countries because of their large forested areas. Statistics on the failure causes of a line over half in the forest show that fallen trees lead to around 27% of permanent failures [1]. It is estimated that weather and tree-related factors account for approximately 62% of the causes of power outages in the United States [2]. More than 80% of all vegetation-related problems in the power system are caused by falling trees or branches [3].

Wildfires caused by electrical utility failures have become increasingly frequent in recent years, particularly in countries like Australia, the United States, and Spain [4]. In 2015, electrical grid failures in California started 8% of wildfires but caused 51% of the total burned area (~150,000 acres). These grid-triggered wildfires accounted for 99% of total fire-related losses in Southern and Northern California that year, amounting to ~USD 6 billion [5]. Fiscal year 2017 was the most expensive fire season for the U.S. Forest

Service, spending USD 2.4 billion to extinguish wildfires. The annual cost of fighting wildfires in the U.S. is estimated to be ~USD 4 billion [6]. Wildfires triggered by electrical faults occur through two mechanisms: arcing between lines and vegetation or leakage current flowing through trees [7].

Trees have high impedance values, and the current research categorizes faults between trees and wires as high impedance faults (HIF). The current flowing through a tree is very small, so an increase in line current caused by a THIF can easily be mistaken for an increase in customer load current [8]. As a result, conventional protection devices (e.g., overcurrent relays) often fail to detect such faults [9] until the tree ignites and causes a forest fire. The use of insulated conductors can significantly reduce the risk of THIFs. However, overhead insulated conductors are vulnerable to lightning strikes and ground faults from broken wires, and non-flame-retardant insulation may propagate fire along the line. Undergrounding distribution lines almost eliminates forest fire risk but requires high capital investment, making them impractical for rural areas [10]. Methods such as manual inspections, drone-based patrols, video monitoring, and modifications to the neutral grounding configurations of power systems [11] have been employed to reduce the risk of wildfires caused by THIFs. But their effect is limited. High winds may cause THIFs, so power companies often mitigate the risk by disconnecting dangerous lines from the power supply during such weather conditions [12]. However, disconnections undermine power supply reliability and significantly impact customers.

In recent years, THIFs have increasingly drawn the attention of researchers on account of their high occurrence frequency, the likelihood of causing significant consequences such as wildfires, and the difficulty in detection. The modeling, detection, and ignition risk of THIFs have become hot topics in relevant research. Trees are living media, and a THIF entails complex interactions between the power system and trees. Through modeling, it is possible to conduct in-depth analyses of the physical processes and electrical characteristics of faults, which is conducive to understanding the essence of a THIF and providing a theoretical foundation for subsequent research. Meanwhile, traditional protection devices and technologies are incapable of effectively detecting a THIF. Research on highly efficient and accurate THIF detection techniques can contribute to the timely discovery of faults and the elimination of potential hazards like fires in the early stage of faults. This is of great significance for ensuring the continuous and stable operation of power systems in complex environments. Furthermore, in response to the social application requirements for preventing forest fires triggered by THIFs, evaluating the ignition risk when a THIF occurs is also of extremely high value. For instance, clarifying the minimum time required for a THIF to ignite trees can offer a reference basis for designing the minimum operating time of relevant protection devices. In conclusion, this paper will conduct a comprehensive review centering on these three aspects.

Distribution systems are prone to a THIF because of the low height of conductors. Additionally, small fault current levels make fault detection challenging. In recent years, research on THIFs has primarily focused on the distribution system environment. This paper is structured as follows. Section 2 reviews THIF-modeling theories and research. Section 3 examines studies on identifying and detecting THIFs in distribution systems, and Section 4 highlights the current research on tree ignition risks during faults.

2. THIF Models

Modeling plays a crucial role in describing fault behavior and investigating fault characteristics. Figure 1a presents a schematic of a THIF. A THIF is widely recognized as a HIF. However, trees exhibit unique characteristics compared to other inanimate media

when acting as grounding materials. This section reviews electrical models of tree structure and THIF models.

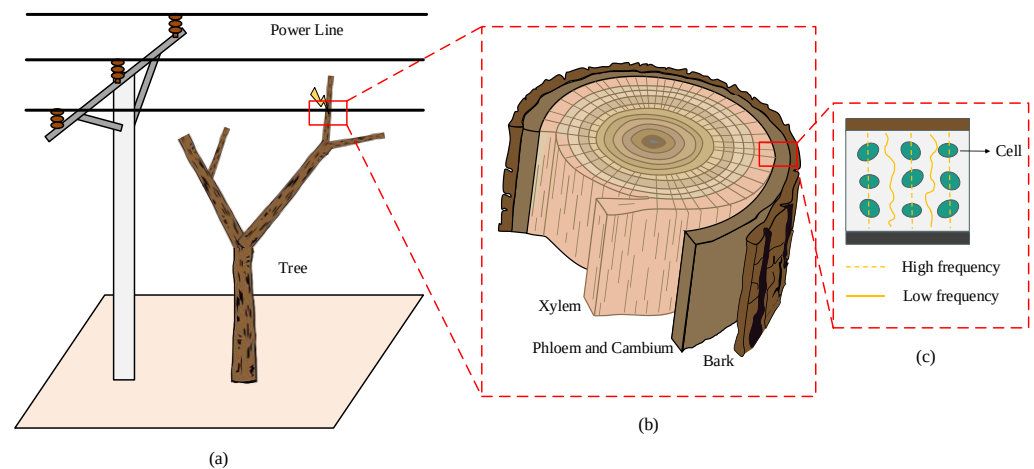


Figure 1. (a) THIF schematic. (b) Tree cross-section structure. (c) Schematic diagram of current path.

2.1. Electrical Models of Tree Structure

Most vegetation, including trees, primarily consists of vascular structures. The outermost layer is the protective bark, followed by the thinner bast layer, which transports leaf-produced nutrients downward. Beneath the bast layer lies the cambium, followed by the xylem, which transports water and minerals upward while providing structural support [13]. Figure 1b illustrates the cross-sectional structure of a tree. Tree impedance represents the electrical properties of plant tissues and was first measured in the early 20th century using a Wheatstone bridge [14]. Tree impedance depends on four factors: tree part, frequency of current, water content, and environmental conditions. Resistivity varies across tree parts, with axial conductivity nearly double that in the radial direction [15]. The electrical impedance of biological tissues combines resistance and capacitance, with its magnitude depending on current frequency. As shown in Figure 1c, ionic current paths in plant tissues vary with frequency. Below 1 kHz, the current primarily flows outside the cell, whereas above 100 kHz, it mainly flows inside the cell [16]. The real part of tree impedance represents resistive pathways, which dominate at low frequencies. The imaginary part is related to cell membranes' capacitive pathways and prevails at high frequencies [17]. Between 10 Hz and 1 MHz, tree impedance is influenced by intracellular and intercellular resistance and water content [18]. Conductivity variations are primarily attributed to water content [13,14,19], which varies by species, age, environment, and season, peaking in spring and reaching its lowest in winter. Higher air humidity and lower temperatures enhance tree conductivity [15].

Several studies have attempted to characterize the impedance of plant tissues using electrical models. Earlier models, such as the Hayden model, include cell membrane capacitance (C), cell wall resistance (R_1), cell membrane resistance (R_2), and cytoplasmic resistance (R_3), as shown in Figure 2a. Let Z represent the impedance of the model, $R_2 \gg R_1 > R_3$, then [20,21]:

$$Z = \frac{R_1^2 R_3 + X^2 R_1 - j X R_1 (R_1 - R_3)}{R_1^2 + X^2}, \quad (1)$$

where $X = 1/(2\pi fC)$, $j = \sqrt{-1}$, and f represents the frequency of the measurement system. It can be observed that $f \rightarrow 0, Z = R_1$ and $f \rightarrow \infty, Z = R_3$.

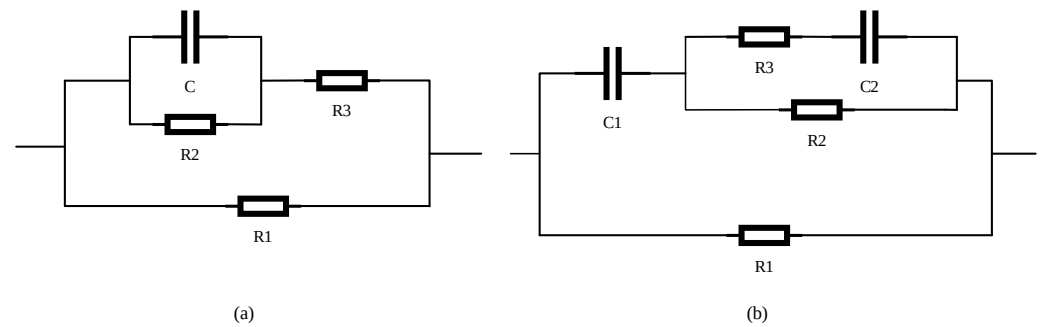


Figure 2. Typical plant tissue electrical model. (a) Hayden model [20]; (b) Double-shell model [22].

The double-shell model considers the resistance of the vesicles in the cytoplasm and the capacitance of the vesicle membrane, as shown in Figure 2b [22]. Here, R_1 represents the resistance of the cell wall and the extracellular space, R_2 represents the resistance of the cytoplasm and the commons, C_1 represents the capacitance of the cell membrane, R_3 represents the resistance of the vesicle, and C_2 represents the capacitance of the vesicle membrane.

Studies have demonstrated that centralized parametric models, such as the double-shell model, are effective at simulating homogeneous plant tissues but are less accurate in simulating complex structures like tree bark and wood [23]. Distributed models, however, enhance the accuracy of impedance simulation for complex tree tissue structures. As illustrated in Figure 3a, the distributed model for tree structures includes a resistor in series with a constant-phase element (CPE). The CPE's precise mathematical expression is provided by Barsoukov and Macdonald [24] (p.88). Multiple impedance and capacitive reactance values measured across a range of current frequencies are plotted on the real and imaginary axes of the impedance vector plane, forming a frequency-dependent trajectory known as the electrical impedance spectrum (EIS) [25]. The EIS of the tree under the distribution model, shown in Figure 3b, adheres to the Cole–Cole arc law, as expressed by Equation (2) [26,27]. In this case, the tree impedance trajectory forms a circular arc with its endpoints on the real axis and its center below the axis.

$$Z = R_s + jX_s = \frac{Z_0 - Z_\infty}{1 + (j\omega\tau_m)^\beta} \quad (2)$$

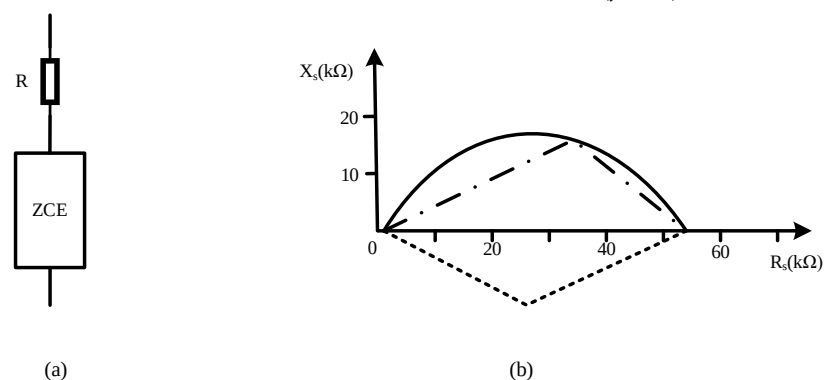


Figure 3. (a) Distributed model of plant tissue [24]; (b) The EIS of the tree under the distribution model [26,27].

In Equation (2), $Z_0 = \lim_{\omega \rightarrow 0} Z$, $Z_\infty = \lim_{\omega \rightarrow \infty} Z$, τ_m represents the central relaxation time of the relaxation phenomenon, β denotes the parameter indicating the degree of deviation from the Debye type, and ω is the angular frequency.

2.2. Tree-Related High-Impedance Fault Modeling

2.2.1. Traditional HIF Models

A THIF is a type of HIF. Previous studies have proposed HIF models to analyze all high-impedance faults, including THIFs. Traditional HIF models can be divided into three categories: single-variable resistor, dual-variable resistor, and diode DC power supply models.

The single-variable resistance model relies on test data to directly fit fault-to-ground resistance. A mathematical function describing changes in ground impedance during a fault serves as a control function for the single-variable resistor, simulating variations in ground impedance, as shown in Figure 4a. During parameter fitting, the effect of arcing can be either ignored [28], reflecting high impedance characteristics, or considered [29], capturing the nonlinear effects of ground arcing. To simulate the phase characteristics during faults, the model can be extended by connecting the variable resistance R_f in series with constant fault inductance L_f [30], as shown in Figure 4b.

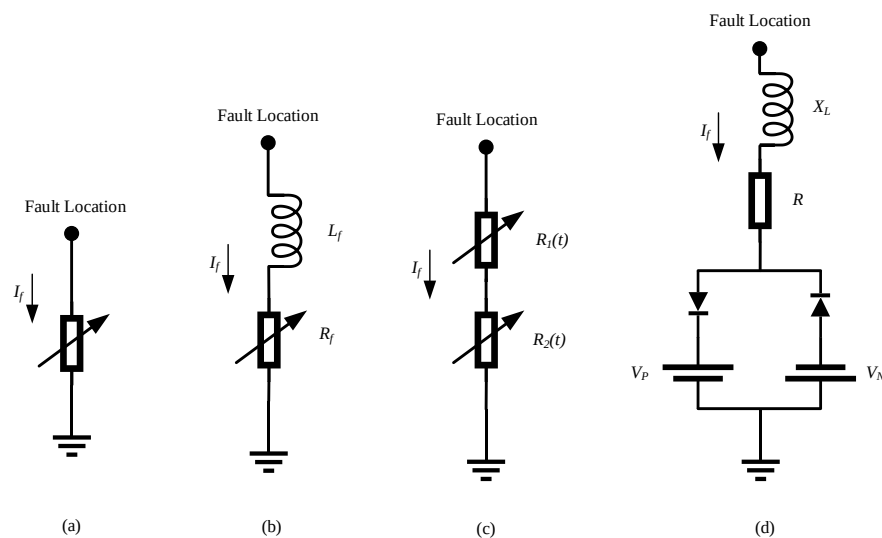


Figure 4. Typical HIF models. (a) Single-variable resistor [28]; (b) Single-variable resistor with inductor [30]; (c) Dual-variable resistor [31,32]; (d) Diode-DC power supply model [33].

The dual-variable resistor model includes two time-dependent resistors in a series, as shown in Figure 4c [31,32]. Resistor $R_1(t)$ models HIF nonlinearity and asymmetry during the transition and steady states, with its value derived from the fault voltage–current curve. Resistor $R_2(t)$ represents the cumulative effect (current rise phase) and shoulder effect (current stabilization before rise) of the fault current determined by the ratio of absolute voltage and current maxima during a half cycle.

Figure 4d illustrates another model comprising a constant resistance R in series with a constant inductance X_L , combined with two reverse-parallel diodes, each in series with a continuous voltage source [33]. The fault current flows through branches V_P and V_N during positive and negative cycles, respectively. Fault currents often exhibit a larger positive than negative half cycle, typically making V_N greater than V_P . This model primarily captures fault currents' nonlinear and asymmetric characteristics.

2.2.2. THIF Models

A. THIF Models Based on Variable Resistance and Arc Model

An important method for modeling THIF involves combining the nonlinear resistor that represents the change of tree impedance with the arc model. Elkalashy et al. [34] developed a single-phase experimental platform to simulate tree–conductor contact in the laboratory, as shown in Figure 5a. Voltage and current measurements after tree–wire contact revealed a tree

resistance of approximately 200 k Ω under normal conditions, increasing to around 800 k Ω at temperatures below -15 $^{\circ}\text{C}$. Tree impedance was fitted using prior voltage and current data and was expressed as resistance, while the arc model parameters were determined based on experimental thermal data. The resulting THIF model was formed by connecting these components in series, as shown in Figure 5b. Similar models have been proposed based on experimental validation [35–37]. Other authors [38–40] focused on early fault characteristics during tree-line fault onset, emphasizing the transient process of tree–conductor contact. During this process, the phases “approach–contact–separation” occur due to physical inertia and related factors, and a segmented model was proposed on this basis, as shown in Figure 5c. The model incorporates tree impedance R_{tree} with dynamic switching to represent different fault phases. During the approach phase, switch S_1 closes, and the model includes R_{bre} and R_{tree} in series with arc resistance. In the contact phase, switch S_2 closes, forming a series connection of $R_{contact}$ and R_{tree} . In the separation phase, switch S_3 closes, and the model includes the air-gap arc resistance R_{sep} in series with R_{tree} . However, this model’s simulation of the complete fault process in trees and wires is limited, failing to reflect the overall trends effectively. Doria-García et al. [41] adapted the concept presented in Figure 4d, replacing fixed resistance R with variable resistance $R_f(t)$. The value of $R_f(t)$ is fitted using the voltage–current relationship of tree–wire contact, as expressed in Equation (3) [41]. The empirical parameter values are $C_1=550$, $C_2 = 2.31$, $C_3 = -44$, $C_4=5$, and $C_5 = 89.75$.

$$R_f(t) = C_1 e^{-C_2 \sqrt{t}} + C_3 e^{-C_4 t} \sin(C_5 t). \quad (3)$$

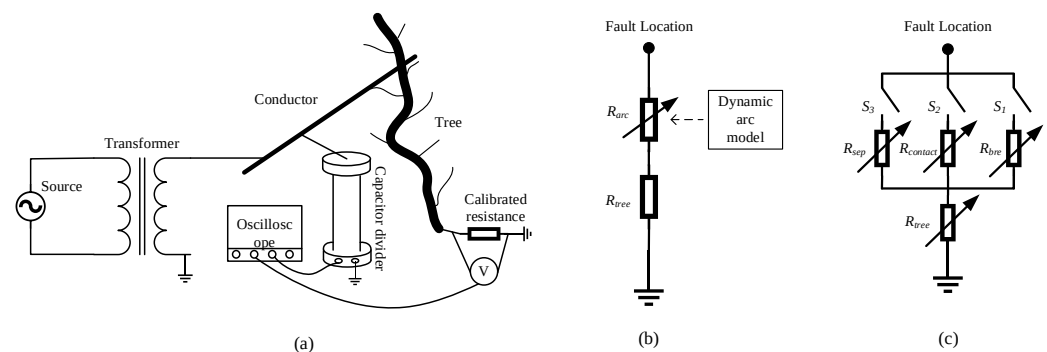


Figure 5. (a) Schematic diagram of THIF experiment. [34]; (b) THIF model proposed in reference [34]; (c) Segmented model of THIF [38].

B. THIF Models Based on Tree Structure

The structural characteristics of a tree’s impedance are crucial for distinguishing it from other inanimate grounding media. Tang and Zhang [42] present a THIF model based on the structural characteristics of trees, which is illustrated in Figure 6a. In this model, R_b represents bark resistance, C_a represents the capacitance of the air gap between the bark and ligamentous part, R_{pr} represents the radial resistance of the ligamentous part, R_{pa} represents its axial resistance, and R_x represents the resistance of the woody part. Similar work has been conducted by Zhao et al. [43], also starting with the tree’s structure while ignoring the effect of arcing. However, Zhao et al.’s model [43] is more applicable to transient cases with shorter time scales, assuming constant circuit parameters over brief periods. In contrast, Tang and Zhang [42] concluded from their experiments that current primarily flows through the bark and bast, simplifying the model to a series connection of two variable resistors, as shown in Figure 6b.

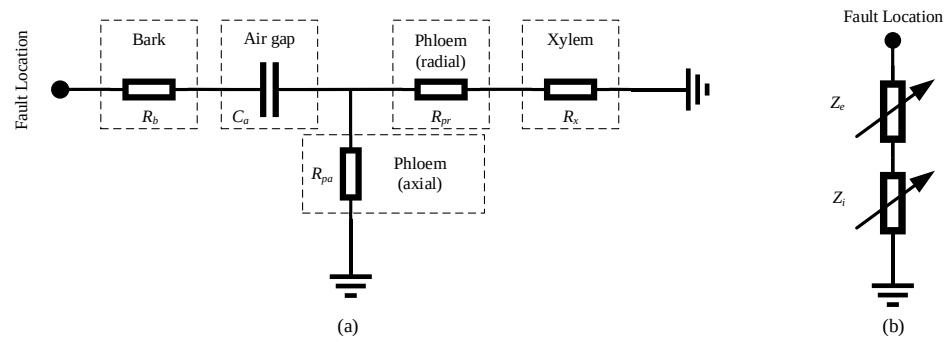


Figure 6. THIF models based on tree structure [42]. (a) Complex Version; (b) Simplified Version.

The impedance between the fault point and the ground decreases for a few seconds after the tree contacts the conductor. The decreasing trend is fitted, and the tree impedance $Z_t(t)$ at the early stage of the fault is modeled as [42]:

$$Z_t(t) = Z_e e^{\tau_1 t} + Z_i e^{\tau_2 t} \quad (4)$$

where Z_e denotes the impedance of the bark in series with the air gap, Z_i denotes the impedance of the axial sieve tubes in the bast, and τ_1 and τ_2 are the respective attenuation coefficients.

C. THIF Models Based on Heat Input

Heat input and moisture precipitation cause corresponding changes in tree impedance. Liang et al. [44] analyzed the overall impedance trend of trees in contact with conductors, linking electrical and thermal models by introducing the wood resistivity–temperature relationship and calculating the slow-change curve of fault transition resistance using a heat balance analysis. The current channel after tree–conductor contact is considered to comprise four components: arc resistance (R_{arc}), contact resistance (R_{con}), trunk resistance (R_v), and grounding resistance (R_G). Because the R_G from the developed root system is typically small, it is neglected in the model shown in Figure 7a. The detailed calculation formula for R_{con} is provided, along with a model correlating tree temperature and R_v , which is verified experimentally. In another study, Liang et al. [45] further modeled R_v based on branch thickness, as shown in Figure 7b. However, the models in Figure 7 focus on macroscopic trends in R_v , simplifying factors like the arc and consequently providing only limited guidance for short-term fault identification.

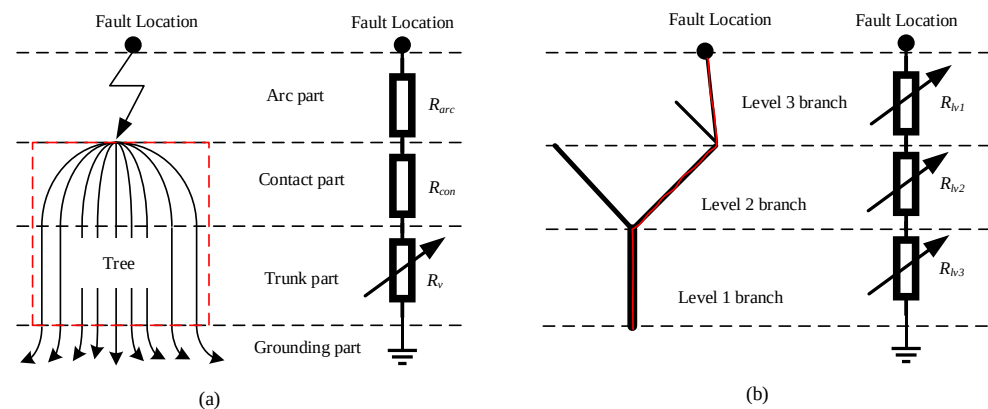


Figure 7. THIF models based on heat input. (a) The model proposed in reference [44]; (b) The model proposed in reference [45].

D. Other THIF Models

The black-box model establishes correlations between input and output signals. Bahador et al. [46] collected data by simulating a THIF using a real 20 kV feeder under field conditions. Considering the nonlinear relationship between fault current and conductor voltage, the Hammerstein–Wiener (HW) nonlinear model was used to establish a mathematical correlation, minimizing the errors between the simulated and experimental data. Measured THIF data were compared with simulated data using an optimization technique in which the cost function was derived from the least squares error between empirical and modeled fault current signals. Environmental conditions are crucial factors affecting the electrical properties of trees. Namdari and Bahador [15] state that a tree's daily equilibrium water content depends on relative temperature and humidity, which directly influence its electrical conductivity. They also proposed a mathematical model that considers environmental factors to estimate leakage current in tree–conductor contact under varying weather conditions, as well as a method to abstract 2D tree resistivity tomography into a 3D finite-element model for simulating THIFs, validating its effectiveness experimentally. Bahador et al. [2] identified a correlation between the tree spectral indices and conductivity using a regression analysis of the laboratory data. Additionally, they proposed a method for estimating vegetation conductivity using spectral data from satellite remote sensing. This method, combined with the finite-element model of tree tissues, enables fault current estimation in THIFs.

3. THIF Detection

Effective THIF detection is an important part of disconnecting fault currents and suppressing the risk of fire. Currently, power-operating companies still detect some potential sources of tree discharge hazards using manual inspections. Research on THIF detection has been ongoing for several years. THIF detection has three main types that are based on electrical waveforms, magnetic field signals, and partial-discharge signals.

3.1. Electrical Waveform-Based THIF Detection

Electrical waveforms, including current and voltage waveforms measured at substations, are easily obtained and widely utilized for fault detection and identification. The waveforms can be obtained from fault recorders (FR) and power quality monitors (PQM). There are currently three main sources of data for electrical waveforms: publicly available datasets (e.g., PBSP: Powerline Bushfire Safety Program) [47–49], experimental platforms (simulated or physical) [34,50,51], and electric utilities [52–54]. This section will review the following two key areas of THIF: electrical waveform analysis and feature extraction and detection methods.

3.1.1. Electrical Waveform Analysis

The analysis of electrical waveforms is the basis for further feature extraction and detection. Typical THIF leakage current waveforms are shown in Figure 8.

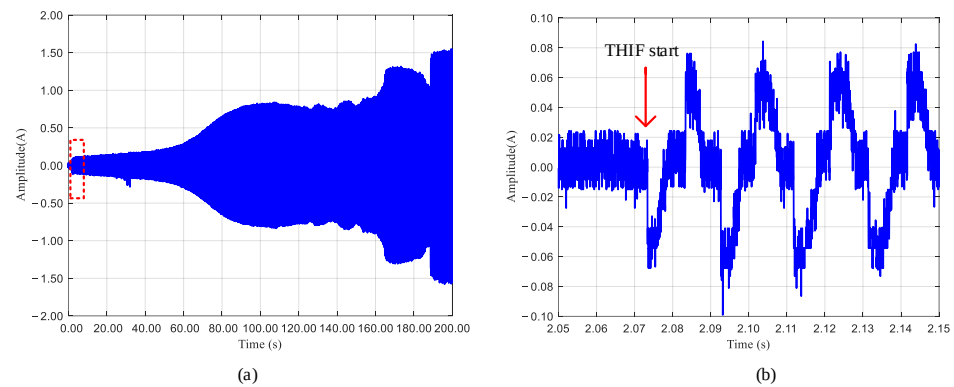


Figure 8. Typical THIF leakage current waveforms: (a) prolonged waveforms; (b) localized waveforms (red box in (a)).

Several studies [7,38,55–59] analyzed the voltage and current waveforms of different tree species in the distribution system and found the following characteristics of THIF electrical waveforms:

- (1) The leakage current does not increase monotonically over extended time periods. As trees dry out and become charred, the leakage current exhibits a “rise–fall–rise” pattern, as illustrated in Figure 8a. Changes in both zero-sequence voltage and zero-sequence current are associated with leakage current;
- (2) The current waveform will continue to be at a very low assignment level—near zero—at some fault stages, as illustrated in Figure 8b. However, different fault stages have different durations. High harmonics in the waveform accompany the arc;
- (3) Due to the arcing characteristics of the early stages of THIFs, the leakage current arc shoulder exhibits nonlinear characteristics and varying durations independent of branch type, speed of travel, or method of neutral grounding of the power system;
- (4) There are significant differences in the level of initial fault current magnitude due to the type, length, and thickness of the trees.

The components of the waveforms at different frequencies have been analyzed [8,60–62]. When a THIF occurs, there is strong high-frequency noise in the waveforms in the frequency range of 50–400 kHz [60]. In most fault waveforms, the increase in the content of high-frequency components is always ahead of the low-frequency components, such as the third harmonic, with a lead time of more than 20 s [61,62]. High-frequency signals have more potential for fault detection [8]. The 800–900 kHz band has the best performance in terms of the fault signals’ growth rate, and taking speed and robustness into consideration, 1.8 MHz is the preferred sampling frequency for studying THIFs [61].

3.1.2. Feature Extraction and Detection Methods

Feature extraction is the key step to finding the features that represent THIFs, which are mainly divided into three types: time domain features, frequency domain features, and time–frequency domain features. Once the features are found, a combination of metric descriptions or classifiers (such as support vector machine (SVM), decision tree, etc.) can be used to detect faults. This section develops an overview of the different types of features used for detection.

A. Time Domain Features

In recent years, several studies have been devoted to analyzing the time domain characteristics of voltage and current waveforms for the purpose of THIF detection. One study simulated THIF events in a 10 kV distribution system, recorded the voltage and current variations during faults, and proposed a THIF detection method based on the

Hausdorff distance between the zero-sequence current waveforms and an ideal sinusoidal waveform [50]. Another method utilizes the volatility of the relative root mean square (RMS) current to detect THIFs [63]. In addition, researchers have built an experimental platform for investigating the dynamic characteristics of zero-sequence voltages and currents during the occurrence of THIFs in a 10 kV system and proposed a detection method based on the slow and monotonic rise of zero-sequence currents beyond a preset threshold. However, this method still faces challenges regarding long-term validation and threshold setting [51]. By analyzing the zero-sequence current waveforms under various HIF ground-fault conditions, significant features, such as volatility, monotonicity, and sharpness of the RMS waveforms, were identified. By introducing a multi-featured parameter set, including standard deviation, skewness, and polynomial fitting coefficients, the SVM model achieved a classification accuracy of 98% [64]. Reference [65] conducted similar work, achieving a THIF identification accuracy of 97.5% using an improved Grey Wolf Optimization probabilistic neural network (IGWO-PNN).

Some studies have also extended fault detection methods to power quality analysis during fault events. For example, power data collected during the 2007 Southern California wildfires were analyzed, and differential waveform analysis effectively filtered out background loads and harmonic disturbances, enabling the extraction of event characteristics. Similarity metrics quantified the relationship between fault waveforms and helped identify potential fire triggers [66]. Complementary multivariate statistical analyses and rule-based methods (e.g., CN2) further correlate the waveform features, identifying representative feature combinations for different fault types. However, classification accuracy is still limited due to the overlap of feature sets between fault types (e.g., animal contact, lightning strike, and THIF) [53,54].

B. Frequency Domain Features

Fast Fourier transform (FFT) was applied to extract arc features from current signals by utilizing high-frequency components. The specificity of the arc pattern was identified using RMS, unevenness factor, and randomness factor, and these metrics were combined with conventional detection methods. A THIF detection accuracy of 95.5% was achieved for the PBSP dataset [49]. Sudden changes in third harmonic voltage were identified as a key characteristic of THIFs [67], and synchronized measurement devices were proposed to calculate the voltage difference at both ends of a line for accurate fault localization. Reference [68] indicates that the arc generated by a THIF primarily introduces the third and fifth harmonics. Additionally, as the fault persists, higher-order harmonics, such as the eleventh and thirteenth, also emerge.

C. Time–Frequency Domain Features

A THIF simulation model for medium-voltage (MV) distribution systems was developed using ATP/EMTP, collecting zero-sequence voltage and current data from faulty feeders [34]. Discrete wavelet transform (DWT) was applied to these collected voltage and current signals using appropriate wavelet functions, allowing for fault identification by detecting over-zero-point distortions caused by arc re-ignition characteristics. Additionally, Elkalashy et al. [69] proposed a method combining DWT and transient power direction to detect and locate THIF dumping in MV distribution systems. Sparse coding was utilized to extract time–frequency features from faulted phase voltage and leakage current signals, generating a feature dictionary. Combined with a decision tree classifier, this approach achieved a 94% accuracy for THIF detection [70]. A single-phase THIF detection method using multi-resolution wavelet transform and multi-parameter information fusion has also been introduced [71]. Reconstructed zero-sequence current signals within target fre-

quency bands were analyzed using power spectral density. Features such as standard deviation and mean were extracted and combined with threshold values for THIF detection. However, the algorithm's sensitivity to interference was not addressed. Lopes et al. [72] utilized FFT, wavelet transform (WT), and Stockwell transform (ST) to extract features like characteristic frequency, energy, and amplitude variations, constructing evaluation metrics such as roughness (R), local inclination (LI), and global trend (GT). Combined with metric descriptions for THIF detection, empirical modal decomposition (EMD) was applied to analyze the fault current volatility, correlating it with arc development using Pearson's coefficient [73]. Gomes et al. [74] combined WT and power spectral density to detect a THIF at currents as low as 0.5 A, achieving over 90% accuracy with a boosted decision tree classifier. Experiments were conducted to evaluate the HIF characteristics of three materials—tree branches, grass, and concrete—under dry and wet conditions in a 7.2 kV test circuit [75]. A time–frequency analysis (TFA) and a joint time–frequency moment (JTfM) were applied to extract features from faulted phase voltages and currents and were combined with SVM classifiers for fault identification. A TFA captures nonstationary signal characteristics, while a JTfM simplifies feature dimensions for fault identification. Guo et al. [35] proposed an incremental learning-based method for HIF (THIF) detection, analyzing zero-sequence current signals and extracting time–frequency domain features using stationary wavelet transform (SWT). The method leverages a backpropagation neural network (BPNN) for fault classification and density-based spatial clustering of applications with noise (DBSCAN) for evaluating data distribution, demonstrating adaptability to non-stationary data streams and high detection accuracy in simulated and real-world 10 kV systems. Kulkarni et al. [52] proposed a method for THIF detection by using an orthogonal wavelet transform to decompose voltage and current waveforms into multiple scales, extracting both high- and low-frequency features from the decomposed signals. Additionally, the method integrates time and phase characteristics to enhance fault detection accuracy. Table 1 presents a comparison of the various detection methods.

Table 1. Comparison of detection methods using electrical waveforms.

Year	Reference	Fs (Hz)	Test Type	Analyzed Data	Feature Extraction and Detection Methods	
2010	[53]	7.68k	Field data	Voltage, current	Time and waveform features, SVM	Time domain
2010	[54]	7.68k	Field data	Voltage, current	Time and waveform features, MANOVA, CN2 rule extraction	
2021	[51]	10k	Lab test	ZSC	Over-threshold time characteristics	
2021	[63]	100k/2M	Lab data	Current	Volatility detection	
2023	[50]	10k	Lab test	ZSC	Hausdorff distance	
2023	[66]	/	Field data	Voltage, current	Differential waveform analysis, Event similarity analysis	
2024	[64]	10k	Lab test	ZSC	Time domain features (standard deviation, etc), SVM	
2025	[65]	10k	Lab test	ZSC	Time domain features (standard deviation, etc), IGWO-PNN	
2024	[49]	100k/2M	Lab data	Current	FFT	Frequency domain
2024	[67]	7.68k	Simulation	Voltage	Third harmonic	
2007	[34]	100k	Lab test and Simulation	ZSV, ZSC	DWT	Time–frequency domain
2008	[69]	25k–100k	Simulation	ZSV, ZSC	DWT, Transient power direction	
2010	[52]	7.68k	Field data	Voltage, current	WT	
2015	[75]	20k	Lab test	Voltage, current	Time–frequency analysis, Joint time–frequency moment, SVM	
2018	[74]	100k/2M	Lab data	Voltage	DWT, Boosted decision tree	
2020	[70]	100k/2M	Lab data	Current	Sparse coding, Decision tree	
2022	[72]	100k/2M	Lab data	Current	FFT, WT, ST	

Table 1. Cont.

Year	Reference	Fs (Hz)	Test Type	Analyzed Data	Feature Extraction and Detection Methods
2023	[71]	/	Lab test	ZSC	WT, Multi-parameter information fusion
2023	[73]	100k/2M	Lab data	Current	EMD, Variance analysis of volatility
2024	[35]	10k	Lab test	ZSC	SWT, BPNN, DBSCAN

where ZSC represents the zero-sequence current, and ZSV represents the zero-sequence voltage.

3.2. Magnetic Field Signal-Based THIF Detection

Magnetic field signals can be measured at any point around the power line using a single sensor mounted on a pole [76]. The magnetic field signal measurement schematic is shown in Figure 9. Sifat et al. [77] developed a 400 V distribution system experimental platform to monitor current and magnetic field signals with a magneto-resistive sensor during THIFs. Fault characteristics were analyzed using time–frequency methods, including FFT and Hilbert transform (HT). Several studies conducted experiments on live trees under 20 kV power lines in Hamadan, Iran [46,78,79]. For branch testing, 20 kV single-core copper conductor XLPE-insulated power cables were used to connect the power line to the tree. Bahador et al. [46] measured magnetic field intensity signals, performed wavelet decomposition, and extracted third-level detail coefficients before calculating the energy spectra, which were normalized to identify THIFs. In another study, Bahador et al. [78] used high-frequency magnetic field phase shift measurements to detect THIFs. The fault distance was estimated by measuring phase changes in the magnetic field on a plane perpendicular to the conductor axis. Fault location can be calculated from the phase shifts assumed to occur during the transmission of high-frequency magnetic field signals at the fault point. This method can locate THIFs with a localization error of less than 1.5%. However, this depends on high signal-to-noise ratio magnetic field signals, with the detection accuracy decreasing below 15 dB. Furthermore, it was discovered that broadband frequencies generated during THIFs cause electromagnetic interference (EMI) in neighboring electronic equipment [79]. EMD was applied to decompose the EMI signals measured during tree-line faults and to extract intrinsic mode functions (IMFs). The energy distribution characteristics of IMFs were analyzed using quantile regression (QR) to determine signal distribution patterns and identify tree-line fault characteristics. Table 2 summarizes the relevant literature.

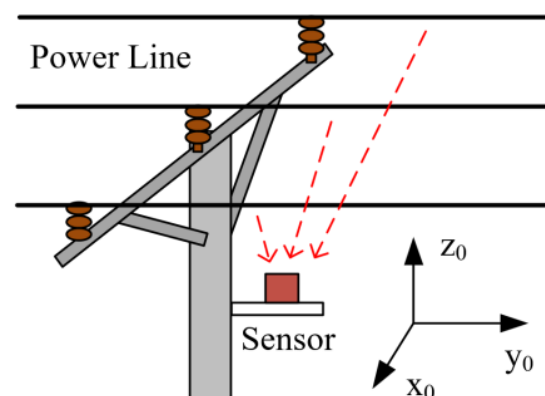


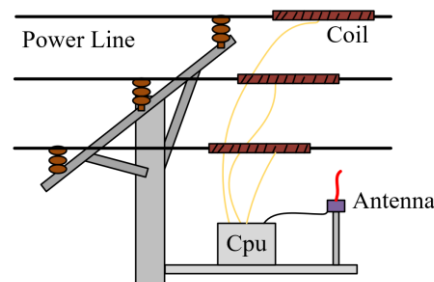
Figure 9. Schematic diagram of magnetic field signal acquisition.

Table 2. Comparison of detection methods using magnetic field signals.

Year	Reference	Fs (Hz)	Test Type	Analyzed Data	Feature Extraction and Detection Methods
2017	[79]	51.2k	Field test	Current, Magnetic interference signals	EMD, QR
2018	[46]	2M	Field test	Current, Magnetic field	WT, Kernel density estimation
2018	[78]	51.2k	Lab test	Magnetic field phase shift signal	High-frequency magnetic field phase shift measurement method
2021	[77]	28k	Field test	Current, Magnetic field	FFT, HT

3.3. Partial-Discharge Signal-Based THIF Detection

A THIF is a localized source of discharge for the power system. The partial-discharge signal acquisition schematic is shown in Figure 10. By detecting partial-discharge activity under medium-voltage lines, THIFs can be efficiently monitored and identified without disrupting normal operation [80,81]. Data are acquired using sensors such as whip antennas, Rogowski sensors, and capacitive voltage dividers. Noise is removed using high-pass filtering, signal gradient analysis, thresholding, and cluster analysis to ensure the clarity and accuracy of partial-discharge patterns. However, detection accuracy decreases in high-noise environments, particularly in cases of dry branches or long-distance conditions where partial-discharge signals are weak. To enhance detection capabilities, it has been proposed to install directional antennas every five kilometers along poles to enable detection of the partial-discharge signals generated by tree-branch contact with wires [82]. This approach utilizes a field-programmable gate array (FPGA) for peak detection and cloud servers for data analysis to enable fault identification and localization. A strong relationship exists between localized discharge signal intensity and voltage level. Table 3 summarizes the relevant literature.

**Figure 10.** Schematic diagram of partial-discharge signal acquisition.**Table 3.** Comparison of detection methods using partial-discharge signals.

Year	Reference	Fs (Hz)	Test Type	Analyzed Data	Feature Extraction and Detection Methods
2015	[81]	/	Field test	The impulse component generated by the voltage signal of the electric stray field	Spectral, Time domain
2019	[82]	2G	Lab test	Electromagnetic radiation	Peak detection
2021	[80]	20M	Field test	Antenna signals	Spectral, Time domain

4. Fault-Induced Fire Risk Assessment

Wildfire initiation in electrical systems requires two key events: line faults and ignition of nearby vegetation fuel beds [3]. Line faults that can induce wildfires are classified as THIFs, electrical equipment faults, overhead line support infrastructure faults (e.g., poles and cross-arms), and overhead line faults [83]. This paper focuses on the ignition risks caused by electric arcs and currents flowing through trees after a THIF occurs in a distribution system. The process of a THIF igniting a tree is shown in Figure 11.

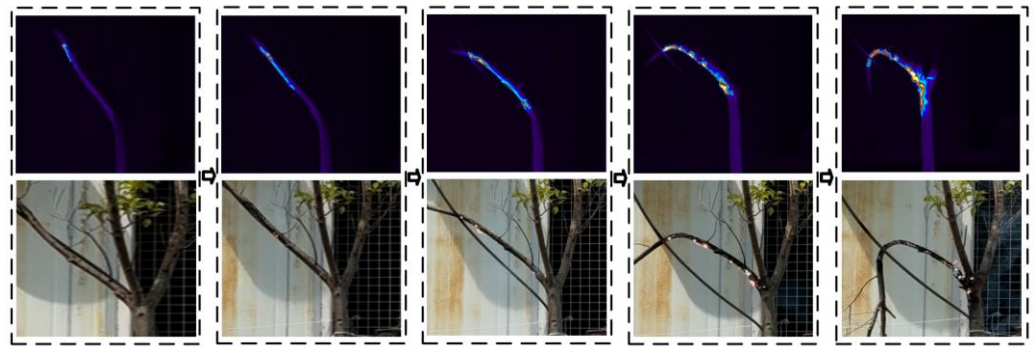


Figure 11. Schematic diagram of tree ignition process.

Related work by Martinez-Canales et al. [84], supported by Spanish power-operating companies, assessed the ignition risk of Mediterranean vegetation. Ignition times in dry environments were significantly shorter than in humid environments, and certain plants (e.g., rosemary) retained high ignition probabilities even in high humidity. Arc intensity demonstrated a positive correlation with vegetation ignition risk. But, the conclusions were limited to Mediterranean vegetation, and few environmental factors were considered. Muhs et al. [85] proposed a model to characterize the probabilities of wildfires caused by faults in distribution systems. The model integrates data on environmental conditions, power system protection settings, and line current magnitudes. Wildfire probability is determined by two components: line fault probability and arc ignition probability. Line fault probability is derived from modeling interactions between mechanical and electrical failures and environmental factors (e.g., wind speed), while arc ignition probability assesses whether the arc reaches the ignition threshold, depending on humidity and vegetation type.

Studies have been conducted on the PBSP dataset to evaluate the risk of tree ignition. Marxsen [7] identified four stages of tree ignition: tree–conductor contact, moisture evaporation, gradual charring, and ignition. Reducing the fault current to 500 mA within 2 s decreases the fire risk tenfold. Vegetation moisture below 10–15% prevents thermal runaway. Additional studies provide insights into ignition mechanisms. One study found that the ignition probability is nearly zero when I^2t remains below $0.1 \text{ A}^2\text{s}$, and cutting off the current below 500 mA reduces the ignition risk by 80% [10]. The fault current volatility was analyzed using EMD in another study [73], and a strong correlation between current volatility and arc development was identified (Pearson coefficient = 0.99). Kandanaarachchi et al. [86] extracted 240 time domain and frequency domain features and reduced redundancy using Partition Around Medoids (PAM) clustering, achieving accurate ignition predictions with random forest. Another study linked the odd harmonic current characteristics with fire risk using FFT analysis and identified high-risk species based on harmonic patterns [87]. A multi-head Convolutional Neural Network - Long Short-Term Memory (CNN-LSTM) model distinguished fire-causing faults by extracting spatial and temporal features [88], while Hybrid Step XGBoost enabled real-time fire risk detection based on voltage and current signals [89].

5. Discussion

Figures 12 and 13 display the statistical conditions regarding the publication years and keywords in the literature that are strongly correlated with THIF. Judging from the publication years of the relevant papers, it can be seen that the papers published after 2016 account for the largest proportion. This may be related to the fact that the government of Victoria State in Australia invested AUD 750 million to establish the Powerline Bushfire Safety Program (PBSP) in 2015, as well as the forest fires induced by THIFs that occurred around the world. It also reveals that THIFs have gradually drawn the attention

of researchers. From the perspective of the statistical data on the keywords, THIFs are still widely categorized into the research scope of HIFs. The starting points and focuses of many studies also lie in the fact that THIFs can induce bushfires (wildfires).

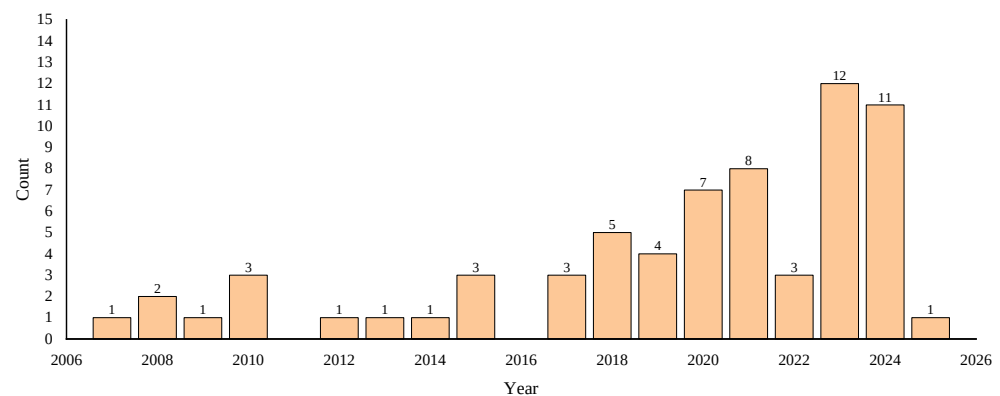


Figure 12. Statistical chart of the publication years of relevant literature.

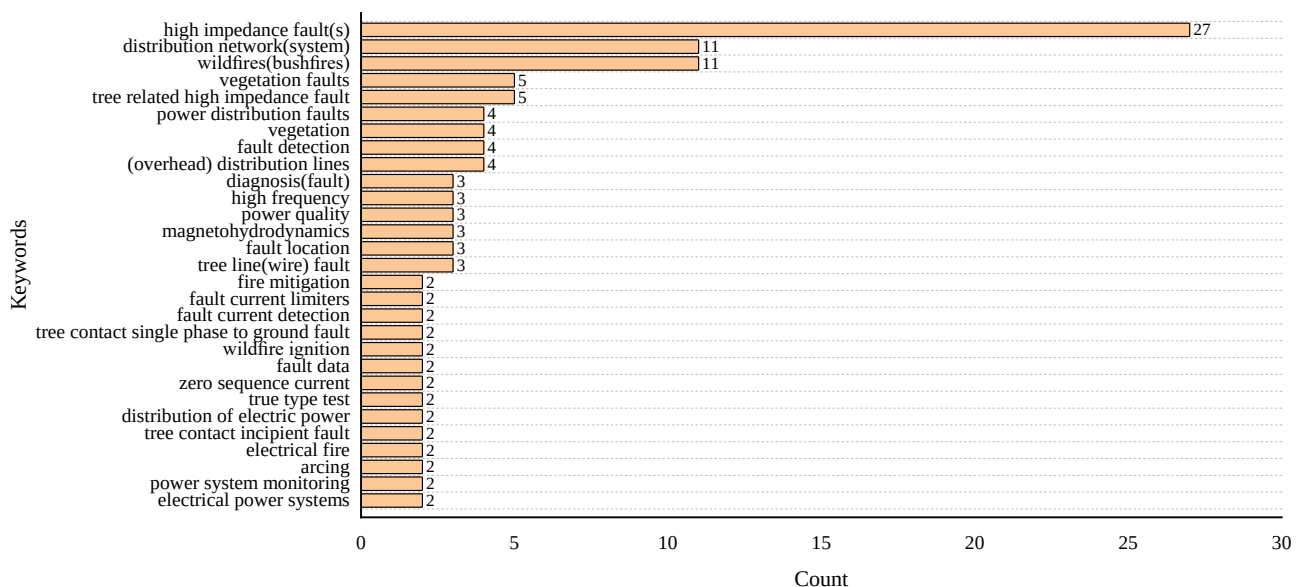


Figure 13. Statistical chart of the keywords of the relevant literature.

5.1. THIF Model

Until now, most of the proposed HIF models have belonged to the category of electrical models, which comprise components such as variable impedance, diode, DC voltage source, and controlled switches, in addition to models for presenting the dynamics of the arc. Different types of HIFs are not identical in a series of characteristics, such as fault current amplitude, waveform nonlinearity, etc., so the proposed HIF model is not fully applicable to all HIF cases. However, according to the previous review, a large number of correlations with HIF modeling research can still be found in the current work on THIF-related modeling, such as the relationship between the works illustrated in Figures 6b and 4c, and that between the works by Doria-García et al. [41] and Emanuel et al. [33]. According to the review in Section 2.1, trees have different properties from other inanimate media when used as a grounding medium. Their own physical structure and electrical properties are rarely taken into account in current modeling efforts. When describing the dynamic change in the THIF impedance value, the macroscopic impedance value change of the fault point to ground is mostly realized by a single adjustable resistor, which does not fit with the physical and mechanical changes to the tree itself. The impedance changes in the tree itself when the fault occurs are mainly caused

by the discharge of water, pyrolysis of tree tissues, and changes in charring channels. In the future, we should consider that the impedance change of the tree itself includes two parts: the lengthening of the carbonized channel and the shortening of the non-carbonized channel in the modeling. Longer carbonization channels mean more local series arcs and smaller impedance values for local lengths of branches. The shorter length of the non-carbonized channel also implies a smaller water content in this part and a dynamic change in the structural and electrical modeling of various parts of the plant tissue. Most of the current THIF modeling work still focuses on the nonlinear characteristics of the fault waveform over a short period of time and the macroscopic impedance changes over a long period of time. Further detailed incorporation of the physical and mechanical changes of the trees themselves during the fault into the modeling after consideration is of significance for the study of the signal characteristics at different stages of the fault. In addition, related studies have shown that the same tree exhibits different electrical characteristics under different environmental conditions, so it is necessary to consider adding environmental factors as variables into the model in further studies.

5.2. THIF Detection

According to the previous review, the work related to THIF detection in a distribution system environment is summarized in Tables 1–3. In terms of publication dates, the related literature is divided into three main phases: 2007–2010, 2011–2020, and 2021–2024. In particular, the total number of articles published in the 2021–2024 period accounts for about half of all papers listed in Table 1. This also indicates that the related issues have gradually been emphasized by scholars and research institutions around the world in recent years. In terms of the sampling rate of detection methods, less than one-third of the articles explicitly mention a sampling rate of less than or equal to 10 kHz. In China, for example, the sampling rate of the widely used power system monitoring equipment is only around 10 kHz. Too high a sampling rate means high costs for the sampling equipment and remodeling of the existing equipment when the technology is popularized and applied. It also creates the burden of signal processing and signal transmission. Therefore, the balance between the accuracy of the detection algorithm and the sampling rate needs to be considered in future research.

A small portion of the analyzed signals come from local discharge signals, magnetic field signals, and power quality data; most of the analyzed signals come from fault recording data. The sampling rate required for the acquisition of localized discharge signals and magnetic field signals is generally high, and the acquisition process is susceptible to environmental interference. Ways to improve this for a wide range of applications is an additional issue for future research. Most of the studies on the use of fault recording data have adopted the PBSP dataset. However, this dataset only considers the leakage current flowing through the tree and the fault phase voltage and does not consider the zero-sequence voltage and zero-sequence current that can be easily measured from the substation side, as well as the load current flowing through the line. Therefore, the studies based on this dataset have not yet considered the problems of unmeasured leakage current in the actual field and the problem of selecting the fault phase from the three voltage phases. Of course, a few self-built experimental platforms also have similar problems. The accessibility of data sources for real-world applications still needs to be considered in the future. At the same time, since leakage currents and zero sequence currents tend to be small in magnitude, the rated parameters of transformers commonly used in power systems are often quite high. It will be worth researching ways to improve the existing measuring equipment and instruments to accurately measure the amount of current mutation.

In addition, the test environments in the studies of different testing algorithms mentioned in this paper are relatively homogeneous. In the future, the efficiency and accuracy

of different testing methods should be investigated in more complex environments in order to be better oriented towards practical engineering applications. The effects of differences in environmental factors, vegetation types, and grid structures on the applicability of algorithms are also worthy of in-depth study.

5.3. THIF Ignition Risk Assessment

The reviewed studies were conducted under specific experimental conditions, including restricting the experimental current to specific ranges and terminating tests at set thresholds. This approach prevents investigation of whether ignition occurs when the fault current briefly exceeds the limit before decreasing. Experimental voltages, often fixed at 22 kV, fail to simulate the typical voltage levels of the medium-voltage distribution grids that are common in many regions. Whether vegetation would continue to carbonize or burn under sustained exposure to lower voltage and current levels remains unclear. Additionally, the experiments did not consider environmental factors such as humidity, temperature, and wind speed, which significantly influence plant conductivity and fire risk. The PBSP experimental procedure defines fire-igniting failures as sparks above a certain temperature falling to the ground. Most studies have based their correlation analysis with fault waveforms on this definition. Bushfires primarily derive energy from dead ground fuels, such as grass and fallen leaves. Research on the correlation between tree ignition and the triggering of forest fires—considered from the perspective of forest fire prevention—is still lacking. An assessment model with a precise definition of ignition and strong generalizability has not yet been developed. The current research on fire risk is not sufficient to provide early warning of forest fires caused by THIFs.

6. Conclusions

This paper provides a comprehensive review of THIFs, which are challenging to detect due to small leakage currents and pose a forest fire risk due to the thermal effects of sustained arcing and currents. The review focuses on three aspects: modeling, detection, and ignition risk assessment.

Most of the existing THIF models follow the traditional HIF model concept, which cannot fully reflect the special characteristics of trees as grounding mediums. Over shorter time scales, studies have solved the problems of nonlinear waveforms and small currents caused by high resistance during air gap breakdown. However, over longer time scales, the simple use of variable resistance and constant arc parameters is still insufficient to describe the dynamic evolution of water release, tissue pyrolysis, and carbonization channels in trees during the fault process. Future models should more fully incorporate the dynamic changes in the arc and the internal structure of the tree, as well as environmental factors (humidity, temperature, etc.), to more accurately characterize the THIF mechanism and provide a more reliable basis for subsequent fault detection methods.

In most of the literature, THIF detection studies are based on fault waveform analysis. The data-based approach can realize preliminary THIF detection. However, the dependence of current methods on high sampling rates does not match with the actual power system measurement capability. At the same time, the signal amplitude of a zero-sequence current and other signals is small, which makes it difficult to accurately detect using traditional transformers. Future THIF detection research should be more closely integrated with the THIF dynamic mechanism. Priority should be given to the use of a zero-sequence voltage and current, which can be conveniently collected by the substation. Future research efforts should reduce the requirements for high sampling rates, enhance the measurement accuracy of transformers for small amplitude signals, and improve the anti-interference capability of magnetic field and partial-discharge detection methods. The effects of differences in

environmental factors, vegetation types, and grid structures on the applicability of the algorithms are also worthy of in-depth study for future engineering applications.

Finally, in terms of ignition risk assessment, the current research provides an approximate mechanism for tree ignition. The relationship between ignition and current parameters has been experimentally derived. However, the existing experimental conditions are too idealized, involve fixed current ranges and termination thresholds, and have limited tree species, and they lack consideration of real environmental factors (e.g., humidity, temperature, and wind speed). This leads to a lack of understanding of fire risk when fault currents exceed extreme values for a short period of time and then drop again, as well as when vegetation exhibits continued carbonization or burning behavior at lower currents. The adaptability of their relevant conclusions needs to be improved. In addition, current research is mostly based on the PBSP program for analyzing the definition of fire and fault waveform correlation. A generalized model for studying the relationship between tree ignition and forest fire triggering from the perspective of forest fire prevention is lacking.

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