

Faulty Feeder Identification and Fault Area Localization in Resonant Grounding System Based on Wavelet Packet and Bayesian Classifier

Jingwen Chen, Enliang Chu, Yingchun Li, Baoji Yun, Hongshe Dang, and Yali Yang

Abstract—Accurate fault area localization is a challenging problem in resonant grounding systems (RGSs). Accordingly, this paper proposes a novel two-stage localization method for single-phase earth faults in RGSs. Firstly, a faulty feeder identification algorithm based on a Bayesian classifier is proposed. Three characteristic parameters of the RGS (the energy ratio, impedance factor, and energy spectrum entropy) are calculated based on the zero-sequence current (ZSC) of each feeder using wavelet packet transformations. Then, the values of three parameters are sent to a pre-trained Bayesian classifier to recognize the exact fault mode. With this result, the faulty feeder can be finally identified. To find the exact fault area on the faulty feeder, a localization method based on the similarity comparison of dominant frequency-band waveforms is proposed in an RGS equipped with feeder terminal units (FTUs). The FTUs can provide the information on the ZSC at their locations. Through wavelet-packet transformation, ZSC dominant frequency-band waveforms can be obtained at all FTU points. Similarities of the waveforms of characteristics at all FTU points are calculated and compared. The neighboring FTU points with the maximum diversity are the faulty sections finally determined. The proposed method exhibits higher accuracy in both faulty feeder identification and fault area localization compared to the previous methods. Finally, the effectiveness of the proposed method is validated by comparing simulation and experimental results.

Index Terms—Resonant grounding system, single-phase earth fault, faulty feeder identification, fault area localization, wavelet packet, Bayesian classifier.

I. INTRODUCTION

IN medium- and low-voltage power distribution networks, single-phase earth faults account for more than 80% of all electrical faults [1]–[4], which makes the location of the single-phase earth fault extremely important. Appendix A Fig. A1

depicts a typical single-phase earth fault in an n -feeder system, where phase A of feeder 1 is grounded at point F . The phase-B and phase-C earth capacitance currents of feeder 1, which are denoted as i_{B1} and i_{C1} , respectively, flow to point F . The earth capacitance currents i_{Bn} and i_{Cn} of the other feeders flow in the same direction. The non-fault phase-B and phase-C earth capacitance currents of other networked power lines, which are denoted as i_{BG} and i_{CG} , respectively, also flow to point F . These capacitance currents, collectively defined as the fault current i_F , highly increase electric arc risks at point F and tend to induce multi-point earth faults. They can even lead to power outage accidents.

To reduce the total current at the earth fault point F , an arc suppression coil (ASC) is always connected between the neutral point N and earth. When a single-phase earth fault occurs, the voltage at the neutral point N shifts to a higher level. The current of the ASC i_L appears and also flows to point F , which can compensate other capacitive currents. Then, the current of the single-phase earth fault point i_F is reduced to a lower level and system risks decrease accordingly. This kind of power system is called resonant grounding systems (RGSs).

The zero-sequence current (ZSC) of all feeders contains the fault information of the RGS system and is always an important variable in fault localization. However, owing to the ASC compensation, the ZSC of a faulty feeder has no distinguished characteristics over that of the non-faulty feeder, which makes it difficult to identify the faulty feeder and further locate the earth fault [5], [6].

Faulty feeder identification in RGSs is a challenging problem. The traveling-wave-based method is an effective solution for fault analysis in power systems [7]–[9]. In [10], the voltage and current traveling-waves of all feeders were measured, and their polarities were compared to identify the faulty feeder. In [11], wavelet transform was used to decompose the current traveling-waves of each feeder. The transform results of all feeders were compared in magnitude and polarity to identify the faulty feeder. Nevertheless, since traveling waves in complex power networks are sensitive to wave impedances, it is difficult to extract exact fault information, which decreases the accuracy rate in faulty feeder identification [12], [13].

Intelligent algorithms, including wavelet transformation combined with neural network, adaptive fuzzy inference, and

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pattern recognition [14]-[19], have attracted considerable attention for RGS faulty feeder identification [20], [21]. However, these algorithms require large amounts of data for model training, and the mathematic solving process mostly involves a large number of nonlinear iterations, which makes them strongly reliant on powerful processors. Furthermore, when the power network is changed, the training process should be repeated, making it inefficient in different system applications.

In this study, we propose a novel algorithm based on a Bayesian classifier to identify the faulty feeder in RGSs. Three synthetic parameters of the RGS, namely the energy ratio, impedance factor, and energy spectrum entropy, are calculated using wavelet packet transformations. The three parameters are sent to a pre-trained Bayesian classifier to categorize single-phase earth faults into three kinds of faulty modes. Then, the faulty feeder can be easily identified. The Bayesian classifier is an effective tool that requires less training data and shorter learning time than other classifiers. We demonstrate that with the Bayesian classifier, the accuracy rate can be significantly improved.

Another challenging problem in RGSs is the fault area localization. Several techniques, including traveling-wave-based methods, fuzzy inference, and neural networks, are widely used for fault area localizations [22]-[27]. In applications of fault area localization, these techniques have the same disadvantages as in applications of faulty feeder identification [28]-[30]. Many RGSs, especially in China, are equipped with feeder terminal units (FTUs), which divide feeders into many sections. The FTUs can provide information on the ZSC at their installation location [31]. By comparing the characteristics of ZSC at the locations of two FTUs, the possible fault area can be restricted [32]-[35].

In [36], the fifth harmonic components of the ZSC at two neighboring FTUs were extracted and compared. If the difference value exceeds a predefined constant threshold, the two FTUs demarcate the faulty section. In [37], the phase angles of the ZSC at two neighboring FTUs were determined and compared. If the difference value exceeds a predefined threshold, the two FTUs demarcate the faulty section. In [38], the line voltages of each feeder are measured for Hilbert transformation. The transformation result multiplied by the transient zero-modulus current of each FTU determines the fault direction parameter. These direction parameters can be compared with a threshold of zero to demarcate the two FTUs of the faulty section.

The above FTU methods generally set a constant threshold to identify the two FTUs of the faulty section for all single-phase earth faults. In practice, the accuracy rate of fault area localization highly depends on the threshold, and a single constant threshold may not be suitable for all scenarios. Therefore, the accuracy rate of the localization results is relatively limited.

In this study, we propose a novel fault area localization method based on the similarity comparison of dominant frequency-band waveforms to localize the fault area in an RGS. Through wavelet packet transformation, the ZSC dominant frequency-band waveforms are obtained at all FTU points.

The similarities of these waveforms are further determined and compared. The neighboring FTU points with the minimum similarity are finally determined faulty sections. Such similarity comparison does not require thresholds and its accuracy rate is higher than that of the previous methods.

The main contributions of this paper are as follows.

1) A faulty feeder identification algorithm based on a Bayesian classifier is proposed. The Bayesian classifier is an effective tool that requires less training data and shorter learning time than other classifiers. We demonstrate that with the Bayesian classifier, the accuracy rate can be significantly improved.

2) A fault area localization method based on the similarity comparison of dominant frequency-band waveforms is proposed. The waveforms after wavelet packet transformation can greatly highlight the differentiating features of the original ZSCs. Their similarity comparison does not require any thresholds and their accuracy rates are high.

The rest of this paper is organized as follows. Section II introduces the fundamentals of wavelet packet transformation and Bayesian classification. Section III illustrates the proposed faulty feeder identification algorithm, and Section IV illustrates the fault area localization method based on similarity comparison. Simulation and experimental results are demonstrated in Section V to validate the proposed method, and Section VI draws the conclusions.

II. FUNDAMENTALS OF WAVELET PACKET TRANSFORMATION AND BAYESIAN CLASSIFIER

A. Wavelet Packet Transformation

Wavelet packet transformation is an elaborate analysis tool specifically developed for transient signals. It implements multi-scale decomposition for both high- and low-frequency bands. It can provide detailed information on a non-periodic signal with both the time and frequency domains.

Wavelet packet transformation uses a series of low-pass filters $h(k)$ and high-pass filters $g(k)$ to decompose an input signal $y_n(t)$. The transformation process can be expressed as follows:

$$\begin{cases} y_{m,2j-1}(t) = h(k)y_{m-1,j}(t) \\ y_{m,2j}(t) = g(k)y_{m-1,j}(t) \end{cases} \quad (1)$$

where $y_{m,2j-1}(t)$ and $y_{m,2j}(t)$ are the $(2j-1)^{\text{th}}$ and $2j^{\text{th}}$ wavelet packets in the m^{th} decomposition layer, respectively; and $y_{m-1,j}(t)$ is the j^{th} wavelet packet in the $(m-1)^{\text{th}}$ decomposition layer.

Figure 1 shows a schematic of the three-layer wavelet packet transformation process. The sampling frequency of the input signal $y_n(t)$ is defined as f_s . An m -layer decomposition generates 2^m frequency bands. The range of each frequency band can be written as:

$$F_{m,j} = \left[\frac{f_s}{2^{m+1}} j, \frac{f_s}{2^{m+1}} (j+1) \right] \quad j = 1, 2, \dots, 2^m \quad (2)$$

where f_s is the sample frequency; and j is the number of frequency bands.

dbN wavelet packet transformation is widely used in sig-

nal processing. It applies compact-support orthogonal wavelet-basis with an N -order vanishing-moment, and its support region is within $[0, 2N - 1]$. It can provide more detailed information on the input signal.

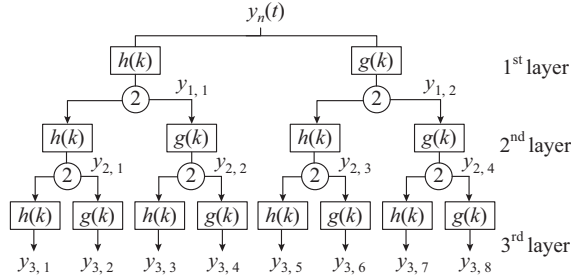


Fig. 1. Schematic diagram of a three-layer wavelet packet decomposition process.

After dbN wavelet packet transformation, we can derive the wavelet coefficient of every frequency band as well as the frequency-band energy. The frequency-band energy can be expressed as:

$$e_{m,j} = \sum_{n_w=1}^N (c_{m,j}(n_w))^2 \quad (3)$$

where $e_{m,j}$ and $c_{m,j}$ are the energy and wavelet coefficient of the j^{th} frequency band in m^{th} decomposition layer, respectively.

With the energy of each frequency band, three parameters can be calculated. The energy spectrum entropy H can be calculated as in (4), which is an indicator of the distribution complexity of the frequency-band energies of the input signal $y_n(t)$.

$$H = - \sum_j \frac{e_{m,j}}{\sum_j e_{m,j}} \ln \frac{e_{m,j}}{\sum_j e_{m,j}} \quad (4)$$

The frequency-band energy ratio α is calculated as in (5), and it is the ratio of the energy of the lowest frequency band $e_{m,0}$ to the total energy of the rest frequency bands.

$$\alpha = \frac{e_{m,0}}{\sum_j e_{m,j} - e_{m,0}} \quad (5)$$

The frequency band with the maximum energy, defined as the dominant frequency band F_B , can be calculated as in (6), and it is an indicator of the amplitude and phase angle of the input signal $y_n(t)$.

$$F_B = F_{m,j} \Big|_{\max\{e_{m,j}\}} \quad (6)$$

B. Bayesian Classifier

The Bayesian classifier is based on Bayes theorem. Naive Bayesian classifiers assume that the effect of an attribute value on a given class is independent of the values of the other attributes. This assumption is called the class conditional independence and is made to simplify the required computations.

Let T be a training set of samples, each with their class labels. There are k classes, $C_1, C_2, \dots, C_k$. Each sample is represented by an n -dimension vector, $X = [x_1, x_2, \dots, x_n]$, depicting n measured values of the n attributes, $A_1, A_2, \dots, A_n$, respec-

tively.

Given a sample X , the classifier will predict which class having the highest posteriori probability X belongs to, conditioned on X . That is, X is predicted to belong to the class C_i if and only if:

$$P(C_i|X) > P(C_j|X) \quad j \neq i \quad (7)$$

Thus, we find the class that maximizes $P(C_i|X)$. The class C_i by which $P(C_i|X)$ is maximized is called the maximum posteriori hypothesis. According to Bayes theorem,

$$P(C_i|X) = \frac{P(X|C_i)P(C_i)}{P(X)} \quad (8)$$

Given data sets with many attributes, it would be computationally expensive to compute $P(X|C_i)$. In order to reduce the computations required to evaluate $P(X|C_i)P(C_i)$, the naive assumption of conditional independence of class is made. This presumes that the values of the attributes are conditionally independent of each other, given the class label of the sample. Mathematically, this can be expressed as:

$$P(X|C_i) \approx \prod_{k=1}^n P(x_k|C_i) \quad (9)$$

The probabilities $P(x_1|C_i), P(x_2|C_i), \dots, P(x_n|C_i)$ can easily be estimated from the training set.

It is easy and fast to predict the class of the test data set. Naive Bayesian classifier also performs well in multi-class predictions. When the assumption of independence holds, a naive Bayesian classifier performs better than other models such as logistic regression and classifiers with supervised learning. Furthermore, naive Bayesian classifiers require less training data.

III. FAULTY FEEDER IDENTIFICATION BASED ON BAYESIAN CLASSIFIER

Figure 2 shows the RGS with FTUs on n feeders considered in this study. The RGS has FTUs on its feeders, and each FTU can provide current information at its location. During system operation, the current waveforms of every phase are automatically recorded.

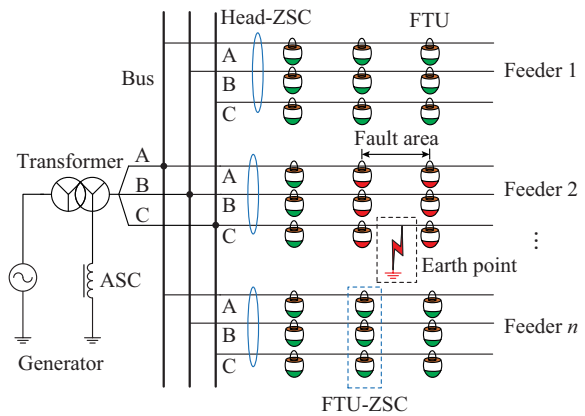


Fig. 2. RGS with FTUs on n feeders.

When one single-phase earth fault occurs, current waveforms of every phase before and after the fault will be extracted. Firstly, the ZSC at the head terminal of each feeder,

defined as Head-ZSC $i_H(t)$, is calculated. Then, the Head-ZSCs are further processed through a db10 wavelet packet transformation, as commonly performed in other literatures. According to (3), (4), and (5), the energy spectrum entropy and frequency-band energy ratio of the Head-ZSCs can be derived as $[H_1, H_2, \dots, H_n]$ and $[\alpha_1, \alpha_2, \dots, \alpha_n]$, respectively. Their average values are derived as two system synthetic parameters of the RGS.

$$H_{RGS} = \frac{1}{n}(H_1 + H_2 + \dots + H_n) \quad (10)$$

$$\alpha_{RGS} = \frac{1}{n}(\alpha_1 + \alpha_2 + \dots + \alpha_n) \quad (11)$$

Another system synthetic parameter is the impedance factor h_{RGS} . After zero-sequence voltages of the RGS are measured, the impedance ratio h_{RGS} can be calculated by:

$$h_{RGS} = \frac{S_1}{S_2} = \frac{\sum_{i=1}^{\frac{n}{2}} |u_i| \Delta T}{\sum_{i=1+\frac{n}{2}}^n |u_i| \Delta T} = \frac{\sum_{i=1}^{\frac{n}{2}} |u_i|}{\sum_{i=1+\frac{n}{2}}^n |u_i|} \quad (12)$$

where S_1 and S_2 are the integral areas of the front and back half waves of the first cycle, respectively; u_i is the zero-sequence voltage sample; and ΔT is the sampling period.

The impedance ratio h_{RGS} is a direct indicator of the zero-sequence voltage of the system after earth fault occurs. Generally, $h_{RGS} \geq 0.7$ indicates that the earth impedance is low, and $h_{RGS} < 0.7$ indicates that the earth impedance is high.

The three system synthetic parameters, namely H_{RGS} , α_{RGS} , and h_{RGS} , can provide comprehensive fault information of the RGS. They are sent to a pre-trained high-efficiency Bayesian classifier for fault mode recognition. Generally, single-phase earth faults in RGSs can be categorized into three modes: strong fault mode, small-angle fault mode, and weak fault mode. In these modes, the dominant frequency-band of the Head-ZSCs mainly locates in the high-frequency, power-frequency, and low-frequency regions, respectively. For a certain fault mode, the existing method performs excellently in the faulty feeder identification. In strong fault mode, the Head-ZSC correlation of every two feeders is first calculated by:

$$\rho_{ij} = \frac{\sum_{k=1}^{N-1} i_{Hi}(k) i_{Hj}(k)}{\left(\sum_{k=1}^{N-1} i_{Hi}^2(k) i_{Hj}^2(k) \right)^{\frac{1}{2}}} \quad i, j = 1, 2, \dots, n \quad (13)$$

where ρ_{ij} is the correlation coefficient; and $i_{Hi}(k)$ and $i_{Hj}(k)$ are the Head-ZSCs of certain feeders. Then, a Head-ZSC correlation matrix considering all feeders can be derived as in (14). By comparing the row sums of this matrix, the one with the smallest sum indicates the faulty feeder.

$$\boldsymbol{\rho}_{RGS} = \begin{bmatrix} \rho_{11} & \rho_{12} & \dots & \rho_{1n} \\ \rho_{21} & \rho_{22} & \dots & \rho_{2n} \\ \vdots & \vdots & & \vdots \\ \rho_{n1} & \rho_{n2} & \dots & \rho_{nn} \end{bmatrix} \quad (14)$$

For the small-angle fault mode, the fundamental component of the Head-ZSC of each feeder is first extracted. Then,

using (3), the power-frequency band energy e_ω of each Head-ZSC is calculated. The one with the maximum e_ω indicates the faulty feeder.

$$\mathbf{e}_\omega = [e_{\omega 1} \quad e_{\omega 2} \quad \dots \quad e_{\omega n}] \quad (15)$$

For the weak fault mode, the Head-ZSC energy spectrum entropies of the feeders are compared, and the feeder with the minimum energy spectrum entropy indicates the faulty feeder.

$$\min\{H_i\} = \min[H_1 \quad H_2 \quad \dots \quad H_n] \quad (16)$$

In the proposed faulty feeder identification algorithm, the pre-trained Bayesian classifier can easily and quickly predict the fault mode of the RGS. Its inherent high-efficiency character will greatly improve the accuracy rate in the faulty feeder identification.

IV. METHOD OF FAULT AREA LOCALIZATION BASED ON SIMILARITY COMPARISON

After faulty feeder identification, the fault area is localized. This paper proposes a novel fault area localization method based on the similarity comparison of dominant frequency-band waveforms in an RGS equipped with FTUs.

As displayed in Fig. 2, FTUs are equipped on all feeders in the target RGS. Firstly, the ZSC data at each FTU points before and after the fault moment, denoted as FTU-ZSC, are exported. Then, using (6), the dominant frequency-bands of each FTU-ZSC on the faulty feeder can be calculated as follows:

$$\mathbf{F}_B = [F_{B1} \quad F_{B2} \quad \dots \quad F_{Bn}] \quad (17)$$

The similarity between two dominant frequency-band waveforms can be represented by their correlations. Two kinds of correlation coefficients of the dominant frequency-band waveforms are calculated. The first correlation coefficient is the cross-correlation coefficient $C_{ij}^C(\tau)$ expressed in (18), which describes the distance between two waveforms in the time domain.

$$C_{ij}^C(\tau) = \lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T F_{Bi}(t) F_{Bj}(t + \tau) dt \quad (18)$$

The second is the Pearson correlation coefficient C_{ij}^P calculated in (19), which describes the linear correlation degree of two dominant frequency-band waveforms.

$$C_{ij}^P = \frac{N \sum F_{Bi} F_{Bj} - \sum F_{Bi} \sum F_{Bj}}{\sqrt{\left(N \sum F_{Bi}^2 - \left(\sum F_{Bi} \right)^2 \right) \left(N \sum F_{Bj}^2 - \left(\sum F_{Bj} \right)^2 \right)}} \quad (19)$$

The two correlation coefficients can reveal the correlation degree of neighboring FTU-ZSCs in two different dimensions. In this work, we combine them together with average weights as in (20).

$$C_{ij} = \frac{C_{ij}^C + C_{ij}^P}{2 \sqrt{\left(\frac{1}{N} \sum F_{Bi}^2 \right) \left(\frac{1}{N} \sum F_{Bj}^2 \right)}} \quad (20)$$

The coefficient C_{ij} of every neighboring FTU-ZSC is calculated, and the two with the lowest similarity indicate the faulty section on the feeder.

The coefficient C_{ij} is a more comprehensive and distinctive similarity index, leading to a more accurate fault area localization result. The proposed similarity comparison method does not require any thresholds and thus, leads to a higher accuracy rate.

V. SIMULATIONS AND EXPERIMENTS

A. Simulation Verification

A four-feeder RGS simulation model is built on ATP/EMTP, as shown in Fig. 3, where R_{ASC} is the internal resistance of the ASC; L_{ASC} is the inductance of the ASC; and R_f is the earth resistance. The FTU interval of every feeder is set to be 1 km.

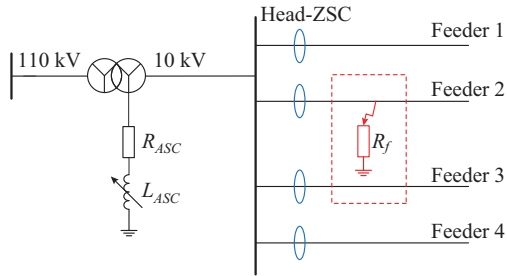


Fig. 3. Four-feeder RGS model used in the simulation.

The values of the parameter set in the simulation are listed in Table I. After single-phase earth fault occurs, three system synthetic parameters, namely the energy spectrum entropy H_{RGS} , frequency-band energy ratio α_{RGS} , and impedance factor h_{RGS} , can be derived through db10 wavelet packet transformation. Then, the three parameters are sent to a Bayesian classifier, which is pre-trained with 500 sets of data, including 100 sets of non-fault data.

TABLE I
PARAMETERS OF RGS USED IN SIMULATION

Parameter	Value
Voltage level of substation	110 kV/10 kV
Number of feeders	4
Length of feeder 1	6 km
Length of feeder 2	10 km
Length of feeder 3	15 km
Length of feeder 4	20 km
Positive-sequence impedance	$0.17+j0.38 \Omega/\text{km}$
Zero-sequence impedance	$0.23+j1.72 \Omega/\text{km}$
Positive-sequence admittance	$j3.045 \mu\text{S}/\text{km}$
Zero-sequence admittance	$j1.884 \mu\text{S}/\text{km}$
Inductance of ASC L_{ASC}	10.22 H
Resistance of ASC R_{ASC}	321 Ω
Sample frequency f_s	6 kHz

We design 600 fault scenarios to evaluate the Bayesian classifier, 200 for each fault mode. The results indicate that 583 of them are correctly classified, which account for 97.2% of all observations. The confusion matrix is shown in

Fig. 4, where the rows represent the true classes of the test sets, and the columns represent the classes recognized by the Bayesian classifier. For a certain fault mode, the existing methods can correctly identify the faulty feeder. Therefore, the final accuracy rate of the proposed faulty feeder identification algorithm is also 97.2%.

True class	Recognized class		
	Small-angle fault	Weak fault	Strong fault
	Small-angle fault	Weak fault	Strong fault
	Weak fault	Strong fault	
	Strong fault		
Small-angle fault	0.97	0.01	0.02
Weak fault	0.02	0.96	0.02
Strong fault	0	0.03	0.97

Fig. 4. Performance evaluation diagram of Bayesian classifier.

For the faulty area localization, 570 of the 582 identified fault scenarios are correctly localized. The final accuracy rate of the proposed fault area localization method is 97.9%.

We compare the proposed method with some existing methods. In faulty feeder identification, the typical travelling-wave-based method used in [9] is applied for comparison. With the same test data sets, its accuracy rate is about 93.3%. In faulty area localization, the threshold-based method reported in [36] is applied for comparison. Dominant-frequency-band waveforms are compared with a constant threshold to find the fault area. With the same test data sets, its accuracy rate reaches 94.2%.

The results in some of the 600 investigated fault scenarios, including faulty feeder identification and fault area localization, are reported in Table II, where “ Δ ” denotes a small-angle fault mode, “ $\uparrow$ ” denotes a strong fault mode, “ $\downarrow$ ” denotes a weak fault mode, and (x, y) is the faulty section indicated by FTUs.

A case study is described in this paper, in which a single-phase earth fault occurs at 0.02 s with a fault angle of 0° . The faulty feeder is feeder 2, the faulty phase is B, and the faulty section is (2, 3). The measured transient Head-ZSC waveforms of the four feeders are shown in Fig. 5.

After db10 wavelet packet transformation, the three parameters are calculated as $\alpha_{RGS}=3.337$, $h_{RGS}=0.271$, and $H_{RGS}=0.756$. The above three parameters are sent to the Bayesian classifier, which correctly recognize the small-angle fault mode. Then, the faulty feeder is correctly identified as feeder 2.

After db10 wavelet packet transformation, the dominant frequency-band waveforms of all FTU-ZSCs of feeder 2 are derived. Their similarities are calculated and compared. The results are demonstrated in Fig. 6. It can be seen from the figure that the minimum similarity 0.126 locates in feeder 2. Then, it indicates that (2, 3) is the faulty section, which is the correct result.

TABLE II
FAULTY FEEDER IDENTIFICATION AND FAULT AREA LOCALIZATION RESULTS

Fault angle (°)	R_f (Ω)	Faulty section	Fault mode	Faulty feeder identification	Fault area localization
0	10	(1, 2)	Δ	True	True
	100	(8, 9)	Δ	True	True
	1000	(1, 2)	Δ	True	True
	5000	(1, 2)	Δ	True	True
30	10	(1, 2)	$\uparrow$	True	True
	200	(8, 9)	$\uparrow$	True	True
	1000	(4, 5)	$\downarrow$	True	True
	5000	(1, 2)	$\downarrow$	True	True
70	10	(8, 9)	$\uparrow$	True	True
	200	(4, 5)	$\uparrow$	True	True
	1000	(8, 9)	$\uparrow$	True	True
	5000	(1, 2)	$\uparrow$	True	True
90	10	(1, 2)	$\uparrow$	True	True
	200	(8, 9)	$\uparrow$	True	True
	1000	(8, 9)	$\uparrow$	True	True
	5000	(8, 9)	$\uparrow$	True	True

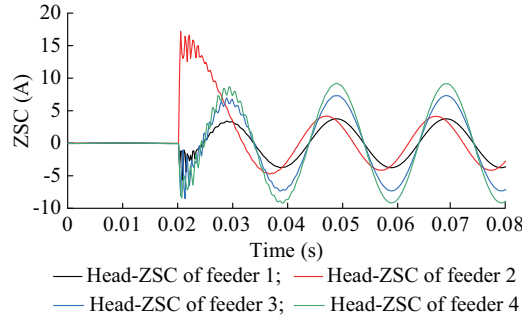


Fig. 5. Head-ZSCs of four feeders at fault moment.

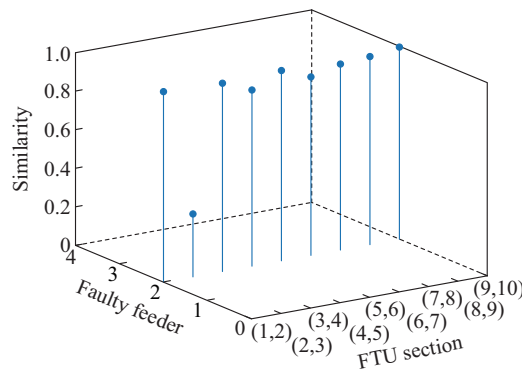


Fig. 6. Similarity comparison of dominant frequency-band waveforms on feeder 2.

The dominant frequency-band waveforms of section (2, 3), as well as those of neighboring sections (1, 2) and (3, 4) are presented in Fig. 7; the calculated similarities are 0.835, 0.126 and 0.831, respectively. Finally, the calculated minimum similarity locates in section (2, 3). The two waveforms have almost opposite polarities; therefore, their similarity is

small.

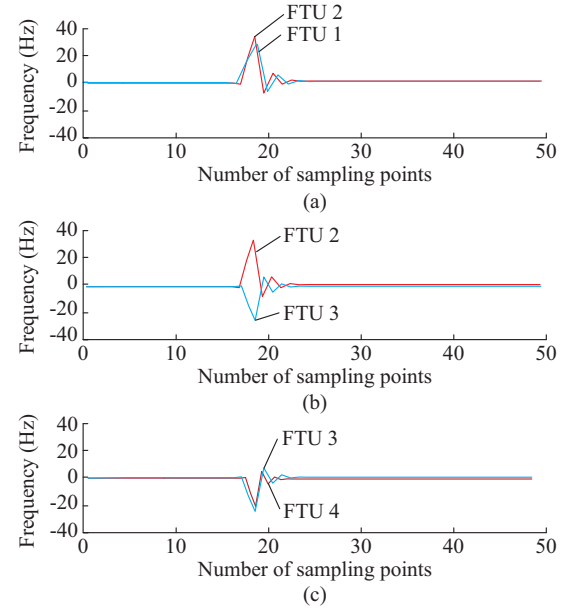


Fig. 7. Dominant-frequency-band waveforms of sections (1, 2), (2, 3), and (3, 4). (a) Section (1, 2). (b) Section (2, 3). (c) Section (3, 4).

B. Experiment Verification

For the experiments, we develop a prototype for faulty feeder identification, which is shown in Appendix A Fig. A2. The relay protection tester ONLY is utilized to simulate grid faults. The PC is used as an interactive tool, and the faulty feeder identification device with display panel shows the results. We designed 44 earth fault scenarios on Real Time Digital Simulator (RTDS) in China Kaipu Lab. Furthermore, we collected 35 actual single-phase earth fault data from Anhui Province, China.

For the 44 designed earth fault scenarios on RTDS and the 35 sets of field data, the proposed faulty feeder identification algorithm correctly identified the faulty feeder with an accuracy rate of 100%.

VI. CONCLUSION

To localize single-phase earth faults in RGSs with FTUs, this study proposes a faulty feeder identification algorithm based on a Bayesian classifier and a fault area localization method based on the similarity comparison of dominant frequency-band waveforms. We use db10 wavelet packet transformation to calculate the energy spectrum entropy, frequency-band energy ratio, and impedance factor, and a pre-trained Bayesian classifier to recognize the exact fault mode. The faulty feeder is effectively identified, and the exact faulty section is correctly localized. We collect the results of 600 simulation scenarios and 79 experiments for verification. The results indicate that the accuracy rate of faulty feeder identification reaches 97.2%, and the accuracy rate of fault area localization reaches 97.9%. The proposed method has an improved accuracy rate and can greatly benefit fault area localization and fault clearance in RGSs.

APPENDIX A

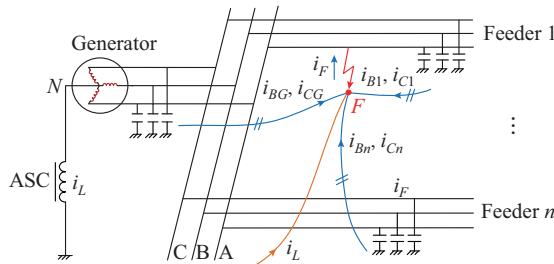
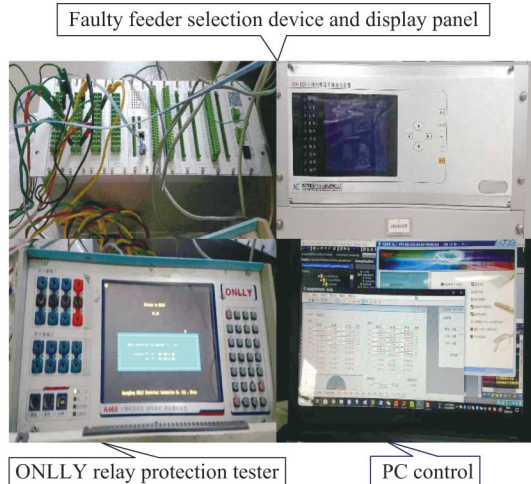
Fig. A1. Typical single-phase earth fault in an RGS with n feeders.

Fig. A2. Experimental platform.

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