

## Article

# Fault Distance Measurement in Distribution Networks Based on Markov Transition Field and Darknet-19

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**Abstract:** The modern distribution network system is gradually becoming more complex and diverse, and traditional fault location methods have difficulty in quickly and accurately locating the fault location after a single-phase ground fault occurs. Therefore, this study proposes a new solution based on the Markov transfer field and deep learning to predict the fault location, which can accurately predict the location of a single-phase ground fault in the distribution network. First, a new phase-mode transformation matrix is used to take the fault current of the distribution network as the modulus 1 component, avoiding complex calculations in the complex field; then, the extracted modulus 1 component of the current is transformed into a Markov transfer field and converted into an image using pseudo-color coding, thereby fully exploiting the fault signal characteristics; finally, the Darknet-19 network is used to automatically extract fault features and predict the distance of the fault occurrence. Through simulations on existing models and training and testing with a large amount of data, the experimental results show that this method has good stability, high accuracy, and strong anti-interference ability. This solution can effectively predict the distance of ground faults in distribution networks.

**Keywords:** distribution network; fault distance measurement; Markov transition field; deep learning

**MSC:** 68T20



**Citation:** Wang, H.; Guo, W.; Shi, Y. Fault Distance Measurement in Distribution Networks Based on Markov Transition Field and Darknet-19. *Mathematics* **2024**, *12*, 1665. <https://doi.org/10.3390/math12111665>

Academic Editors: Jie Hu, Sheng Du and Pan Yu

Received: 25 April 2024

Revised: 15 May 2024

Accepted: 16 May 2024

Published: 27 May 2024



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## 1. Introduction

The distribution network plays a crucial role in the electrical grid by ensuring the safe, efficient, and reliable delivery of electricity to end users. With an increasingly complex network structure and diverse operational conditions, the system is more susceptible to faults, particularly single-phase grounding faults [1,2]. If single-phase grounding faults are not rectified for a long time, they can easily escalate into two-point or multiple-point grounding short circuits, causing damage to equipment and even posing risks to personal and property safety [3,4]. Timely localization of fault occurrences is essential for rapid risk mitigation, holding significant theoretical and practical importance.

The structure of the power distribution network is often in a radial pattern, characterized by multiple branches and short line lengths. When a small-current ground fault occurs, the fault signal tends to exhibit non-linear, weak, and complex characteristics. Existing fault localization methods may struggle to meet the accuracy requirements for localization. At current, the main research methods for fault location can be roughly divided into several types, such as the fault analysis method, artificial intelligence method, signal injection method, traveling-wave method, and impedance method [5,6]. One of the most effective methods to calculate the fault distance is the traveling-wave method [7,8]. However, due to the intricate line structure of the distribution network, it is challenging to differentiate and recognize the wave head type and time information. Karmacharya and Gokaraju [9] employed wavelet transformation to decompose the monitoring signal and extract fault

features, facilitating the utilization of a three-layer feedforward artificial neural network classifier for automated fault localization. Nevertheless, manual extraction of fault features is imperative, with the precision of outcomes being heavily reliant on the scale of decomposition and wavelet basis functions. Elkalashy [10] utilized a controlled thyristor to ground the neutral point and generate traveling waves for fault distance estimation. However, this approach is limited to neutral ground systems and necessitates signal injection. Sun [11] proposed a method for calculating the fault area by establishing an adjacency table of distribution network equipment to illustrate the relationship between each piece of equipment. However, this approach requires a substantial amount of electrical data from customers, making the collection process cumbersome. Liao [12] proposed a novel integrated fault location solution for overhead distribution systems, contingent upon the prior knowledge of network parameters and topology. Hua Fu et al. [13] proposed a traveling-wave fault detection method that combines variational mode decomposition (VMD) and synchrosqueezing wavelet transform (SWT). However, the VMD algorithm lacks adaptability as it requires a manual setting of decomposition levels. Peng Hua et al. [14] utilized the full-phase fast Fourier transform spectrum correction to extract the fundamental effective values and phase information of voltage and current at measurement points as feature vectors. They established a fault locator using the extreme gradient boosting method to achieve fault location and distance measurement. However, in the case of single-phase grounding faults in low-current grounded systems, the effective value of the power frequency current changes minimally. This effect is especially pronounced when there is a large transition resistance, leading to further weakening of the fundamental fault characteristics and affecting the distance measurement accuracy of this method. The impedance method calculates the impedance by measuring the voltage and current when a fault occurs in the circuit. Since the line impedance is directly proportional to the length of the line, this method can be used to determine the distance between the measuring device and the fault point [15]. Zheng Tao et al. [16] used a node impedance matrix and network equivalence method for fault location. This algorithm utilizes the node impedance matrix formed after a distribution network fault to establish a distance measurement expression based on the physical significance of node impedance. Qi Zheng et al. [17] proposed a fault location technique for distribution networks based on the zero-sequence impedance method. This technique utilizes the zero-sequence voltage on both sides of the distribution network lines and the zero-sequence current on the busbar side to establish distance-related measurement equations for each section of the network. However, these methods require prior knowledge of the distribution network parameters and topology, making them difficult to apply to increasingly complex distribution network structures. In recent years, with the development of artificial intelligence, machine learning has been widely used in the field of fault diagnosis, and many new fault diagnosis models have been proposed [18,19]. Researchers have integrated neural network technology into the field of distribution network fault location. They use artificial intelligence algorithms to address the challenges in fault location within distribution networks. Refs. [20–22] propose the utilization of artificial intelligence algorithms for distribution network fault location. These approaches integrate traditional methods with artificial intelligence algorithms, utilizing AI to predict fault location, streamline the complex steps of traditional fault location algorithms, and demonstrate certain resistance to interference. However, Ref. [20] artificially decomposes fault signals and extracts fault features using wavelet packets, which introduces a subjective element. In Ref. [21], neural networks are employed for automatic extraction of fault features; however, the samples used for training do not fully capture fault information. Ref. [22] utilizes a backpropagation (BP) neural network for fault localization; nevertheless, the BP neural network is susceptible to local minima, gradient vanishing or exploding, overfitting, and other issues. Additionally, the BP neural network is sensitive to input data, limiting its generalization ability in processing noise or unseen data.

In summary, in response to the current issues of complex and inaccurate fault localization in fault location methods, this paper proposes a new approach for predicting fault

positions using Markov transition fields and deep learning, effectively achieving fault distance prediction. Firstly, a new phase-shifting matrix is used to extract the modulus 1 component of the fault current in the distribution network, ensuring that this modulus 1 component can represent single-phase ground faults for all phases; then, the extracted current modulus 1 component is transformed into a Markov transition field, which is visually encoded as an image using pseudo-colors; finally, this image is used as input for the Darknet-19 model, which automatically extracts fault features of the line through multilayer convolution and pooling operations, and calculates fault distance through a regression model. Simulation results show that this approach has lower errors and stronger robustness. Compared with traditional methods, it improves detection reliability.

The paper is structured into the following sections. Section 2 introduces the phase-mode transformation. In Section 3, a signal-to-image conversion method is proposed. Section 4 describes fault location based on Darknet-19. The results of fault-ranging experiments are presented in Section 5.

## 2. Phase-Mode Transformation

The parameters of the ABC three-phase current in the power distribution network exhibit complex electromagnetic coupling, making their calculation complex. However, the phase-shifting transformation can simplify this and avoid complex calculations in the complex domain, making it suitable for decoupling electrical quantities from discrete sampling [23]. The relationship between phase-mode transformation and inverse transformation in the time domain is as follows:

$$\begin{cases} \begin{pmatrix} i_m^{(0)} & i_m^{(1)} & i_m^{(2)} \end{pmatrix}^T = S^{-1} \begin{pmatrix} i_a & i_b & i_c \end{pmatrix}^T \\ \begin{pmatrix} i_a & i_b & i_c \end{pmatrix}^T = S \begin{pmatrix} i_m^{(0)} & i_m^{(1)} & i_m^{(2)} \end{pmatrix}^T \end{cases} \quad (1)$$

where  $i_m^{(0)}$ ,  $i_m^{(1)}$ , and  $i_m^{(2)}$  represent the current modulus components of 0, 1, and 2.

The ABC three-phase parameters, after undergoing phase-mode transformation, are converted into modulus 0, modulus 1, and modulus 2 components. Because the modulus 0 component is connected to the ground, its loop parameters are affected by complex factors related to the ground, such as resistivity and grounding conditions. Therefore, for fault analysis problems, most researchers use the modulus 1 or modulus 2 components.

The commonly used phase-mode transformation methods include the Clarke transformation, the Karenbauer transformation, and the Wedpohl transformation. These three methods demonstrate good analytical capabilities in certain fields, but they are unable to achieve a single modal component that reflects all types of faults in fault analysis problems. The decision has been made to implement a new phase-mode transformation matrix, which not only retains the advantages of the time-domain matrix but also achieves the objective of single-modulus response for all types of faults [23]. The original matrix is represented by Equation (2).

$$S = \frac{1}{15} \begin{pmatrix} 5 & 5 & 5 \\ 5 & -1 & -4 \\ 5 & -4 & -1 \end{pmatrix}; S^{-1} = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 2 & -3 \\ 1 & -3 & 2 \end{pmatrix} \quad (2)$$

The phase-mode transformation matrix  $S^{-1}$  can transform the current vectors into a modal form, as follows:

$$\begin{pmatrix} i_m^{(0)} \\ i_m^{(1)} \\ i_m^{(2)} \end{pmatrix} = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 2 & -3 \\ 1 & -3 & 2 \end{pmatrix} \begin{pmatrix} i_a \\ i_b \\ i_c \end{pmatrix} \quad (3)$$

Table 1 provides the mode components obtained using the phase-mode transformation matrix for various fault types. From this table, we can observe that the mode components for

all types of faults are non-zero, indicating that their modulus 1 and modulus 2 components can individually reflect all fault types.

**Table 1.** Current modes of different faults.

| Fault Type        | Boundary Condition             | Modulus 1                    | Modulus 2                    |
|-------------------|--------------------------------|------------------------------|------------------------------|
| AG <sup>1</sup>   | $i_{fb} = i_{fc} = 0$          | $i_{fa}$                     | $i_{fa}$                     |
| BG <sup>2</sup>   | $i_{fa} = i_{fc} = 0$          | $2i_{fb}$                    | $-3i_{fb}$                   |
| CG <sup>3</sup>   | $i_{fa} = i_{fb} = 0$          | $-3i_{fc}$                   | $2i_{fc}$                    |
| AB <sup>4</sup>   | $i_{fc} = 0; i_{fa} = -i_{fb}$ | $i_{fb}$                     | $-4i_{fb}$                   |
| BC <sup>5</sup>   | $i_{fa} = 0; i_{fb} = -i_{fc}$ | $5i_{fb}$                    | $-5i_{fb}$                   |
| CA <sup>6</sup>   | $i_{fb} = 0; i_{fa} = -i_{fc}$ | $4i_{fa}$                    | $-i_{fa}$                    |
| ABG <sup>7</sup>  | $i_{fc} = 0$                   | $i_{fa} + 2i_{fb}$           | $i_{fa} - 3i_{fb}$           |
| BCG <sup>8</sup>  | $i_{fa} = 0$                   | $2i_{fb} - 3i_{fc}$          | $2i_{fc} - 3i_{fb}$          |
| CAG <sup>9</sup>  | $i_{fb} = 0$                   | $i_{fa} - 3i_{fc}$           | $i_{fa} + 2i_{fc}$           |
| ABC <sup>10</sup> | $i_{fa} + i_{fb} + i_{fc} = 0$ | $i_{fa} + 2i_{fb} - 3i_{fc}$ | $i_{fa} - 3i_{fb} + 2i_{fc}$ |

<sup>1</sup> Phase A single phase to ground; <sup>2</sup> Phase B single phase to ground; <sup>3</sup> Phase C single phase to ground; <sup>4</sup> Phase A is connected to phase B; <sup>5</sup> Phase B is connected to phase C; <sup>6</sup> Phase C is connected to phase A; <sup>7</sup> Phase A and phase B are simultaneously grounded; <sup>8</sup> Phase B and phase C are simultaneously grounded; <sup>9</sup> Phase C and phase A are simultaneously grounded; <sup>10</sup> Phase A, phase B, and phase C are interconnected with each other.

### 3. Markov Transition Field

To maximize the convolutional neural network's ability to extract image features, an algorithm can be used to transform one-dimensional time-series signals into two-dimensional matrices. Markov transition field (MTF) [24] is one such method, wherein the transition probabilities of a Markov process are sequentially represented, allowing the signal to be transformed into an image while retaining the temporal information.

The principle of MTFs involves first identifying  $Q$  quantile bins based on the given one-dimensional time-series signal  $X = \{x_1, x_2, \dots, x_n\}$  and assigning each value  $x_i$  to its corresponding unit  $q_j (j \in [1, Q])$ , expressing relationships in terms of single-step transition probabilities and multi-step transition probabilities defined in Markov chains.

$$\begin{cases} P_{i,i-1} = p_{i,i-1}(x_t \in q_i | x_{t-1} \in q_{i-1}) \\ P_{i,j} = p_{i,j}(x_t \in q_i | x_{t-1} \in q_j) (i - j > 1) \end{cases} \quad (4)$$

where  $P_{i,j}$  represents the multi-step transition probabilities. It represents the probability that an element located in the  $q_j$  quantile bin region will multi-step to the  $q_i$  quantile bin at the next moment. Then, the transition probabilities between quantile bins can be calculated using a first-order Markov chain method along the time axis. By arranging all the transition probabilities of the Markov chain according to the transition rules, a  $Q \times Q$  weighted adjacency matrix, i.e., the Markov transition matrix (MTM)  $W$ , can be constructed, as shown in Equation (5). From the equation, it is evident that the MTM is entirely determined by the Markov chain, indicating a strong correspondence between the two [25].

$$W = \begin{pmatrix} w_{1,1}(x_t \in q_1 | x_{t-1} \in q_1) & \cdots & w_{1,Q}(x_t \in q_1 | x_{t-1} \in q_Q) \\ w_{2,1}(x_t \in q_2 | x_{t-1} \in q_1) & \cdots & w_{2,Q}(x_t \in q_2 | x_{t-1} \in q_Q) \\ \vdots & \ddots & \vdots \\ w_{Q,1}(x_t \in q_Q | x_{t-1} \in q_1) & \cdots & w_{Q,Q}(x_t \in q_Q | x_{t-1} \in q_Q) \end{pmatrix} \quad (5)$$

Due to the Markov chain's lack of memory, whereby the current state depends only on the previous state, so  $p(x \in \sum_{j=1}^Q q_j | x_{t-1} \in \sum_{j=1}^Q q_j, \dots, x_1 \in \sum_{j=1}^Q q_j) = p(x_{t-1} \in \sum_{j=1}^Q q_j | x_{t-1} \in \sum_{j=1}^Q q_j)$ , the MTM also exhibits this lack of memory. This characteristic causes it to lose the dependence on the time steps of the one-dimensional time series  $X$ . Directly using the Markov matrix would result in the loss of much information from the one-dimensional time series.

Conversely, the improved MTF, as the sequence follows a time-ordered arrangement, can effectively utilize the sequential signal. The definition of the MTF is shown in Equation (6).

$$M = \begin{pmatrix} w_{ij}|x_1 \in q_i, x_1 \in q_j & \cdots & w_{ij}|x_1 \in q_i, x_n \in q_j \\ w_{ij}|x_2 \in q_i, x_1 \in q_j & \cdots & w_{ij}|x_2 \in q_i, x_n \in q_j \\ \vdots & \ddots & \vdots \\ w_{ij}|x_n \in q_i, x_1 \in q_j & \cdots & w_{ij}|x_n \in q_i, x_n \in q_j \end{pmatrix} \quad (6)$$

Here,  $w_{ij}$  represents the transition probability of the quantile relationship between  $q_i$  and  $q_j$  on the matrix  $W$ , while the elements on the diagonal represent the self-transition probabilities. Consequently, the information derived from the Markov chain can be expressed on the MTF  $M$ , constructed based on the sequence of data length. Finally, by visually encoding the obtained Markov field matrix using pseudo-colors, a two-dimensional image containing fault information can be obtained. The transformation process is illustrated in Figure 1.

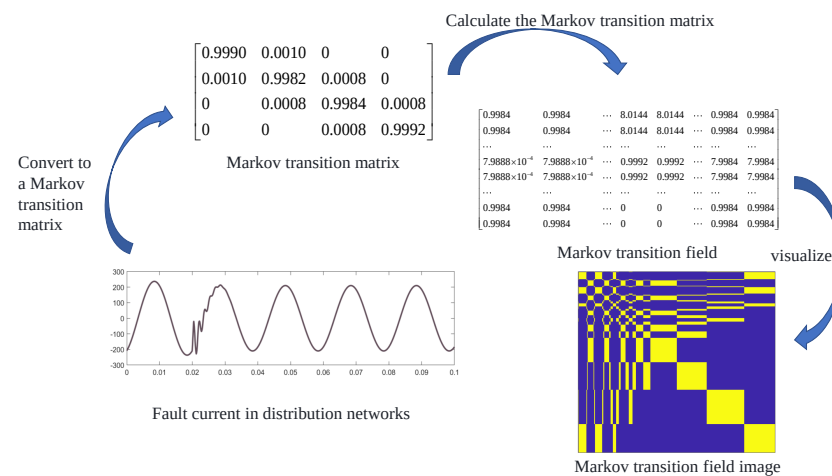


**Figure 1.** The MTF transformation process.

#### 4. Fault Distance Measurement Based on Logistic Regression

Convolutional neural networks (CNNs) not only possess strong feature extraction capabilities, widely used in image classification, but also harbor powerful advantages for handling regression problems [26]. However, conventional convolutional neural networks are prone to issues such as gradient saturation and local optima. To address these problems, it is important to sensibly design the neural network’s structure. Darknet-19 [27] incorporates the advantages of VGG-16 [28] while discarding unnecessary complex structures. It primarily utilizes convolutional layers with filters, doubling the number of channels after each pooling step. Following the network-in-network (NIN) operation, global average pooling is performed for prediction, and filters are used to compress feature representations between the convolutions. Lastly, batch normalization is employed to stabilize training, accelerate convergence, and regularize the model. The network structure is depicted in Figure 2, with detailed explanations provided in Table 2.

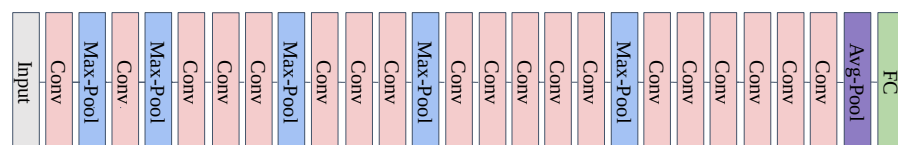
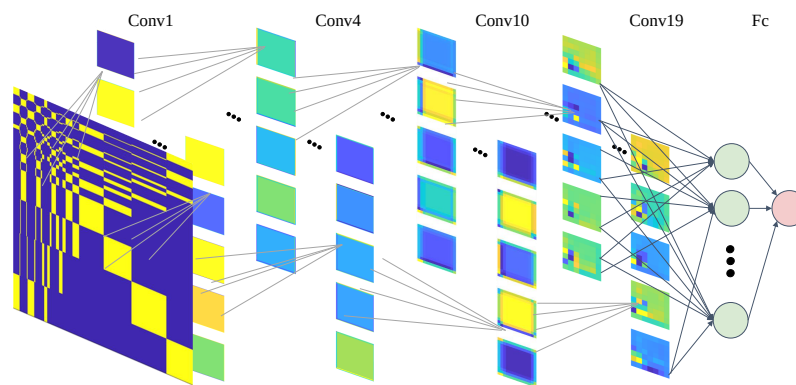


**Figure 2.** The Darknet-19 network model.

**Table 2.** Parameters of the Darknet-19 network structure.

| Layer   | Filters | Size/Stride | Input        | Output       |
|---------|---------|-------------|--------------|--------------|
| 0 conv  | 32      | (3,3)/1     | (256,256,3)  | (256,256,32) |
| 1 max   |         | (2,2)/2     | (256,256,32) | (128,128,32) |
| 2 conv  | 64      | (3,3)/1     | (128,128,32) | (128,128,64) |
| 3 max   |         | (2,2)/2     | (128,128,64) | (64,64,64)   |
| 4 conv  | 128     | (3,3)/1     | (64,64,64)   | (64,64,128)  |
| 5 conv  | 64      | (1,1)/1     | (64,64,128)  | (64,64,64)   |
| 6 conv  | 128     | (3,3)/1     | (64,64,64)   | (64,64,128)  |
| 7 max   |         | (2,2)/2     | (64,64,128)  | (32,32,128)  |
| 8 conv  | 256     | (3,3)/1     | (32,32,128)  | (32,32,256)  |
| 9 conv  | 128     | (1,1)/1     | (32,32,256)  | (32,32,128)  |
| 10 conv | 256     | (3,3)/1     | (32,32,128)  | (32,32,256)  |
| 11 max  |         | (2,2)/2     | (32,32,256)  | (16,16,256)  |
| 12 conv | 512     | (3,3)/1     | (16,16,256)  | (16,16,512)  |
| 13 conv | 256     | (1,1)/1     | (16,16,512)  | (16,16,256)  |
| 14 conv | 512     | (3,3)/1     | (16,16,256)  | (16,16,512)  |
| 15 conv | 256     | (1,1)/1     | (16,16,512)  | (16,16,256)  |
| 16 conv | 512     | (3,3)/1     | (16,16,256)  | (16,16,512)  |
| 17 max  |         | (2,2)/2     | (16,16,512)  | (8,8,512)    |
| 18 conv | 1024    | (3,3)/1     | (8,8,512)    | (8,8,1024)   |
| 19 conv | 512     | (1,1)/1     | (8,8,1024)   | (8,8,512)    |
| 20 conv | 1024    | (3,3)/1     | (8,8,512)    | (8,8,1024)   |
| 21 conv | 512     | (1,1)/1     | (8,8,1024)   | (8,8,512)    |
| 22 conv | 1024    | (3,3)/1     | (8,8,512)    | (8,8,1024)   |
| 23 conv | 1000    | (1,1)/1     | (8,8,1024)   | (8,8,1000)   |
| 24 avg  |         |             | (8,8,1000)   | 1000         |
| 25 fc   |         |             |              | 1            |

Figure 3 demonstrates the process of image feature extraction using Darknet-19. As shown in Figure 3, it is evident that the features extracted from lower layers are relatively elementary. As the network deepens and new layers are added, the receptive field mapped to the input layer expands. The output of the preceding convolutional layer acts as the input for the subsequent convolutional layer, enabling feature accumulation. Consequently, features extracted by later convolutional layers gradually become more sophisticated, equipping the network with enhanced capability to model complex functions and extract robust features.

**Figure 3.** The feature extraction process in Darknet-19.

## 5. Experimental Validation and Analysis

### 5.1. Experimental Simulation Model and Data Sampling

Training deep neural networks necessitates a substantial quantity of samples for iteration. MATLAB/SIMULINK is employed to conduct simulations on various types of faults within the distribution network. The simulated power line operates at a voltage of 10 kV and a frequency of 50 Hz, encompassing pure cable, pure overhead line, and hybrid line configurations with both cable and overhead components, spanning a total length of 10 km.

The zero-sequence and positive-sequence parameters of the overhead line are given in Equation (7).

$$\begin{cases} R_0 = 0.251 \, \Omega/\text{km} & L_0 = 4.560 \times 10^{-3} \, \text{H}/\text{km} \\ C_0 = 0.0056 \times 10^{-6} \, \text{F}/\text{km} & R_1 = 0.178 \, \Omega/\text{km} \\ L_1 = 1.250 \times 10^{-6} \, \text{H}/\text{km} & C_1 = 0.0098 \times 10^{-6} \, \text{F}/\text{km} \end{cases} \quad (7)$$

The zero-sequence and positive-sequence parameters of the cable are shown in Equation (8).

$$\begin{cases} R_0 = 2.850 \, \Omega/\text{km} & L_0 = 1.218 \times 10^{-3} \, \text{H}/\text{km} \\ C_0 = 0.490 \times 10^{-6} \, \text{F}/\text{km}, & R_1 = 0.288 \, \Omega/\text{km} \\ L_1 = 0.266 \times 10^{-6} \, \text{H}/\text{km} & C_1 = 0.538 \times 10^{-6} \, \text{F}/\text{km} \end{cases} \quad (8)$$

Next, on the established simulation model, fault current data are sampled to create a training dataset. The total number of samples is 6000, with fault types set as A, B, and C single-phase grounding faults. The fault angles are  $0^\circ$ ,  $90^\circ$ ,  $180^\circ$ , and  $270^\circ$ , with fault resistance ranging from 1 to  $1500 \, \Omega$ . Five fault points are uniformly distributed along the 10 km distribution network line. Detailed information about the dataset is provided in Table 3.

**Table 3.** Parameters of the training sample dataset.

|                               |                                                      |
|-------------------------------|------------------------------------------------------|
| Fault Types                   | AG, BG, CG                                           |
| Fault Resistance ( $\Omega$ ) | 1–1500                                               |
| Fault Angle                   | $0^\circ$ , $90^\circ$ , $180^\circ$ , $270^\circ$   |
| Line Type                     | Overhead Line, Cable, Overhead Line and Cable Hybrid |
| Size of the Dataset           | 6000                                                 |

Finally, the time-series current data are transformed into a two-dimensional image using MTFs. To reduce the computational load of the MTF, the data from two periods before and after the occurrence of the fault are taken, and the difference in current data between these two periods is used for the MTF transformation. This not only reduces the computational load but also highlights the fault characteristics. Figure 4 shows partial images of the transformation of the distribution network after ground fault occurrence at different distances.

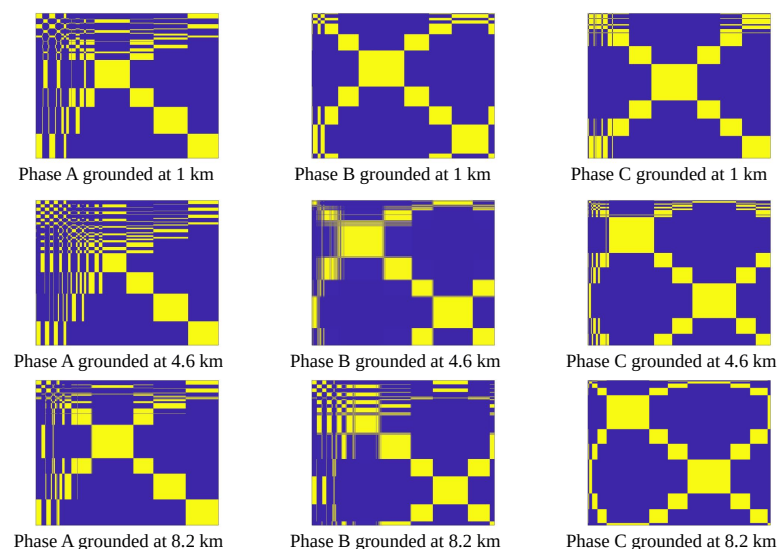


**Figure 4.** MTF images of distribution network ground faults at different distances.

### 5.2. Building a Fault Distance Measurement Model

Based on the solution for the regression problem, it is only necessary to build a single-output Darknet-19 neural network. After the convolution calculation, the Darknet-19 analyzes and calculates the predicted distance through a fully connected layer. In this article, the current signal of the distribution network is first collected, and its phase transformation is performed to obtain the modulus 1 component. Then, the obtained component is used to intercept the data of the current for two cycles before and after the occurrence of the fault. The difference between the current data of these two cycles is used to perform an MTF transformation. First, the Markov matrix is calculated, and then, it is transformed into an MTF. Finally, Darknet-19 is used to predict the fault distance. The model flowchart is shown in Figure 5.

The prepared dataset is imported into the Darknet-19 model for training. The learning rate during training is set to 0.0001, using the mean square error loss function, and the Adam optimizer is used to optimize the gradient descent process. A total of 30 epochs are trained, and the gradient descent process is shown in Figure 6. From Figure 6, it can be observed that the network convergence speed is very fast during the first training iteration. However, as the number of iterations increases, the convergence speed decreases. The training sample loss function and the validation sample loss function gradually approach zero. At the same time, the loss function of the validation sample dataset also gradually decreases in the same trend, indicating that the training model continuously fits the fault distance model without overfitting. Ultimately, a stable, fast, and highly accurate fault distance prediction model is obtained.

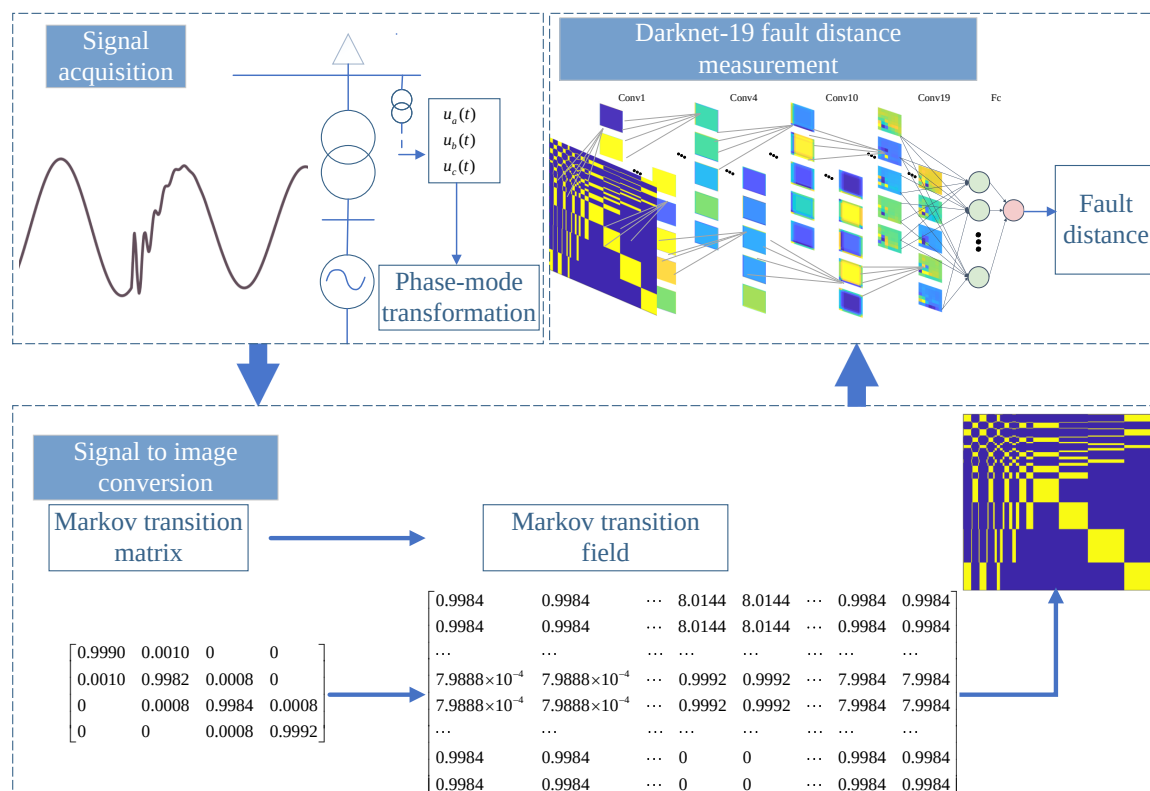


Figure 5. Fault distance measurement process.

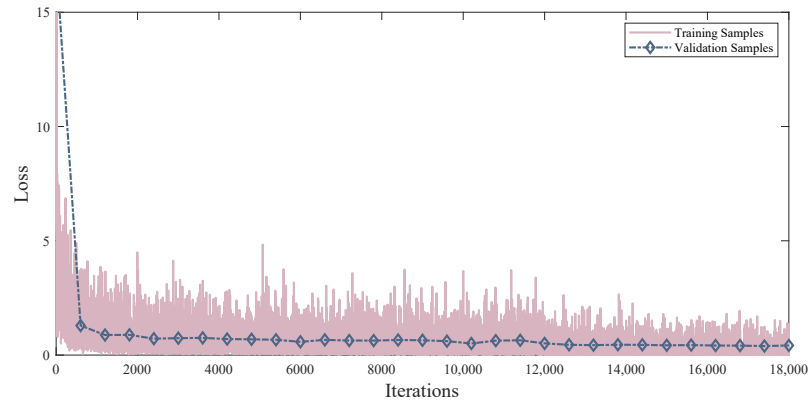


**Figure 6.** Training and validation loss function curves of the Darknet-19 model.

### 5.3. Analysis of Test Sample Results

To verify the experimental results, the fault data were resampled, and the same method was used to convert them into an MTF. The trained neural network was then used for testing, with the results shown in Table 4. From Table 4, it can be seen that the predicted results of the test samples have a relatively high accuracy and a small range of prediction errors. This demonstrates that the method can fully leverage the feature extraction ability of the convolutional neural network to extract fault characteristics from the MTF images, thereby predicting the distance of the fault occurrence and avoiding the issues of detecting the traveling-wave head and predicting traveling-wave speed. Compared to traditional traveling-wave distance measurement methods, this approach has a certain advantage in distance measurement accuracy.

**Table 4.** Prediction results of fault position under different conditions.

| Fault Angle | Fault Types | Fault Distance | PFD <sup>1</sup> | Error   |
|-------------|-------------|----------------|------------------|---------|
| 0°          | AG          | 6.2            | 6.2102           | 0.0102  |
|             |             | 3              | 3.0740           | 0.0740  |
|             |             | 4.5            | 4.5926           | 0.0926  |
| 0°          | BG          | 6.2            | 6.0879           | −0.1121 |
|             |             | 4.5            | 4.4904           | −0.0096 |
| 0°          | CG          | 6.6            | 6.5543           | −0.0457 |
|             |             | 4.5            | 4.4982           | −0.0018 |
| 90°         | AG          | 6.6            | 6.4959           | −0.1041 |
|             |             | 3              | 2.9966           | −0.0034 |
| 90°         | BG          | 1.2            | 1.1788           | −0.0212 |
|             |             | 3              | 3.1047           | 0.1047  |
| 90°         | CG          | 0.9            | 0.9189           | 0.0189  |
|             |             | 1.2            | 1.1343           | −0.0657 |
| 180°        | AG          | 8.3            | 8.3005           | 0.0005  |
|             |             | 1.2            | 1.1008           | −0.0992 |
| 180°        | BG          | 4.5            | 4.6239           | 0.1239  |
|             |             | 1.2            | 1.2005           | 0.0005  |
| 180°        | CG          | 8.3            | 8.3167           | 0.0167  |
|             |             | 3              | 2.8889           | −0.1111 |
| 270°        | AG          | 6.2            | 6.2829           | 0.0829  |
|             |             | 1.2            | 1.4509           | 0.2509  |
| 270°        | BG          | 6.2            | 5.9876           | −0.2124 |
|             |             | 0.9            | 0.9173           | 0.0173  |
| 270°        | CG          | 4.5            | 4.6401           | 0.1401  |

<sup>1</sup> Predicted fault distance. Distance units are kilometers.

Different phasor transformation methods have a significant impact on fault distance estimation. To compare the fault distance estimation performance under different phasor transformation methods, the Clarke transformation, the Schmidt orthogonalization matrix of the new phasor transformation, and the transformation matrix used in this study were selected for comparison. The results in Table 5 show that the fault distance estimation

performance under the Clarke transformation is poor. This is because when phase B of the distribution network is single-phase grounded, the modulus 2 component remains zero according to the Clarke transformation matrix. However, the method used in this study can uniquely identify the fault regardless of the phase in which the fault occurs, thereby having a lower prediction error.

**Table 5.** Fault distance estimation performance under different phasor transformation matrices.

| Fault Types | Fault Distance | Clarke Transformation |         | Proposed Method |         |
|-------------|----------------|-----------------------|---------|-----------------|---------|
|             |                | PFD <sup>1</sup>      | Error   | PFD             | Error   |
| AG          | 0.9            | 1.2354                | 0.3354  | 0.9637          | 0.0637  |
|             | 1.2            | 2.2067                | 1.0067  | 1.0999          | −0.1001 |
|             | 3              | 2.5721                | −0.4279 | 3.0355          | 0.0355  |
|             | 4.5            | 5.1885                | 0.6885  | 4.6337          | 0.1337  |
|             | 6.2            | 6.3321                | 0.1321  | 6.2102          | 0.0102  |
|             | 8              | 6.0578                | −1.9422 | 7.867           | −0.133  |
| BG          | 0.9            | 1.3433                | 0.4433  | 0.9595          | 0.0595  |
|             | 1.2            | 1.9279                | 0.7279  | 1.0321          | −0.1679 |
|             | 3              | 4.5361                | 1.5361  | 2.9007          | −0.0933 |
|             | 4.5            | 3.5951                | −0.9049 | 4.3358          | −0.1642 |
|             | 6.2            | 4.0899                | −2.1101 | 6.0346          | −0.1654 |
|             | 8              | 5.6227                | −2.3773 | 8.3237          | 0.3237  |
| CG          | 0.9            | 2.3222                | 1.4222  | 0.9647          | 0.0647  |
|             | 1.2            | 0.926                 | −0.2704 | 1.3775          | 0.1775  |
|             | 3              | 3.5651                | 0.5651  | 3.0293          | 0.0293  |
|             | 4.5            | 4.6647                | 0.1647  | 4.5468          | 0.0468  |
|             | 6.2            | 5.6867                | −0.5133 | 6.2735          | 0.0735  |
|             | 8              | 6.5404                | −1.4596 | 7.8009          | −0.1991 |

<sup>1</sup> Predicted fault distance. Distance units are kilometers.

In actual distribution network lines, current signals are susceptible to noise interference, and as a result, the prediction results are also affected by the noise. To verify the advantages of the method proposed in this paper, a comparison was made between the MTM and the MTF under four different signal-to-noise ratios (SNRs): 10 dB, 20 dB, 30 dB, and 40 dB. As shown in Table 6, the traveling-wave fault distance estimation method shows unstable performance. The results for samples at different signal-to-noise ratios and different phases and fault distances show significant variations. While the method accurately predicts the distance for samples with an actual fault distance of 1 km, the prediction errors for other samples are large. This is because the traveling-wave fault distance estimation algorithm has strict requirements for various parameters of the actual system. The speed of the traveling-wave front differs for different distribution network line parameters, so the prediction algorithm needs to be modified according to the actual line. Additionally, the method is highly reliant on empirical selection for the detection range and lacks reliable methods for range selection, making the method's conditions for use strict and inflexible, and thus, difficult to effectively apply in practice.

The algorithm transforms the current signal into an MTM and an MTF, and then, uses a neural network for fault distance prediction. Both methods outperform the traveling-wave fault detection method. However, due to the MTF incorporating temporal information under the premise of the MTM, it effectively utilizes sequential signals and exhibits stronger resistance to noise interference. This results in the MTF generally demonstrating lower fault distance prediction errors than the MTM under various degrees of noise impact.

To validate the effectiveness of the method proposed in this paper, we compared it with two other fault location methods. As shown in Table 7, the results obtained using our method exhibit lower errors. This is due to the fact that the method proposed in this paper does not require the detection of the wavefront and wave speed of traveling waves, and it can automatically extract fault features, instead of relying on manual extraction.

**Table 6.** Resistance to interference in fault distance measurement under different methods.

| Fault Types | SNR   | Fault Distance | TW <sup>1</sup>  |         | MTM    |         | MTF    |         |
|-------------|-------|----------------|------------------|---------|--------|---------|--------|---------|
|             |       |                | PFD <sup>2</sup> | Error   | PFD    | Error   | PFD    | Error   |
| AG          | 10 dB | 1              | 0.7352           | −0.2648 | 0.6332 | −0.3668 | 1.7009 | 0.7009  |
|             |       | 6.4            | 1.1259           | −5.2741 | 5.0566 | −1.3434 | 6.7567 | −1.3434 |
|             | 20 dB | 2.8            | 0.6452           | −2.1548 | 3.8229 | 1.0229  | 3.0667 | 1.0229  |
|             |       | 4.6            | 0.733            | −3.867  | 3.917  | −0.683  | 4.4469 | −0.683  |
|             | 30 dB | 1              | 0.9898           | −0.0102 | 1.782  | 0.782   | 0.8517 | 0.782   |
|             |       | 2.8            | 0.6052           | −2.1948 | 3.6214 | 0.8214  | 2.6883 | −0.1117 |
| BG          | 40 dB | 4.6            | 0.6057           | −3.9943 | 4.1397 | −0.4603 | 4.5495 | −0.0505 |
|             |       | 8.2            | 0.8724           | −7.3276 | 7.7062 | −0.4938 | 8.2631 | 0.0631  |
|             | 10 dB | 1              | 0.6716           | −0.3284 | 0.6946 | −0.3054 | 1.4819 | 0.4819  |
|             |       | 6.4            | 0.6386           | −5.7614 | 7.218  | 0.818   | 6.9242 | 0.5242  |
|             | 20 dB | 2.8            | 0.7594           | −2.0406 | 3.6459 | 0.8459  | 2.5137 | −0.2863 |
|             |       | 4.6            | 0.7835           | −3.8165 | 5.3376 | 0.7376  | 4.3951 | −0.2049 |
| CG          | 30 dB | 1              | 1.06             | 0.06    | 1.572  | 0.572   | 0.8517 | −0.1483 |
|             |       | 2.8            | 0.7725           | −2.0275 | 2.475  | −0.325  | 1.966  | −0.834  |
|             | 40 dB | 4.6            | 0.6716           | −3.9284 | 4.8053 | 0.2053  | 4.5233 | −0.0767 |
|             |       | 8.2            | 0.8976           | −7.3024 | 8.3398 | 0.1398  | 8.314  | 0.114   |
|             | 10 dB | 1              | 0.8263           | −0.1737 | 0.7619 | −0.2381 | 2.0776 | 1.0776  |
|             |       | 6.4            | 1.0315           | −5.3685 | 5.4536 | −0.9464 | 7.1384 | 0.7384  |
|             | 20 dB | 2.8            | 0.665            | −2.135  | 3.4514 | 0.6514  | 2.6055 | −0.1945 |
|             |       | 4.6            | 0.9964           | −3.6036 | 3.8594 | −0.7406 | 4.6252 | 0.0252  |
|             | 30 dB | 1              | 0.6979           | −0.3021 | 2.4312 | 1.4312  | 0.9356 | −0.0644 |
|             |       | 2.8            | 0.6863           | −2.1137 | 2.1011 | −0.6989 | 2.9104 | 0.1104  |
|             | 40 dB | 4.6            | 1.0095           | −3.5905 | 4.0632 | −0.5368 | 4.6597 | 0.0597  |
|             |       | 8.2            | 0.9174           | −7.2826 | 4.5419 | −3.6581 | 8.2511 | 0.0511  |

<sup>1</sup> Traveling wave. <sup>2</sup> Predicted fault distance. Distance units are kilometers.

**Table 7.** Results of fault location under three different kinds of methods.

| Fault Types | Fault Distance | Ref. [29] | Ref. [30] | Proposed Method |
|-------------|----------------|-----------|-----------|-----------------|
|             |                | Error     | Error     | Error           |
| AG          | 1.2            | 0.968     | 2.374     | −0.100          |
|             | 3.6            | 1.126     | 1.562     | 0.090           |
| BG          | 5              | 1.413     | 1.827     | 0.274           |
|             | 4.3            | 1.237     | 1.635     | 0.133           |
| CG          | 6.2            | 1.819     | 2.078     | 0.010           |
|             | 2.6            | 1.068     | 1.235     | 0.251           |

Distance units are kilometers.

To validate the practical application value of the proposed method, the trained model was tested on an embedded device. The raw fault current data obtained from the simulation platform were imported into a Raspberry Pi, where they were converted into an MTF. The fault distance prediction was then made using the fault distance estimation method proposed in this paper. The results presented in Table 8 demonstrate that the method exhibits minimal error across various fault angles and ground fault types, indicating its significant practical applicability. The experimental setup is depicted in Figure 7.

**Table 8.** Raspberry Pi device fault prediction results.

| Fault Angle | Fault Types | Fault Distance | Predicted Fault Distance | Error   |
|-------------|-------------|----------------|--------------------------|---------|
| 0           | BG          | 3              | 3.1104                   | −0.1104 |
| 90          | AG          | 8.3            | 8.4258                   | −0.1258 |
| 270         | CG          | 3              | 2.8469                   | 0.1531  |

Distance units are kilometers.

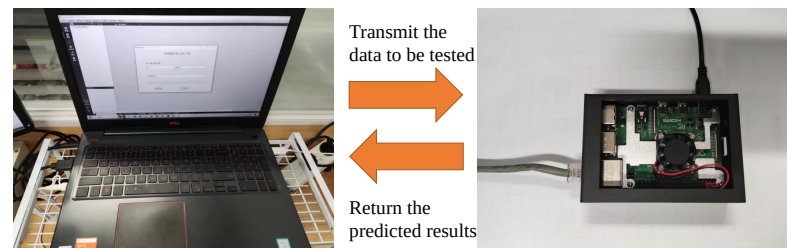


**Figure 7.** Physical simulation of fault distance detection.

## 6. Conclusions

This paper proposes a novel method for accurately and simply predicting the distance of single-phase grounding faults in distribution networks, leveraging the ground regression capability of neural networks and the reliable and anti-interference characteristics of MTF. This study presents a prediction method for single-phase grounding fault distances in distribution networks based on MTF and Darknet-19, and conducts simulation experiments using MATLAB. The final experimental conclusions are validated accordingly.

(1) The new phase-mode transformation matrix can effectively capture all types of fault separately in the distribution network, reflecting both the modulus 1 and modulus 2 components of the fault current. This enables a comprehensive expression of fault features in the sample.

(2) The MTF is capable of effectively extracting the fault features from one-dimensional signals, demonstrating a certain degree of resistance to interference. Furthermore, the visual representation produced can accurately convey the fault information present in the sample.

(3) The fault distance regression model of the Darknet-19 neural network was trained using MTF images. The entire system exhibits strong noise robustness. In simulated verification, the average prediction error is 330 m under a 40 dB noise condition. Additionally, test samples generated by the simulation platform at various distances demonstrate that the constructed regression model can predict labels that were not present during training, indicating its strong generalization ability.

**Author Contributions:** Conceptualization, Y.S., W.G., and H.W.; methodology, W.G.; software, H.W.; validation, W.G. and H.W.; formal analysis, H.W.; investigation, H.W.; resources, Y.S., W.G., and H.W.; data curation, W.G. and H.W.; writing—original draft preparation, H.W.; writing—review and editing, W.G. and H.W.; visualization, H.W.; supervision, H.W.; project administration, Y.S. and H.W.; funding acquisition, Y.S. and W.G. All authors have read and agreed to the published version of the manuscript.

**Funding:** This work was sponsored by the National Natural Science Foundation of China (62373006).

**Data Availability Statement:** The results/data/figures in this manuscript have not been published elsewhere, nor are they under consideration by another publisher.

**Conflicts of Interest:** The authors declare no conflicts of interest.

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