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Research Article

Identification Method of Dynamic Parameters of Distribution Network Lines

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Accurate network parameters are of great importance for the accurate control of the power distribution network (PDN). In fact, the line parameters of the PDN are always affected by external operating conditions. However, most of the line parameters in the PDN account are static parameters. In order to obtain the dynamic parameters that reflect the line operating condition, this study presents a method that uses only the RMS voltage of the first section of the line and the RMS voltage and power at the low-voltage side of the transformer. This study introduces the processing method of abnormal measurement data, constructs a derivative-free identification equation represented by a matrix, and uses the designed loss function combined with a heuristic method to solve the equation. An actual feeder is used in the experimental part. The experimental data show that the method has some antipower noise ability, and the identification accuracy of this method is better than that of the genetic algorithm and random search algorithm.

1. Introduction

The use of distributed generation and user-side energy storage devices leads to changes in PDN operation conditions. Therefore, the state of PDN is required to ensure its safety and stability [1–3]. Accurate line parameters are indispensable for analyzing the state of the distribution network. At each measurement time point, the power flowing through the line and the different meteorological environment will cause different line parameters. The different line parameters at each measurement time point are called dynamic parameters and are also the identification objects of the study. In reality, due to the frequent maintenance and renovation of the PDN and the limited number of real-time measurement device [4], the PDN line resistance and reactance parameters at each measurement time point are difficult to measure. Therefore, when calculating the PDN business, the line nameplate parameters that do not consider the working conditions in the PDN account are often used, which may easily lead to an inaccurate analysis of the distribution network status. Thus, there is an urgent need for a method for identifying line dynamic parameters.

Methods for identifying linear parameters include the formula [5], instrument [6], and digital methods [7]. The formula method greatly idealizes the electromagnetic model and the conversion of the line and does not consider the influence of uncertain factors such as temperature and sag. The instrument and digital methods are offline power outage measurements, and the measurement results are easily affected by the interference of environmental factors and induced voltage [8]; it is difficult to reflect the different working conditions of line parameters. With the proposal and application of SCADA, PMU, and advanced metering infrastructure (AMI), various identification methods suitable for different working conditions have been proposed. Based on customer AMI data, the linear regression parameter estimation (LRPE) method of line parameters and upstream node voltage was established, as well as the layer-by-layer identification of observable lines in the entire network [9]. In [10], a method was proposed to identify the full line parameters of the PDN using the PMU data of the node voltage and branch current and considered the uncertainty of the measurement device and the phase angle error; however, each node is required to install an expensive PMU device. In [11], it establishes the relationship equation between line parameters and node voltage, the first step assumes the initial value of line parameters and substitute it into the equation to obtain the calculated voltage value, the second step calculates the error between the calculated voltage and the measured voltage value of AMI, and the third step uses the "effective set method" to update the parameters according to the error value and finally gets the parameter value. Yang et al. [12] build identification equations with line resistance and reactance on the basis of multiperiod SCADA measurement data and uses the least squares method to solve equations, finally realizing the identification of line parameters in the whole network. The method proposed in [10–12] requires multitime section measurement data for line parameter identification, while the real-time measurement equipment of the PDN is limited, the measurement redundancy is low, and installation of additional measuring devices in distribution networks with multiple load points and supply ranges is impractical. Using weighted least squares estimation (WLS) or weighted least absolute value estimation (WLAV) to identify parameters, approximate convexity of solution space of hypothetical parameter equation is necessary [3]. However, in reality, the identification equation is nonlinear, and it is difficult to satisfy the approximate convexity; therefore, the method is sensitive to the initial value, and the calculation process is easy to converge to an abnormal result; in addition, the parameter calculation process is very time-consuming, and the amount of computation increases exponentially with the increase of the network size. With the rapid development of artificial intelligence technology, research has been conducted on the identification of distribution network parameters using deep learning and machine learning [13, 14]. Researchers use a convolutional neural network to extract long-term massive data for regression calculation of distribution network parameters, considering the problems of lack of measurement devices and deviation of original data of some lines in the distribution network, and the characteristics of line parameters that are invariant in a short period of time. However, the method has accurate RMS and voltage phase angle data, which requires the installation of an expensive PMU.

In summary, the difficulties of PDN line parameter identification can be summarized as follows:

(a) The medium voltage (MV) PDN has many nodes and limited dedicated measurement equipment, and the measurement data may not meet the observability

(b) Because of many bus and branch lines in PDN, it is difficult to establish identification equations

(c) Currently, WLS or WLAN method is a feasible method, but WLS or WLAN method is not satisfactory in accuracy and computational efficiency

Considering the problems (point a to point c), the contributions of this study are as follows (point 1 to point 3):

(1) We identify parameters in case of incomplete high-voltage measurement data and no accurate voltage phase angle

(2) In order to improve the calculation efficiency, this study established the matrix calculation formula of the identification equation

(3) The study uses the TPE method to obtain the relationship between the probability distribution function of the loss function and the dynamic parameters of the line

The working structure of this study is as follows. Section 2.1 introduces the preprocessing method of abnormal measurement data, Section 2.2 introduces the parameter sample generation, Section 2.3 deduces the identification equation, Section 2.4 and 2.5 introduce the solution method of the parameter measurement equation; in Section 3, the test and result in the analysis are carried out by the data of a 10 kV feeder line in actual operation, and Section 4 gives the summary of this study and the prospect of future work.

2. Materials and Methods

During measurement, the power flowing through the line and the different meteorological environment will cause different line parameters. These dynamic parameters are the identification objectives. Because the real dynamic parameters of the line are difficult to know, the study assumes that it follows a certain distribution. In order to avoid the distribution assumption error, the study sets the distribution based on the basic account parameters of the line. With MCMC, parameter samples can be generated effectively. The study uses the sample to perform power flow calculation to obtain the calculated value of the electrical quantity on the low-voltage side of the transformer and calculate the residual (loss function) between the calculated value and the measured value of the electrical quantity at the low-voltage side of the transformer, and finally, with the help of TPE, the parameter samples that optimize the residual equation are obtained and considered as the line dynamic parameters.

This method aims to make limited measurement data in PDN (the voltage of the first section of the feeder U_0 and the active P and reactive Q and voltage amplitudes U at the low-voltage side of the transformer) to identify the line parameters.

The calculation steps of the method are shown in Figure 1.

Step 1: processing the abnormal power measurement data

Step 2: we use the line account data to obtain the initial distribution of the line parameters

Step 3: we generate parameter samples using the Markov chain Monte Carlo method

Step 4: we set the number of iterations of the TPE algorithm

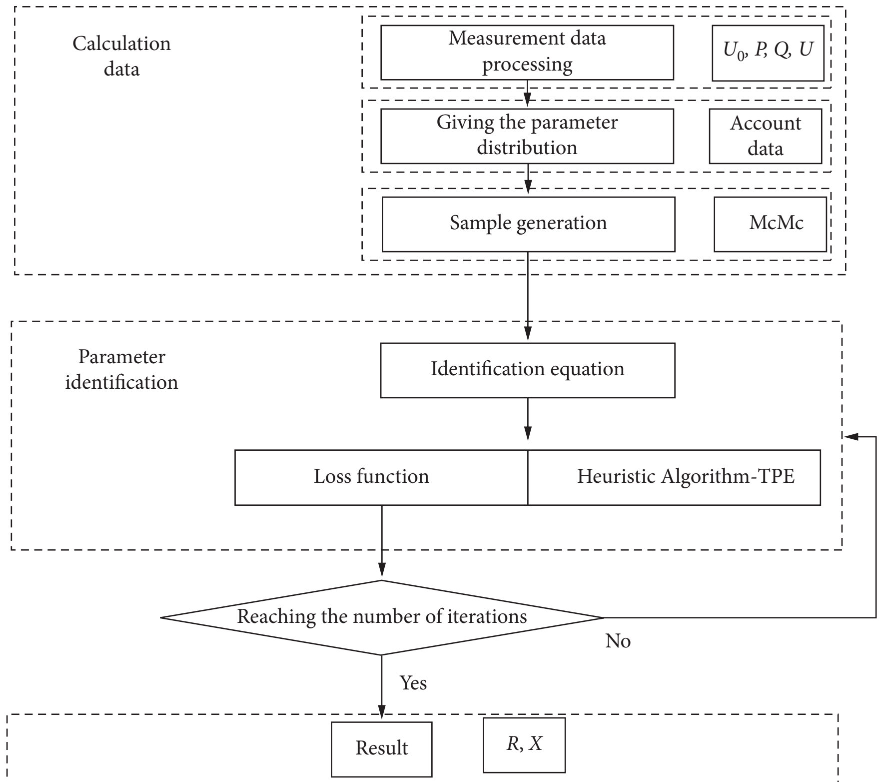

Figure 1: Calculation process.

Step 5: we select the power measurement data of a certain period of time processed in Step 1 and the parameter samples generated in step 3 to calculate the identification equation and obtain the calculated value of the electrical quantity on the low-voltage side of the transformer

Step 6: we calculate the loss function between the calculated value and the measured value of the electrical quantity at the low-voltage side of the transformer

Step 7: TPE uses the loss function value to evaluate the parameter sample, establishes the relationship between the probability density function of the loss function value and the parameter sample, and selects the parameter sample that can make the loss function smaller according to this relationship

Step 8: we output the parameter sample values that make the loss function optimal within the number of iterations and use this parameter sample as the line dynamic parameter at this time

2.1. Research Feeder and Data Processing. This section introduces the measurement conditions required by the method proposed in the study and the processing method of abnormal measurement data. This paper studies an actual 10kV feeder, which has measurement at the low-voltage side of the transformer and first section node measurement, and their measurement cycle is 15 minutes.

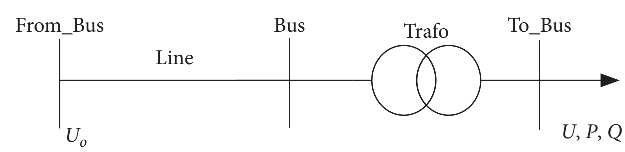

Figure 2: Measurement data source.

As shown in Figure 2, there is the measurement at the low-voltage side of the transformer to obtain power P, Q, and voltage U data. There is the first section node at the high-voltage side of the transformer measures to obtain the first section voltage data U_o, and the middle bus does not have any measurement equipment.

Equipment maintenance, grid interconnection switch action, line transformation, user access, and exit will cause abnormal power data on the user side, which is easy to cause slow convergence of power flow calculation and large error in calculation results. Therefore, it is necessary to preprocess measurement data to eliminate and correct abnormal values. See formula (1), for specific methods as follows:

$$\begin{cases} d = \left|\dfrac{x_{t-1} - x_t}{x_{t-1}}\right|, \\ \\ x_m = \dfrac{1}{n}\displaystyle\sum_{t=1}^{n} x_t, \end{cases} \tag{1}$$

where x_t is measurement data, t is the time point, n is the number of time points for calculation, and d is the data

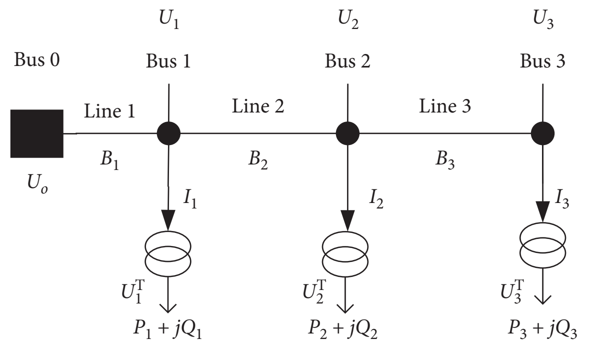

Figure 3: Computational model.

change rate. When the data change rate at a certain time point t is $d \geq 0.8$ or $d = 0$ [15], it is considered that the data at the time point t are abnormal; then, the data at the time point t will be discarded and reselected x_m (the average value of this time data) as the data at the time point t for the calculation.

2.2. Parameter Sample Generation. Because the real dynamic parameters of the line are difficult to know, this study assumes that it follows a certain distribution. In order to avoid the distribution assumption error, this study sets the distribution based on the basic account parameters of the line. The MCMC algorithm generates a large number of line parameter samples. Samples are brought into the calculation of the identification equation. The loss function and heuristic search algorithm use the calculation results to construct a probabilistic model of the parameters, obtain the statistical properties of the parameters, and finally estimate the best parameters. Assuming R, X conform to $\pi(x)$ distribution. In order to obtain parameter samples [16], this study defines the recommended distribution $p(x)$ and acceptance distribution $\alpha(x)$ satisfying equation (3) as follows:

$$\begin{cases} p(R, X \longrightarrow R^*, X^*) = p(R^*, X^* \longrightarrow R, X), \\ \alpha(R, X \longrightarrow R^*, X^*) = \min\left(1, \dfrac{\pi(R^*, X^*)p(R^*, X^* \longrightarrow R, X)}{\pi(R, X)p(R, X \longrightarrow R^*, X^*)}\right), \end{cases} \tag{2}$$

where $p(R, X \longrightarrow R^*, X^*)$ it represents the probability of parameter R, X transfer to the parameter R^*, X^* and $\alpha(R, X \longrightarrow R^*, X^*)$ it represents the probability of acceptance of parameter R, X transfer to the parameter R^*, X^*.

When sampling, first, we select randomly an initial value R, X and set the sampling times. Then, we select a parameter value R^*, X^* randomly from $p(x)$ in each time and calculate $\alpha(R, X \longrightarrow R^*, X^*)$ at the same time. Then, a number χ is randomly selected from the uniform distribution $U(0, 1)$. If $\alpha(R, X \longrightarrow R^*, X^*)$ is greater than χ, this parameter is accepted than carrying out the state transition of the Markov chain at the same time. Finally, we select the sample after the transition times reach a large enough number for calculation.

2.3. Constructing Identification Equation. In this section, a four-node network is used to introduce the construction of the identification equation. To simplify the computation, the three phases are assumed to be balanced as the premise for calculating the power flow in this paper. First, the transformer branch is equivalent to the node injection current by using the voltage drop principle [17]. Second, the equations with line parameters, node voltage, and node injection current are established by using the KCL and KVL principles [17]. Finally, the equations are matrixed as the measurement equation.

Considering that the PDN line is a short line with a low-voltage level, the charging capacitance of the line is ignored [17], the transformer model is the adopted Γ model, and the power flow calculation model is shown in Figure 3.

Bus 1 transformer adopts Γ model. In the low-voltage side of the transformer, power data P_1, Q_1 and voltage data U_1^{T} can be obtained. According to the voltage drop principle, the node injection current I_1 can be obtained [18, 19] as follows:

$$\begin{aligned} I_1 &= \alpha\left(\mathrm{Re} I_1 U_1^T + j \,\mathrm{Im}\, I_1 U_1^T\right), \\ &= \alpha\left(\frac{P_i + jQ_i}{U_1^T}\right)^*, \end{aligned} \tag{3}$$

where P_1 is customer active power, Q_1 is customer reactive power, U_1^{T} is the customer voltage, U_1 is the voltage of node 1, and α is the transformation ratio.

According to the KCL and KVL principles, the relationship of voltage loss between nodes, node injection current, and identification parameters can be established as follows:

$$\begin{cases} U_0 - U_1 = (R_1 + jX_1)(I_1 + I_2 + I_3), \\ U_0 - U_2 = (R_1 + jX_1)(I_1 + I_2 + I_3) + (R_2 + jX_2)(I_2 + I_3), \\ U_0 - U_3 = (R_1 + jX_1)(I_1 + I_2 + I_3) + (R_2 + jX_2)(I_2 + I_3) + (R_3 + jX_3)I_3, \end{cases} \tag{4}$$

where R_1, X_1 represent the resistance and reactance parameters of line 1, R_2, X_2 represent the resistance and reactance parameters of line 2, and I_1, I_2, I_3 represent the node injection current of nodes 1, 2, and 3.

Formula (4) can be transformed into matrix form as follows:

$$\begin{bmatrix} U_0 \\ U_0 \\ U_0 \end{bmatrix} - \begin{bmatrix} U_1 \\ U_2 \\ U_3 \end{bmatrix} = \begin{bmatrix} R_{01} + jX_{01} & 0 & 0 \\ R_{01} + jX_{01} & R_{12} + jX_{12} & 0 \\ R_{01} + jX_{01} & R_{12} + jX_{12} & R_{23} + jX_{23} \end{bmatrix} \begin{bmatrix} I_1 + I_2 + I_3 \\ I_2 + I_3 \\ I_3 \end{bmatrix}, \tag{5}$$

where R_{01}, X_{01} represent the line resistance and reactance parameters between node 0 and node 1, R_{12}, X_{12} represent the sum of line resistance and reactance parameters between node 1 and node 2 and R_{23}, X_{23} represent the sum of line resistance and reactance parameters between node 2 and node 3;

Furthermore, the impedance matrix and node injection current matrix can be simplified as follows:

$$\begin{gathered} \begin{bmatrix} B_1 \\ B_2 \\ B_3 \end{bmatrix} = \begin{bmatrix} I_1 + I_2 + I_3 \\ I_2 \\ I_3 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} I_1 \\ I_2 \\ I_3 \end{bmatrix} = [B][I], \\ \begin{bmatrix} R_{01} + jX_{01} & 0 & 0 \\ R_{01} + jX_{01} & R_{12} + jX_{12} & 0 \\ R_{01} + jX_{01} & R_{12} + jX_{12} & R_{23} + jX_{23} \end{bmatrix} = \begin{bmatrix} Z_{01} & 0 & 0 \\ Z_{01} & Z_{12} & 0 \\ Z_{01} & Z_{12} & Z_{23} \end{bmatrix} = [Z]. \end{gathered} \tag{6}$$

The final identification equation can be written as follows:

$$\begin{gathered} I_i^k = \alpha\left(\mathrm{Re} I_i^k\left(\left(U^T\right)_i^k\right) + j\,\mathrm{Im}\, I_i^k\left(\left(U^T\right)_i^k\right)\right) = \alpha\left(\frac{P_i + jQ_i}{\left(U^T\right)_i^k}\right)^*, \\ [\Delta\mathbf{U}] = [\mathbf{Z}][\mathbf{B}][\mathbf{I}], \\ [\mathbf{U}k + 1] = [\mathbf{U_0}] + [\Delta\mathbf{U}k + 1], \end{gathered} \tag{7}$$

where U_i^k, I_i^k, and U_0 are, respectively, the node voltage, the node injection current, and the initial value of the voltage calculation at the first iteration and $\mathrm{Re}I_i^k$ and $\mathrm{Im}I_i^k$ are, respectively, the real and imaginary parts of the node injection current at the first iteration. The relationship matrix [**B**] between [**Z**] and [**I**] refers to [18].

2.4. Loss Function. In this study, the probability density of the loss function is used to describe the domain space of parameters, so its design core should reflect the real distribution of parameters. The design principles are as follows [3]:

(1) Under the two strong constraints of voltage and current, the relationship between them and parameters is used to construct as many small parts as possible. The more irrelevant small parts, the more the value of the loss function can approach the real distribution of parameters.

(2) The identification parameters are resistance and reactance. When the current passes through the resistance and reactance, not only the voltage changes but also the phase changes. Therefore, the

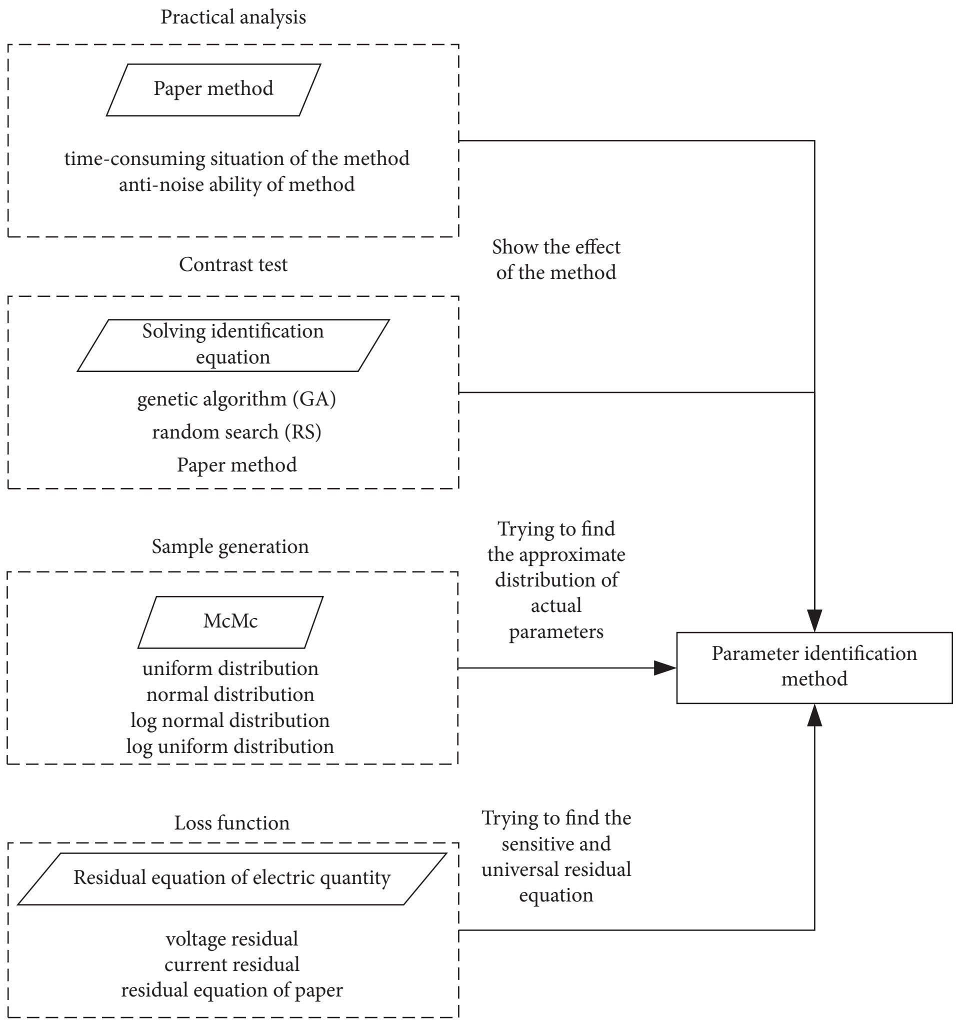

Figure 4: The schematic diagram of this study's experiment.

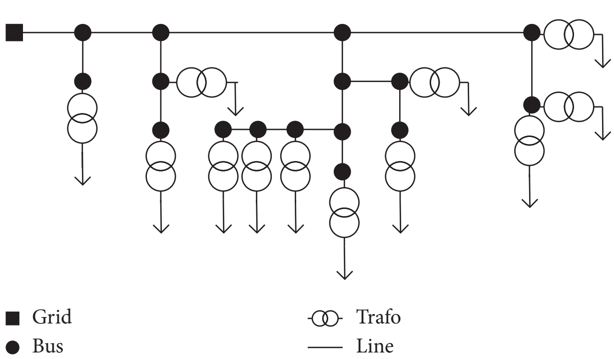

Figure 5: 10 kV feeder topology.

Table 2: Transformer information.

Name	Type	Number	Uk (%)	Pk (kw)	*P*0 (kw)	*I*0 (%)
Transformer	S11-M-400/10	12	4	0.081	0.57	0.8

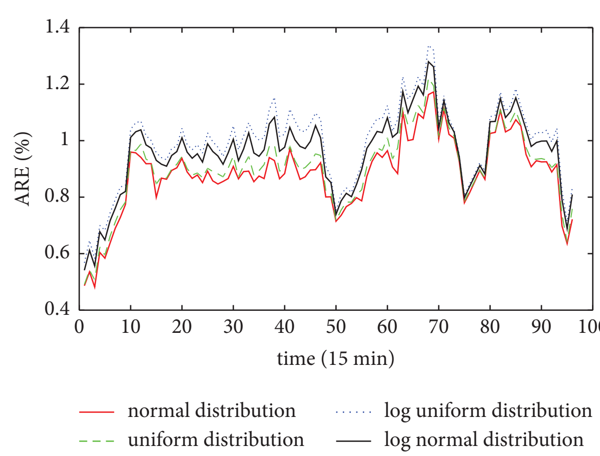

Figure 6: ARE of voltage under different distributions.

Table 1: Line information.

Name	Type	Number	R (Ω/km)	X (Ω/km)
Line	JKLYJ-240	16	0.160	0.281

Table 3: Based on different loss functions, the results of parameter identification.

Name	Mean of ARE	Variance of ARE
Paper	0.38561	0.01272
Voltage residuals	0.44134	0.01331
Current residuals	0.44846	0.01345
Power residuals	0.44561	0.01376
Voltage-MAE	0.43412	0.01502
Voltage-RMSE	0.43453	0.01543
Voltage-MAPE	0.43467	0.01572

value of the loss function should reflect the changes in voltage and phase.

To sum up, the following loss function formula is established:

$$y=\sum_{m=1}^{n}\left(\left|\widehat{U_{m,t}}-U_{m,t}\right|+\left|\frac{\sqrt{P_{m,t}^2+Q_{m,t}^2}}{\widehat{U_{m,t}}}-\frac{\sqrt{P_{m,t}^2+Q_{m,t}^2}}{U_{m,t}}\right|+\left|\widehat{U_{m,t}}\times\frac{\sqrt{P_{m,t}^2+Q_{m,t}^2}}{\widehat{U_{m,s}}}-\sqrt{P_{m,t}^2+Q_{m,t}^2}\right|\right), \tag{8}$$

where t is the time point, m is the node number, $\widehat{U_{m,t}}$ is calculated by the identified parameter, and $P_{m,t}$ and $Q_{m,t}$ are the power measurement at the low-voltage side of m node transformer at the t time. The first part of the loss function is the voltage residual, the second part is the current residual, and the third part is the apparent power residual.

2.5. Solving the Identification Equation. The tree structure estimation method is an intelligent algorithm designed based on the Bayesian optimization framework. In the process of parameter optimization, the probability density of the proxy function is used to describe the domain space of parameters [19–21]. In this study, the loss function is used as the proxy function, and the identification parameters are selected by referring to the historical result evaluation of the loss function.

First, two distributions in equation (9) are generated according to the calculation results of the loss function as follows:

$$p(x|y)=\begin{cases}\ell(x), & \text{if } y<y^*,\\ g(x), & \text{if } y\geq y^*,\end{cases} \tag{9}$$

where y is the value of the loss function, $\ell(x)$ and $g(x)$ is the probability density function, and x is the identification parameters.

Second, a part of the parameter sample is selected randomly for calculating the value of the loss function, and the quantile γ of this value of the loss function is taken as y^* that $p(y<y^*)=\gamma$; then, we construct probability density function $p(x)$ as

$$p(x)=\int_R p(x|y)p(y)\mathrm{d}y=\gamma\ell(x)+(1-\gamma)g(x). \tag{10}$$

Combined with the Bayesian theorem, the parameter is expected to be defined as follows:

$$\begin{cases}E_{y^*}(x)=\displaystyle\int_{-\infty}^{y^*}(y^*-y)p(y|x)\,\mathrm{d}y=\int_{-\infty}^{y^*}(y^*-y)\frac{p(x|y)p(y)}{p(x)}\mathrm{d}y,\\[2ex] =\dfrac{\gamma y^*\ell(x)-\ell(x)\int_{-\infty}^{y^*}p(y)\mathrm{d}y}{\gamma\ell(x)+(1-\gamma)g(x)}\propto\left(\gamma+\dfrac{g(x)}{\ell(x)}(1-\gamma)\right)^{-1},\end{cases} \tag{11}$$

where $\ell(x)$ is the probability that the parameter makes the loss function converge, $g(x)$ is the probability that the parameter makes the loss function not converge, and finally, we select the sample of largest $E_{y^*}(x)$ as the identification parameter.

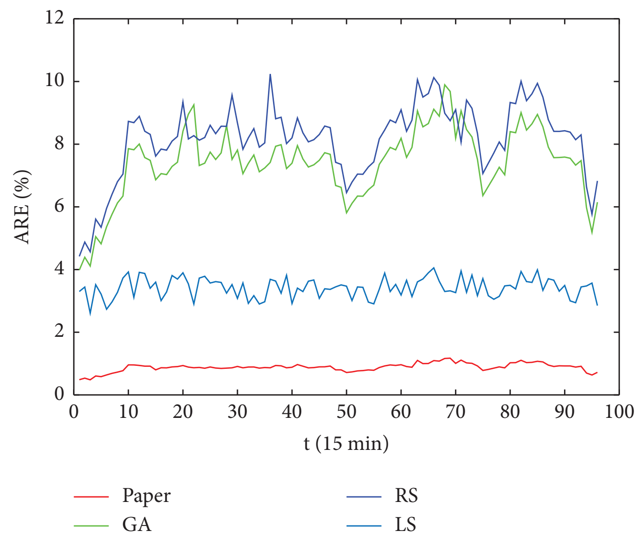

Figure 7: ARE of voltage under different algorithms.

3. Experiment

In this section, this study has carried out four works. These works are displayed in Figure 4.

3.1. Preparation. A 10 kV feeder in actual operation is used for calculation. The feeder includes 12 distribution transformers and 16 liners. The experiment selects the smart meter measurement on June 11, 2020. The measurement frequency of the data is 15 minutes. The topology of the feeder is shown in Figure 5.

The static parameters of the 10 kV feeder network are shown in Tables 1 and 2.

3.2. Error Index. Yang et al. [22] select average relative error (ARE) to represent the final identification result. ARE is calculated as follows:

$$E_{\mathrm{ARE}} = \left| \frac{g_i - g_i^*}{n g_i} \right| \times 100\%, \tag{12}$$

where g_i is electrical quantity measured at the measurement time, g_i^* is electrical quantity calculated by the identification parameters, and n is the number of nodes participating in the calculation.

3.3. Comparison of Identification Effects of Different Parameter Distributions. The real dynamic parameters of the line are unknown, so paper studies the identification effect of different distributions under the same loss function to find the approximate distribution of dynamic parameters. The parameters distribution is selected as uniform distribution $U(a,b)$, normal distribution $N(\mu,\delta^2)$, log normal distribution $\ln X \sim N(\mu,\delta^2)$, and log uniform distribution $\ln X \sim U(a,b)$, and the test is carried out when the loss function is formula (8).

The formulas of $U(a,b)$, $\ln X \sim U(a,b)$, $N(\mu,\delta^2)$, and $\ln X \sim N(\mu,\delta^2)$ are as follows:

$$\begin{gathered}
\begin{cases} U\left(\alpha R_j, \beta R_j\right), \\ U\left(\alpha X_j, \beta X_j\right), \end{cases} \\
\begin{cases} \ln R_j \sim U\left(\alpha R_j, \beta R_j\right), \\ \ln X_j \sim U\left(\alpha X_j, \beta X_j\right), \end{cases} \\
\begin{cases} N\left(R_j, \left(\dfrac{0.2R_j}{3}\right)^2\right), \\ N\left(X_j, \left(\dfrac{0.2X_j}{3}\right)^2\right), \end{cases} \\
\begin{cases} \ln R_j \sim N\left(R_j, \left(\dfrac{0.2R_j}{3}\right)^2\right), \\ \ln X_j \sim N\left(X_j, \left(\dfrac{0.2R_j}{3}\right)^2\right), \end{cases}
\end{gathered} \tag{13}$$

where R_j, X_j are the resistance value and reactance value of the line account. The range coefficient $\alpha, \beta\,(0 < \alpha < \beta < 2)$ is introduced to describe the distribution. This test adopts the range coefficient $\alpha = 0.9, \beta = 1.2$. The range coefficient considers that the parameters of the line are difficult to jump to twice the original value under the influence of temperature changes and voltage fluctuations.

The test results are shown in Figure 6.

When using the same loss function calculation, compared with the other three distributions, the ARE of voltage of the normal distribution is minimum. To sum up, a conclusion can be drawn: when the normal distribution is used as the prior distribution of parameters, the method is easy to obtain the true parameters. It can also be said that the dynamic parameter distribution is approximately a normal distribution, in the experiments of this study.

3.4. Comparison of Identification Effects of Different Loss Functions. The loss function is used to show the degree of error between the identified parameters and the actual parameters. The loss function is usually defined as the mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE) of the voltage residuals. In order to study the sensitive and universal loss

Table 4: Analysis of algorithm time consumption.

Number of iterations	Sampling method	Time consuming (s)	ARE (%)
100	MCMC	6	0.28852
	ARS	5	1.02385
	IS	9	1.25487
300	MCMC	17	0.28851
	ARS	15	0.98574
	IS	19	1.30481
500	MCMC	32	0.28848
	ARS	29	0.90612
	IS	35	1.40632
1000	MCMC	91	0.28711
	ARS	89	1.31701
	IS	108	1.57410

Table 5: Antinoise ability of algorithm (power noise).

Deviation degree of power data (%)	Number of iterations	Paper-ARE (%)	MED-ARE (%)	MOD-ARE (%)
1	100	0.69387	1.22081	1.23082
	300	0.69386	1.19965	1.19875
	500	0.69383	1.10859	1.10726
5	100	0.69503	1.28252	1.25752
	300	0.69499	1.12634	1.15431
	500	0.69498	1.10895	1.14653
10	100	0.69650	1.25390	1.33434
	300	0.69643	1.24331	1.28371
	500	0.69640	1.23499	1.26499

Table 6: Antinoise ability of algorithm (voltage noise).

Deviation degree of power data (%)	Number of iterations	Paper-ARE (%)	MED-ARE (%)	MOD-ARE (%)
1	100	0.81963	1.72542	1.79021
	300	0.81963	1.63435	1.78451
	500	0.81960	1.57203	1.57320
5	100	1.29378	2.20715	2.25094
	300	1.29379	1.92614	1.77916
	500	1.29376	1.89130	1.59404
10	100	1.88657	2.84408	2.80231
	300	1.88654	2.43342	2.30830
	500	1.88658	2.16506	2.02845

function, the normal distribution is taken as the parameter distribution, and six experimental scenarios are constructed with formula (7) and formulas (14)–(19) [23], as the loss function for parameter identification. Equations (14)–(19) are the voltage residuals, current residuals, and power residuals, respectively, and equations (17)–(19) are the mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE) of the discriminated and actual quantities, respectively:

$$y = \sum_{m=1}^{n} \left|\widehat{U_{m,t}} - U_{m,t}\right|, \tag{14}$$

$$y = \sum_{m=1}^{n} \left|\frac{\sqrt{P_{m,t}^2 + Q_{m,t}^2}}{\widehat{U_{m,t}}} - \frac{\sqrt{P_{m,t}^2 + Q_{m,t}^2}}{U_{m,t}}\right|, \tag{15}$$

$$y = \sum_{m=1}^{n} \left|\widehat{U_{m,t}} \times \frac{\sqrt{P_{m,t}^2 + Q_{m,t}^2}}{\widehat{U_{m,s}}} - \sqrt{P_{m,t}^2 + Q_{m,t}^2}\right|, \tag{16}$$

$$y = \frac{1}{n} \sum_{m=1}^{n} \left|\widehat{U_{m,t}} - U_{m,t}\right|, \tag{17}$$

$$y = \sqrt{\frac{1}{n} \sum_{m=1}^{n} \left(\widehat{U_{m,t}} - U_{m,t}\right)^2}, \tag{18}$$

$$y = \frac{100\%}{n} \sum_{m=1}^{n} \left|\frac{\widehat{U_{m,t}} - U_{m,t}}{U_{m,t}}\right|. \tag{19}$$

To avoid the impact of randomness, each method is repeated 25 times to guarantee the correctness and stability of the results.

Two main points can be found in Table 3. The first point is that the performance of parameter identification based on the proposed loss function is all better than that based on a single residual, which indicates the validity and reasonableness of the loss function defined in this study. The second point is that there is no significant difference in performance between the residual functions; the result reflects that the choice of metric with only a single residual function is not optimal, and it is the combined metric of these residual functions that is important. Taking the method in this study as an example, the loss function is combined with several residual functions, and it is found to have a low error after several calculations, indicating the reasonableness of the combined residual function metric.

3.5. Comparison of Identification Results of Different Identification Algorithms. In order to show the identification effect of the parameter identification model, this study model is compared with the genetic algorithm (GA), random search (RS), and least squares estimation (LS). The parameter distribution of the method adopts normal distribution, and the loss function adopts formula (8); GA and RS are optimized equation (8) under the standard model [23]. The results are shown in Figure 7.

It can be seen from the above results that the GA method, RS method, and LS method have poor results in solving the high-dimensional loss function under the standard model. ARE of the GA method, RS method, and LS method are between 4% and 10%; ARE of study is less than 2% and steady; it shows that it is feasible to use the relationship between the probability distribution function of the loss function and the dynamic parameters of the line to identify the dynamic parameters.

3.6. Calculation Time-Consuming Analysis. The identification method in this study includes parameter sample sampling, power flow calculation, and updating parameter distribution. This study has many branch lines in the distribution network, and the speed of line sample generation has a great impact on the identification efficiency. Therefore, based on the data of a measurement time on June 11, 2020, the time-consuming analysis of different iteration times and different sampling algorithms is carried out. The sampling algorithms for contrast are importance-sampling (IS) and acceptance-rejection sampling (ARS) [24]. The distribution adopts normal distribution, the loss function adopts formula (11), and the experimental environment is (CPU-i5-10500, 16 GB RAM). The results are shown in Table 4.

It can be seen that the rejection sampling method takes less time but has a large error, and the importance-sampling method takes more time and has a large error. It can also be seen that the increase in the number of iterations has little effect on the time consumption of the thesis method, and the time consumption of the thesis method is much smaller than the measurement period of the distribution network (15 minutes). On the contrary, the average relative error for a different number of iterations is analyzed, and it is found that the loss function can converge within a limited number of iterations, suggesting that the method is easy to converge.

3.7. Antinoise Capability Analysis. In this study, the low-voltage measured data and the low-voltage data obtained by the power flow calculation are used to construct the loss function to guide the updating and improvement of the parameter distribution. However, there are certain errors in the measured data of the actual distribution network, and there may be real-time problems in the measured results of SCADA and AMI. These problems can cause data anomalies and data noise. The load shows a cyclic pattern of variation on different time scales, so there are few abrupt power changes; therefore, this study proposes a method to determine abnormal data and replace the abnormal value with the mean value, comparing it with the commonly used median-replacement (MED) and mode-replacement (MOD) [25]. In addition, considering the influence of measurement data noise, this study adds power noise and voltage noise to the measurement data based on the data at a measurement time on June 10, 2020, and verifies the antinoise performance of the model. It is explained here that the measurement data noise in this study is constructed by multiplying the measured values of voltage and power by the data deviation degree (positive number), and in order to test the model identification ability, it is assumed that there is noise at all load points. The results are shown in Tables 5 and 6.

The tests show that the anomalous data substitution method proposed in this study can improve the calculation accuracy compared with the traditional method, and the antivoltage noise ability of this method is weaker than the antipower noise ability because the loss function uses the calculation formula composed of the measured voltage value and the calculated value to guide the updating of the parameter distribution, and the voltage noise has a great impact on the model. However, with the reduction of measurement noise, the identification accuracy of the method increases. When the measurement noise gradually increases, the average relative error value is stable, and when the equivalent measurement noise reaches 10%, the average relative error of the method is about 1.8%. Therefore, the method has certain applicability in the environment without measurement noise and the environment with measurement noise of a certain extent.

4. Conclusion

In this study, the identification method of dynamic parameters of distribution network lines is proposed. Based on the experimental results, the following conclusions can be drawn: (1) when the same loss function is used, ARE of the normal distribution is less than 1.4%, so the normal distribution is more suitable for the initial distribution of parameters, (2) when the distribution of line parameters is fixed, the more small parts of the loss function, the better the effect of parameter identification, and (3) under the same iteration times, the antipower noise ability of the method is better than the antivoltage noise ability. However, the existing research work only carries out parameter identification when the topology is known. So, the next step will focus on parameter correlation analysis, joint identification of topology, and parameters of the PDN.

Data Availability

The data used to support the findings of this study are currently under embargo while the research findings are commercialized and can be obtained from the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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