IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received May 16, 2021, accepted June 17, 2021, date of publication June 29, 2021, date of current version July 30, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3093310

Parameter Identification for a Power Distribution Network Based on MCMC Algorithm

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This work was supported by State Grid Jiangsu Electric Power Company Ltd., under Grant J2020097.

ABSTRACT The calculation and analysis of a power distribution network (PDN) require accurate device parameters. However, a PDN has many points, and the distribution area is very wide. The PDN parameters are influenced by manual entry, and most are relatively random. Additionally, these parameters are affected by the operating status. Thus, this paper proposes an algorithm that accurately identifies PDN parameters based on the Markov chain and Monte Carlo (MCMC) method. The algorithm assumes that the PDN parameters conform to a nonlinear probability space. The parameters are the line resistance R_L, line reactance X_L, short-circuit loss P_k, short-circuit voltage percentage $U_k\%$, no-load loss P_0, no-load current percentage $I_0\%$, etc. The algorithm in this paper uses the Monte Carlo method to provide parameter values that conform to the initial probability distribution and then combines the data collected from the actual feeder to perform power flow calculations to obtain the loss function. The data include the head and end voltages and active and reactive power on the low voltage side. The Markov chain and loss function update the initial parameter probability distribution. The low voltage side voltage of the power flow calculation is iteratively calculated under the new given parameters to obtain the new loss function, and finally, the PDN line and transformer parameter values are identified. Actual feeder data verification results show that this MCMC PDN parameter identification method can obtain high-precision parameter values without phase angle information; additionally, this method is insensitive to the initial values and exhibits fast convergence.

INDEX TERMS Distribution network, parameter identification, Markov chain and Monte Carlo, power flow calculation, posterior probability distribution.

I. INTRODUCTION

With increasing power grid construction and economic development, the scale of China's distribution network has gradually expanded, and the power network structure has increased in complexity. In recent years, with the increasing access to distributed generation and new energy vehicles, distribution network operation has also increased in complexity. Therefore, it is necessary to effectively control distribution networks to ensure the security and stability of power systems. Reliable and accurate power network parameters are the basis of the security analysis, control, state estimation, line loss calculation, power flow calculation, protection setting and fault analysis of a power distribution network (PDN). However, most of the distribution network parameters in the current power grid database are static parameters usually provided by the manufacturers. The methods used to obtain these parameters do not take into account the impacts of power grid operation and environmental conditions, and the parameters do not reflect the real-time operation status of electric equipment, results in poor parameter calculations for the distribution network. A distribution network is composed of distribution transformers and lines. At present, the identification methods for the parameters of the transmission lines and transformers are as follows: the theoretical formula calculation method based on the self-geometric spacing method, where the mutual geometric spacing of the conductors and the manufacturing materials of the conductors are combined with the weather, temperature and other external conditions [1], [2], and the identification method based on field measurements of the voltage, current, power, frequency and other network parameters using electrical instruments. With the popularization and application of the supervisory control and data acquisition (SCADA) method, the power

The associate editor coordinating the review of this manuscript and approving it for publication was Fabio Massaro.

management unit (PMU) method and the advanced metering infrastructure (AMI) method, some new identification methods have also been proposed [3]–[9], such as the least squares method, the improved weighted least squares method, the residual method, the sensitivity analysis method and the Lagrange multiplier method [10].

However, the above methods have the following issues. These methods require data regarding the voltage, current, active power and reactive power on the high and low voltage sides, which is constrained by the lack of real-time measurement equipment in a distribution network. The premise of the least squares method assumes that the parameter space is convex and that the default local extremum is the global extremum; hence, this method is sensitive to the initial values of the nonconvex parameters, and the calculations do not easily converge. The experimental data come from a single device and are not obtained from actual production, and the practicability of the above methods need to be discussed. Moreover, the solution time of the parameter calculations is long and increases exponentially with an increasing amount of data. A distribution network covers a large area, and the measurement conditions are not as good as those of the main network. In addition, many differences exist between the topology structure, line impedance characteristics and transmission network [8]. Therefore, the parameter identification methods of the transmission network may not be suitable for the calculation of the PDN parameters. With the rapid development of artificial intelligence technology, some researchers have developed PDN parameter identification methods based on deep learning and machine learning [11]–[14]. Artificial intelligence methods consider the fact that PDN measurement devices lack parts of the original data of the line and exhibit some deviations. According to the time invariant characteristics of PDN line parameters in a short time, a convolutional neural network (CNN) extracts a large amount of data for regression calculations. These methods are proven to be effective with simulation data, but only part of the parameters can be obtained, and the precise voltage and voltage phase angle have to be obtained. The Monte Carlo method (a statistical simulation method) solves these problems with a large number of random simulations. When the problem be solved is based on the probability of the occurrence of a certain random event, according to the means of random trials, this method takes the frequency of the occurrence of the event as the probability of the random event; thereby, the numerical characteristics of a certain random variable are obtained and then taken as the solution of the problem [15]. The Monte Carlo method requires a probability distribution consistent with the actual conditions. That is, we need to determine the actual conditions to obtain the probability distribution consistent with the real situation. According to the ergodic theorem of the Markov chain, an initial random value can quickly converge to the same stationary distribution through the Markov process. The Markov chain method can also make up for the fact that the Monte Carlo method can only statically simulate the experiment, and the convergence speed of the Markov chain is fast when facing multiple high-dimension random variables [16].

The parameters of the PDN lines, R_L, X_L, and transformers, $P_k, U_k\%, P_0, I_0\%$, do not meet the convex function requirements of the optimal iterative solution in a certain range. In this paper, we assume that the PDN parameters conform to the nonlinear relationship in the probability space, set the random distribution of the distribution network parameters, and obtain the random values of the parameters by using the Monte Carlo method. Under the given distribution network parameters, the voltage on the low voltage side is completely calculated with the power flow calculation, and then the deviation between the measured voltage and the calculated voltage on the low voltage side of the actual feeder is calculated with the constraint function. Finally, the probability distribution of the assumed distribution network parameters can be updated by the state transition probability of the Markov chain (the change in the parameters is dynamically simulated by the Markov process), and the optimal solution of the distribution network dynamic parameters can be obtained after iteration.

In conclusion, an accurate identification method for the PDN parameters based on the Markov chain and Monte Carlo (MCMC) algorithm is proposed. First, we assume that the distribution network parameters obey the discrete uniform joint distribution $\pi(R_L, X_L, P_k, U_k\%, P_0, I_0\% \cdots)$, and the random values are given by using the Monte Carlo method.

The constraint function is estimated with the data obtained from the power flow calculation. The constraint function and power flow calculation are used to express the joint probability distribution of the PDN parameters in the actual conditions. When the probability distribution (Bayesian posterior probability distribution) of the Markov chain state transition probability matrix updates the parameters in the Monte Carlo method, a probability distribution that meets the actual conditions is obtained. Finally, the optimal solution for the PDN parameters is obtained after N rounds of iterative computations. The proposed algorithm needs only the voltage of the first section of the feeder and the voltage, active power, and reactive power of the node on the low voltage side of the feeder and does not need the power, voltage phase angle or current phase angle on the high voltage side.

This paper mainly solves the following difficulties:

1). With incomplete high-voltage measurement data and inaccurate voltage amplitude and phase angle, the parameters are identified precisely.

2). Without knowing the distribution of the real parameters, the estimated values of the parameters are calculated by using the Markov process.

The structure of this paper is as follows. Section II introduces the line and transformer models and the formula of the power flow calculations and presents a way to obtain the original distribution of the PDN parameters and the composition of loss function. Section III reveals results for an actual 10 kV feeder. The original parameters and identification parameters are substituted into the power flow calculation. A comparison experiment on the deviation between the calculated voltage and the measured voltage verifies the effectiveness of the proposed algorithm.

II. MATERIALS AND METHODS

A. FLOW CHART OF THE IDENTIFICATION ALGORITHM

In this paper, according to the initial parameters of the network (line length, transformer model, and line default parameters), the first section voltage of the feeder, and the active power and reactive power on the low voltage side, the PDN parameters identified. The flow chart of the identification algorithm is shown in Figure 1.

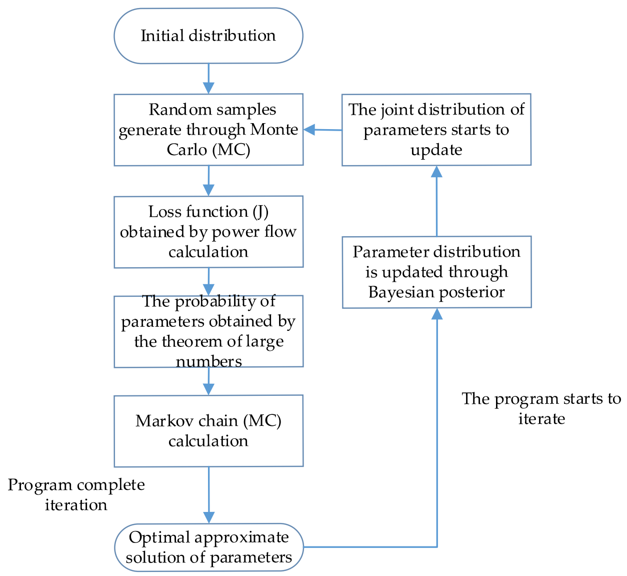

FIGURE 1. Flow chart of the identification algorithm.

B. DETERMINATION OF THE INITIAL DISTRIBUTION

According to the properties of the Markov chain, the selection of the initial values does not affect the smooth convergence, so the initial distribution of the parameters can be set as a normal distribution, a continuous distribution, etc.. Without loss of generality, it is considered that there are m transformers and N lines in the PDN system.

1) The transformer P_k, U_k, P_0, I_0 and the line default R_L, X_L are given.

2) Only the transformer S_N, U_N, I_N, the line length l and the line type are given.

For the first situation, you can set the initial distribution of $P_k^{(i)}, U_k^{(i)}, P_0^{(i)}, I_0^{(i)}, R_L^{(i)}, X_L^{(i)}$ as $\{U(A, B) : A < B\}$.
where i is the transformer number and j is the line number.

Considering the line length, transformer operation status and the meteorological conditions, the range coefficient $\alpha, \beta (0 < \alpha, \beta < 2)$ is introduced to finely describe the distribution, and the distribution is obtained as follows:

$$\begin{cases} P_k^{(i)} = U\left(\alpha P_k^{(i)}, \beta P_k^{(i)}\right) : \alpha < \beta \\ U_k^{(i)} = U\left(\alpha U_k^{(i)}, \beta U_k^{(i)}\right) : \alpha < \beta \\ P_0^{(i)} = U\left(\alpha P_0^{(i)}, \beta P_0^{(i)}\right) : \alpha < \beta \\ I_0^{(i)} = U\left(\alpha I_0^{(i)}, \beta I_0^{(i)}\right) : \alpha < \beta \\ R_L^{(j)} = U\left(\alpha R_L^{(j)}, \beta R_L^{(j)}\right) : \alpha < \beta \\ X_L^{(j)} = U\left(\alpha X_L^{(j)}, \beta X_L^{(j)}\right) : \alpha < \beta \end{cases} \tag{1}$$

We assume that the parameters of the line and transformer cannot change to the twice of the original value under the influence of temperature changes and voltage fluctuations. That is, this constraint is equivalent to doubling the length of the line and the capacity of the transformer, which is obviously unrealistic. The temperature, wind speed and humidity of the geographical location of the line and transformer should be considered when parameters are to be identified. For the range coefficient, when the temperature is high, β should be appropriately increased; when the temperature and humidity change, the coefficient should be tuned to improve the accuracy of the identification and accelerate its convergence.

For the second situation, the distribution can be obtained as follows, where r_{20} is the resistance at 20 °C, which can be obtained by referring to the design manual if the type of circuit is known. k is the temperature coefficient of the resistance. x is the inductive reactance of the line, which can be obtained by referring to the design manual if the type of line is known.

$$\begin{cases} U_k^{(i)} = (4 - 10)\,\% \\ I_0^{(i)} = I_N\,(2 - 10)\,\% \\ P_k^{(i)} = S_N\,(0.4 - 4)\,\%, \\ P_0^{(i)} = S_N\,(0.2 - 1)\,\% \\ R_L^{(j)} = l r_{20}(1 + k(t - 20)) \\ X_L^{(j)} = l x \end{cases} \tag{2}$$

C. MODEL OF THE POWER FLOW CALCULATION

In this paper, a Γ-type equivalent circuit is used for the distribution transformer. The line of the PDN is short and has a low voltage. Consequently, the charging capacitance can be ignored.

Hence, the values of R_T, X_T, G_T, B_T (obtained by $P_k, U_k\%, P_0, I_0\%$ transformation) [17]–[19] and R_L, X_L are calculated by using the Monte Carlo method. Then, these parameters are input into the model of the power flow as variables. Considering that the resistance of the PDN is large, the requirement that the line conductance be far lower than the line susceptance is not satisfied, and the leakage reactance of the transformer is larger than the resistance; the constraints of

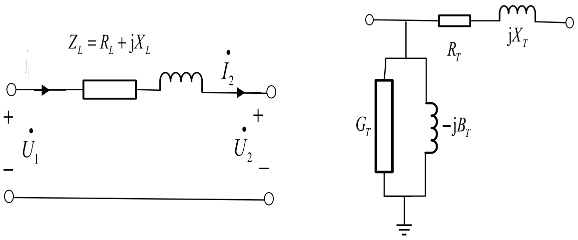

FIGURE 2. Γ type equivalent circuit of the transformer and Π type equivalent model of the low voltage distribution line.

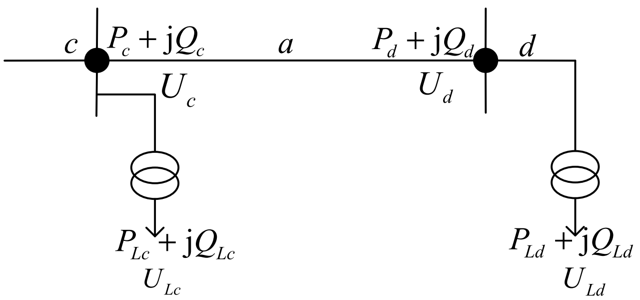

FIGURE 3. Power flow calculation circuit model.

the parameters are set as follows:

$$\begin{aligned} a &< R_L/X_L < b \\ X_T/R_T &> c \\ G_T/B_T &> d \end{aligned} \tag{3}$$

where a, b, c, d are the preset constraint thresholds. If the parameter violates the above constraints, it is discarded. Considering the error and computational complexity, we take the three-phase balance as the premise in the calculation of the power flow. The total power is distributed evenly to each phase for calculation. The method of power flow calculation is as follows:

The active power P_d, reactive power Q_d and voltage U_d on the high voltage side of transformer at bus D are calculated by the following formulas.

$$\begin{cases} P_d = P_{Ld} + \dfrac{P_{Ld}^2 + Q_{Ld}^2}{U_{Ld}^2} R_d^T + U_{Ld}^2 G_d^T \\ Q_d = Q_{Ld} + \dfrac{P_{Ld}^2 + Q_{Ld}^2}{U_{Ld}^2} X_d^T + U_{Ld}^2 B_d^T \\ U_d = \sqrt{(U_{Ld} + \Delta U_d^T)^2 + (\delta U_d^T)^2} \end{cases} \tag{4}$$

ΔU_d^T and δU_d^T are the longitudinal component and transverse component of the transformer impedance voltage drop at bus D in V.

$$\begin{cases} \Delta U_d^T = \dfrac{P_{Ld} R_d^T + Q_{Ld} X_d^T}{U_{Ld}} \\ \delta U_d^T = \dfrac{P_{Ld} X_d^T - Q_{Ld} R_d^T}{U_{Ld}} \end{cases} \tag{5}$$

The voltage of bus C can be expressed as:

$$\begin{cases} U_c = \sqrt{(U_d + \Delta U_{cd}^T)^2 + (\delta U_{cd}^T)^2} \\ \Delta U_{cd}^T = \dfrac{P_d R_{cd}^T + Q_d X_{cd}^T}{U_{Ld}} \\ \delta U_{cd}^T = \dfrac{P_d X_{cd}^T - Q_d R_{cd}^T}{U_d} \end{cases} \tag{6}$$

$$\begin{aligned} f_c(x) = &\sqrt{(U_d + \Delta U_{cd}^T)^2 + (\delta U_{cd}^T)^2} \\ &- \sqrt{(U_{Lc} + \Delta U_c^T)^2 + (\delta U_c^T)^2} \end{aligned} \tag{7}$$

D. DESIGN OF THE LOSS FUNCTION

According to the power flow calculation, the probability value of J is obtained. In this algorithm, the Bayesian posterior probability distribution is first updated using the MCMC method. Random values of the PDN parameters are given using the new probability distribution, and the distribution is calculated and updated in turn. After all iterations are complete, the optimal dynamic parameters of the PDN are obtained. The loss function in this paper is designed as follows:

$$J = \begin{pmatrix} \sum_{k=1}^{T} \left(\left| \hat{u_k} - u_k \right| + \left| \hat{i_k} - i_k \right| \right) \\ + \sum_{k=1}^{T} \left(\left| \left| ang \left(\dfrac{\vec{\hat{U_k}}}{\vec{\hat{I_k}}} \right) \right| - \left| ang \left(P_k + jQ_k \right) \right| \right| \right) \\ + \sum_{k=1}^{T} \left(\left| \hat{U_k} * \hat{I_k} - \sqrt{P_k^2 + Q_k^2} \right| \right) \\ + \sum_{k=1}^{T} \left(\left| \hat{U_k} - u_k * n \right| \right) \end{pmatrix} \tag{8}$$

The core of the algorithm is whether the designed loss function can take into account the real distribution of the parameters. The idea of the above loss function design is as follows:

1) Under the strong constraints of the voltage and current, we construct as many small parts as possible. The more the irrelevant the small part, the closer the value of J is to the real distribution of the parameters.

2) The identified parameters are divided in two types, resistance and inductance. When the current flows, the voltage and the phase change. The design of the loss function should be able to reflect the changes in the voltage and the phase so that the value of J can be closer to the actual conditions and that the distribution of J can be closer to the distribution of the true parameters.

3) Each small part has different loss values, and the unified values need to be the same order of magnitude to prevent a small part from being too large, dominating J, and covering up the influence of other parts on J. According to the experimental results, the loss function is composed of the following parts:

1) The value of the voltage on the low voltage side—the deviation between the calculated value and measured value

2) The value of the current on the low voltage side—the deviation between the calculated value and measured value

TABLE 1. Line information.

Name	Type	Length(km)	R(Ω/km)	X(Ω/km)
0506	JKLYJ-240	0.081	0.160	0.281
0304	JKLYJ-240	0.081	0.160	0.281
0708	JKLYJ-10-120	0.082	0.324	0.303
0203	JKLYJ-240	0.081	0.160	0.281
0405	JKLYJ-240	0.081	0.160	0.281
0102	JKLYJ-10-240	0.020	0.160	0.281
00506	YJV22-3*240	0.208	0.097	0.083
0809	JKLYJ-10-120	0.082	0.324	0.303
0607	JKLYJ-240	0.081	0.160	0.281

TABLE 2. Transformer information.

Name	Type	Uk(%)	Pk(kw)	P0(kw)	I0(%)
99582	S11-M-400/10	4	0.081	0.57	0.8

3) The phase differences of the voltage (on the low voltage side) and current (on the low voltage side)—-the deviations between the calculated values and measured values

4) The apparent power on the low voltage side—-the deviation between the calculated value and the value of the power-factor that comes from the low voltage side

5) The voltage on the low voltage side—-the deviation between the calculated value and the value of measured voltage multiplied by the transformer ratio.

E. UPDATED DISTRIBUTION OF THE MARKOV PROCESS

The Bayesian posterior probability distribution of the Monte Carlo method can be updates by using the Markov process. Random values for the PDN parameters can be used to generate the new probability distribution using the Monte Carlo method, and the random values can make the Markov process stable. In the Markov process, the state of the object depends on the past state and is related only to its previous state.

$$\begin{cases} \pi_1 = \pi_0 P \\ \pi_2 = \pi_0 P^2 \\ \pi_n = \pi_0 p_{ij}^n \\ p_{ij} = P(X_{n+1} = j | X_n = i),\ i, j \in S \end{cases} \tag{9}$$

where π_i represents the state of the object at time i. π_0 is the initial value. When the current state of the discrete-time Markov chain is i. The probability that the next state equals j is the transition probability p_{ij}.

The loss value J generated using the above loss function meets the condition [0, $+\infty$] and can be normalized to [0, 1], which is the transition probability. The optimal solution is yielded by iterating N rounds.

III. EXPERIMENT AND VERIFICATION

Two groups of contrast experiments are performed to prove the effectiveness of the algorithm. The least squares method requires much more data than the dimension of the parameters to identify and ultimately obtains a static result. When solving the nonlinear objective function, this method needs to rely on the linearization method, and there are truncation errors. [20]–[22] This paper addresses this problem from the perspective of probability space and avoids directly solving the nonlinear objective function. Each time point parameter is obtained by the joint distribution of parameters that the loss function and Markov chain update. Then, the dynamic parameters of the equipment at each time point are obtained. A group identification experiment of the parameters is completed using the least squares method, and the parameters are substituted into the network for calculation. Another group of experiments are performed by using the proposed algorithm. Finally, accurate results are obtained via the power flow calculation. In this section, we compare the errors with voltage data parameters. In this paper, an actual 10 kV feeder is selected for the calculations. The 10 kV feeder is composed of a transformer (S11-M-400/10) and eight overhead transmission lines and one cable. The specific topology is displayed in Figure 4.

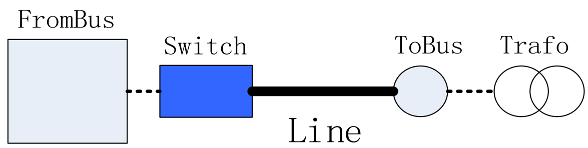

FIGURE 4. Ten-kilovolt feeder topology.

The static parameters of the 10 kV feeder network are as follows:

According to the above calculation algorithm, we set the following conditions:

1) Considering the fluctuations in the weather and the load, the range coefficients of the line are set to $\alpha = 0.9$, $\beta = 1.1$. According to the experience of the workers on site, the fluctuation of the transformer parameters with weather and load is small, and the range coefficients are set to $\alpha = 0.95$, $\beta = 1.05$.

2) The original distribution of the line transformer parameters is set to $\{U(A, B) : A < B\}$, and the accuracy of each generated parameter is set to a micrometer. The number of iterations is 1000.

3) The loss function value is obtained using the power flow calculation.

4) The optimal values is calculated after 1000 iterations.

Without loss of generality, data collected on January 1, 2020 are selected randomly. The data were collected by SCADA, and the sampling period is 15 min. Figure 5 shows the three-phase first section voltage (UA, UB, and UC) on the high voltage side, Figure 6 shows the three-phase voltage (ua, ub, and uc) on the low voltage side, and Figure 7 shows the three-phase active power (Pa, Pb, and Pc) on the low voltage side.

The standard value per unit is used for the voltage data, and the named value is used for the power data. The low voltage side voltage (u *) calculated with the identification parameter value is compared with the low voltage side voltage (u) calculated with the original parameter value.

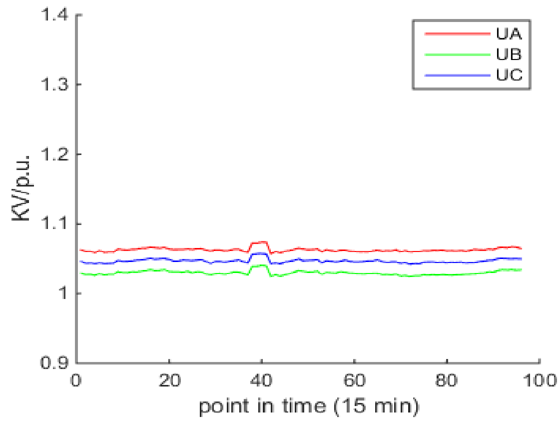

FIGURE 5. UA, UB, and UC on the high voltage side.

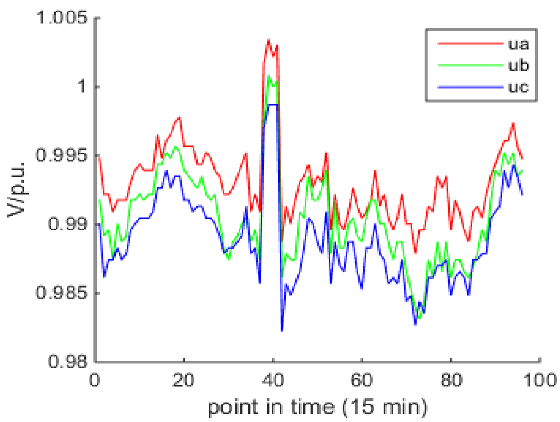

FIGURE 6. Ua, ub, and uc on the low voltage side.

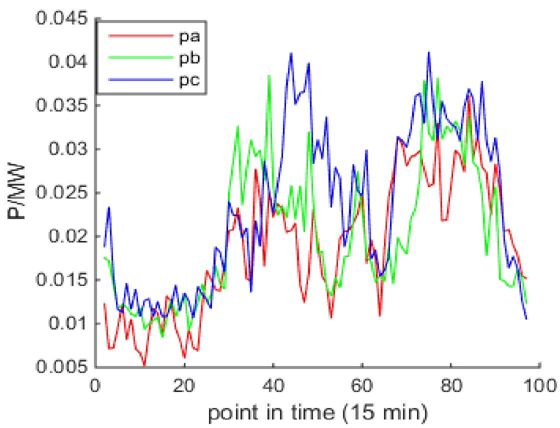

FIGURE 7. Pa, Pb, and Pc on the low voltage side.

A. COMPARISON OF THE PARAMETERS CALCULATED USING THE MCMC IDENTIFICATION METHOD AND THE ORIGINAL VALUES

The red lines represent the identified results for the parameters from the proposed algorithm, and the green lines are the original parameter values. Figures 8 and 9 show that the error between u* and the measured value is less than that between

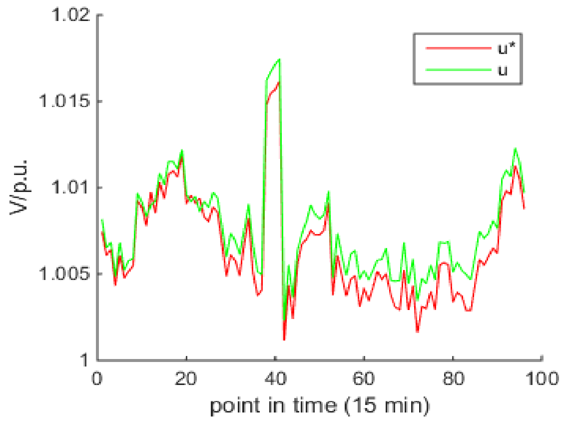

FIGURE 8. Comparison of u* and u.

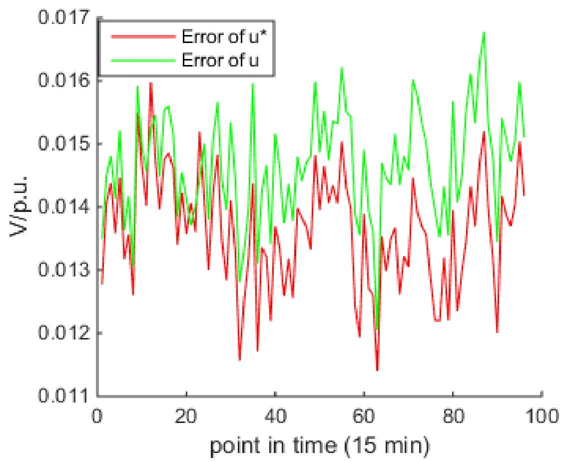

FIGURE 9. Error comparison of u* and u.

u and the measured value, which indicates that the identified value reflects the actual changing network parameters. The voltage error mean of u* is 0.0137(p.u.), but u is 0.0147(p.u.). So parameters of algorithm identification is credible.

The parameters calculated using our proposed method have a good effect on the real voltage conditions of the distribution network and more accurately optimize the reactive power and calculate the line loss of the distribution network.

B. THE CALCULATION RESULTS FROM THE MCMC ALGORITHM AND THE LEAST SQUARES METHOD

According to formulas (2-7), the objective function is constructed and solved by the nonlinear unconstrained least squares method and nonlinear constrained least squares method. The algorithm can identify a group of parameter values at each time point, and 96 groups of data are obtained at 96 time points a day. The random results are shown in Table 3.

The data show that the greatest magnitude of error in the transformer parameters is obtained by the unconstrained least squares method and that the values of the line resistance and inductance are obviously inconsistent. The nonlinear least

TABLE 3. Comparison of parameters obtained using different methods.

Parameter	Original	MCMC	Unconstrained	Constrained
R_L	0.126279	0.12	0.0928	0.93
X_L	0.166502	0.144	-0.0047	0.83
P_k	4.52	1.95	17.808	79.36
$U_k\%$	4%	4.9	0.548	14.32
P_0	0.57	0.57	153000	0.27
$I_0\%$	0.8	0.7	43250	0.2597

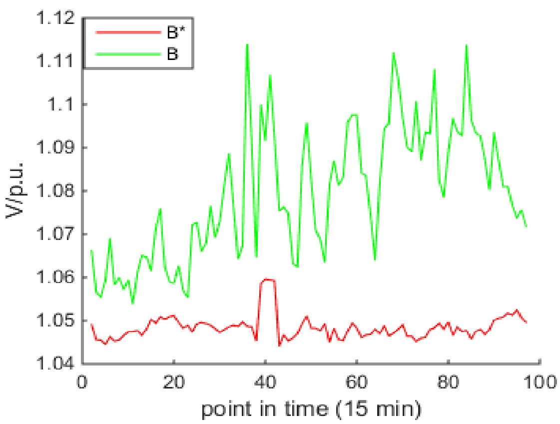

FIGURE 10. Comparison of B* and B.

squares method has less error under the conditions of high latitude identification parameters and incomplete data on the high voltage side. The results calculated using the unconstrained least square method are incorrect and the power flow calculation cannot converge because the parameters of the constrained least squares method are adopted. In this paper, the forward backward method [17] is used to calculate the voltage on the high voltage side (the voltage on the low voltage side has been obtained; the network parameters are calculated with the least squares method and the MCMC method). The first voltage on the high voltage side (B*) calculated via the MCMC identification parameters and the voltage on the high voltage side (B*) calculated using the least squares identification parameters are obtained. The absolute value of the error of B* and the measured value is taken as the error distance. As shown in Figure 10, the first section voltage (B*) of the high voltage side is calculated using the proposed identification parameters, and the low voltage side voltage (B) is calculated via the original values; additionally, the error between these values and the measured value is calculated. The red line represents the calculation result of the parameters identified using the proposed algorithm, and the green line represents the calculation result via the least squares method.

In the calculation of the first voltage and network parameters, the error curve of our algorithm is smoother than the error curve of the least squares method. The voltage error

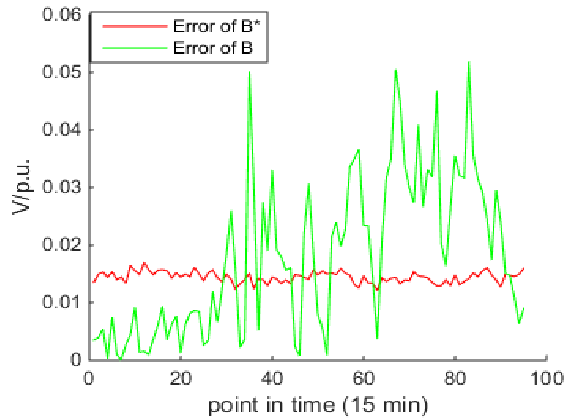

FIGURE 11. Error comparison of B* and B.

mean of B* is 0.0144(p.u.), but B is 0.0179(p.u.). The error mean and variance of this algorithm are smaller than those of the least squares method, which demonstrates that our proposed method has better parameter identification performance for the PDN.

IV. CONCLUSION

This paper presents an accurate identification and calculation method for PDN parameters based on the MCMC algorithm. According to the node type of the PDN, a typical parameter identification model of the PDN is established, and the parameters of the branch and transformer in the PDN are estimated and identified in real time by using the known partial measurement data, power flow calculation method and MCMC algorithm to estimate the minimum loss function. The experimental results demonstrate that the proposed method has a higher accuracy, and the proposed algorithm is better than the current mainstream method. The proposed algorithm is insensitive to the initial measurement value and has fast convergence speed and high calculation efficiency; thus, it can be applied to calculations on a variety of electrical devices in real time.

REFERENCES

[1] J. R. Carson, ''Wave propagation in overhead wires with ground return,'' *Bell Syst Tech. J.*, vol. 5, no. 4, pp. 539–554, Oct. 1926.
[2] P. M. Anderson, *Analysis of Faulted Power Systems*. Hoboken, NJ, USA: Wiley, 1995.
[3] M. Lave, M. J. Reno, and J. Peppanen, ''Distribution system parameter and topology estimation applied to resolve low-voltage circuits on three real distribution feeders,'' *IEEE Trans. Sustain. Energy*, vol. 10, no. 3, pp. 1585–1592, Jul. 2019.
[4] J. Peppanen, S. Grijalva, M. J. Reno, and R. J. Broderick, ''Distribution system low-voltage circuit topology estimation using smart metering data,'' in *Proc. IEEE/PES Transmiss. Distrib. Conf. Expo. (T&D)*, May 2016, pp. 1–5.
[5] Y. Lin and A. Abur, ''Strategic use of synchronized phasor measurements to improve network parameter error detection,'' *IEEE Trans. Smart Grid*, vol. 9, no. 5, pp. 5281–5290, Sep. 2018.
[6] J. Yu, Y. Weng, and R. Rajagopal, ''PaToPa: A data-driven parameter and topology joint estimation framework in distribution grids,'' *IEEE Trans. Power Syst.*, vol. 33, no. 4, pp. 4335–4347, Jul. 2018.
[7] M. Mahmud, M. S. Kaiser, A. Hussain, and S. Vassanelli, ''Applications of deep learning and reinforcement learning to biological data,'' *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 6, pp. 2063–2079, Jun. 2018.

[8] K. K. Yang, Z. N. Wei, F. W. Duan, R. T. Liu, X. Wei, and M. H. Yan, "Power line parameter identification based on multi-innovation least square algorithm," (in Chinese), *Electr. Power Eng. Technol.*, vol. 38, no. 2, pp. 69–74, 2019.

[9] D. S. Lu and P. Ma, "Hybrid bad-data detection and parameter identification based on augmented state estimation," (in Chinese), *Electr. Power Eng. Technol.*, vol. 38, no. 2, pp. 99–104, 2019.

[10] J.-H. Teng, "A direct approach for distribution system load flow solutions," *IEEE Trans. Power Del.*, vol. 18, no. 3, pp. 882–887, Jul. 2003.

[11] J. Sun, M. Xia, and Q. Chen, "A classification identification method based on phasor measurement for distribution line parameter identification under insufficient measurements conditions," *IEEE Access*, vol. 7, pp. 158732–158743, 2019.

[12] Y. F. Zhou, "A hybrid strategy based on interior point method and DPSO for electricity transmission network," (in Chinese), *Electr. Power Eng. Technol.*, vol. 33, no. 1, pp. 22–25, 2014.

[13] Z. Qu, M. Li, Z. Zhang, M. Cui, and Y. Zhou, "Dynamic optimization method of transmission line parameters based on grey support vector regression," *Frontiers Energy Res.*, vol. 9, p. 17, Feb. 2021.

[14] C. Carquex, C. Rosenberg, and K. Bhattacharya, "State estimation in power distribution systems based on ensemble Kalman filtering," *IEEE Trans. Power Syst.*, vol. 33, no. 6, pp. 6600–6610, Nov. 2018.

[15] B. Li, X. Mo, and B. Chen, "Direct control strategy of real-time tracking power generation plan for wind power and battery energy storage combined system," *IEEE Access*, vol. 7, pp. 147169–147178, 2019.

[16] H. Chao, B. Hu, K. Xie, H.-M. Tai, J. Yan, and Y. Li, "A sequential MCMC model for reliability evaluation of offshore wind farms considering severe weather conditions," *IEEE Access*, vol. 7, pp. 132552–132562, 2019.

[17] R. Brown, *Power System Analysis*. Johannesburg, South Africa: Tritech Digital Media, Aug. 2018.

[18] Y. Z. Liu, W. Y. Guan, J. B. Zhao, and C. Qin, "Parameter identification based on equivalent modeling of AWS wave farm," (in Chinese), *Electr. Power Eng. Technol.*, vol. 39, no. 4, pp. 55–60, 2020.

[19] H. Zhou, P. Ju, H. Yang, and Y. Chen, "A review of development in dynamic equivalent technologies for power system modeling," (in Chinese), *Electr. Power Eng. Technol.*, vol. 5, no. 9, pp. 10–13, 2008.

[20] G. M. Wang, L. Yao, and W. W. Wang, "Identification method for transformer parameters based on AMI metering data," (in Chinese), *J. Power Syst. Automat.*, vol. 31, no. 6, pp. 38–42, 2019.

[21] G. M. Wang, J. K. Ling, N. Kang, Y. Ding, and H. Liu, "Line parameter identification method of low voltage distribution network based on AMI measurement information," (in Chinese), *China Electr. Power*, vol. 52, no. 5, pp. 63–69, 2019.

[22] K. Wu, H. H. Yuan, B. Yang, Y. Wang, Y. X. Zhang, L. Wang, and S. Guo, "A method for parameter identification of distribution network equipment based on least square method," (in Chinese), *Energy Energy Conservation*, vol. 5, no. 5, pp. 58–63, 2019.

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