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# Traceability analysis for low-voltage distribution network abnormal line loss using a data-driven power flow model

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The abnormal behavior of end-users is one of the main causes of abnormal line loss in distribution networks. The integration of a large amount of distributed renewable energy into a low-voltage distribution network (LVDN) complicates line loss analysis. Traceability analysis for abnormal line loss aims to identify the specific end-user responsible for the anomaly in line loss. This paper proposes, for LVDNs with incomplete topology and line parameters, a practical traceability analysis approach using a data-driven power flow model. A data-driven power flow model based on a neural network is first established to capture the power flow mapping relationship without topology and line parameter information. A backpropagation algorithm is then presented to correct the actual power consumption data according to the measured voltage data. By comparing actual power consumption data with measured power data, users with abnormal behavior can be accurately identified and tracked. Finally, the effectiveness of the proposed approach is verified by actual data.

## KEYWORDS

traceability analysis, abnormal line loss, data-driven power flow model, backpropagation algorithm, low-voltage distribution network

## 1 Introduction

A low-voltage distribution network (LVDN) is a terminal power grid that serves as a crucial component in delivering electricity to end-users (Li et al., 2021). With the increasing integration of distributed renewable energy resources (Xu et al., 2022) such as distributed photovoltaic energy and wind energy, the traditional consumption model of LVDNs has changed (Dou et al., 2023). The emergence of “prosumers,” who can both consume and produce electricity, has transformed the dynamics of power flow in the distribution network (Zhao et al., 2020). This bidirectional power flow will make distribution network line loss analysis more complex (Luo et al., 2020).

“Line loss” refers to energy loss during the transmission and distribution of electrical power (Zhang et al., 2022) and is an important indicator of the economical operation of LVDN. The management of abnormal line loss is crucial for improving the efficiency and economy of the power system (Enshae et al., 2019). Abnormal line loss can result from factors such as inaccurate metering, power theft, and other user behaviors, leading to energy wastage and economic loss (Kong et al., 2021). Traceability analysis for abnormal line loss

aims to identify the users causing these losses. By pinpointing the sources of line loss anomalies, targeted measures can be implemented to address and reduce these losses, ultimately improving the overall economy of power grid operation (Hu et al., 2022).

At present, analysis methods for abnormal line loss in LVDNs can be divided into three categories: state estimation, game theory, and data-driven. The first is based on state estimation (Xiao et al., 2018; Chen et al., 2019) and uses random matrix theory and other methods to estimate the LVDN state. It identifies abnormal line loss by comparing the state estimate results with the measured values. State estimation relies too much on the topology of the distribution network and the accuracy of line parameters (Zhang et al., 2020). In an LVDN, the network topology and line parameters are unknown due to the lack of intermediate measurement nodes, so the state estimation method is not applicable (Feng et al., 2022). Moreover, the actual operation of the distribution network may be nonlinear and complicated, and the state estimation method cannot fully reflect that, thus affecting the accuracy of the result (Zhao et al., 2020). The second category of analysis methods for abnormal line loss in LVDNs is based on game theory (Amin et al., 2015). Abnormal line loss is identified through the interaction game between the user and the power supply enterprise. However, such methods involve decisions and interactions by multiple players and can therefore lead to complex mathematical models and computational processes (Wang et al., 2023). This application of game theory has not been tested in practice but only through theoretical analysis (Mohammadi et al., 2019). The third analysis category is data-driven (Buzau et al., 2019; Lin et al., 2021; Pamiir et al., 2022). XGBoost, LogitBoost, sparse random forest, and other supervised learning methods are proposed to extract features from manually labeled electricity datasets to identify abnormal electricity users. However, data-driven methods cannot provide a direct explanation of the cause of line loss anomalies and their physical mechanism.

Consequently, this paper proposes a neural network-based data-driven power flow model to locate the traceability of abnormal line losses in LVDN caused by users. The data-driven power flow model can adapt to LVDN. Because the middle node of the actual LVDN is not installed with measuring devices, its topology and line parameters are unknown. The trained data-driven power flow model calculates the voltage of each end-user directly from their measured power data without the need for topology and line parameters. First, a data-driven power flow model is established to fit the mapping relationship between power and voltage through the neural network. Second, voltage is calculated by the data-driven power flow model. The input power is updated by backpropagation. This process helps the calculated voltage to approximate the measured voltage. Then, by comparing the difference between the corrected and measured power of each user, the user causing the abnormal line loss is found. Finally, the accuracy and effectiveness of the proposed method are verified by combining the historical data and simulation of LVDNs.

The rest of the paper is organized as follows: Section 2 analyzes the feasibility of establishing a data-driven power flow model, and the data-driven power flow model based on neural networks is established. Section 3 uses the data-driven power flow model to trace the anomaly and find the user causing the abnormal line loss.

Section 4 and Section 5 verify the validity and superiority of the proposed method and draw conclusions, respectively.

## 2 Neural network-based data-driven power flow model

This section first analyzes the functional relationship of the variables in the power flow constraint. It establishes that there is a unique mapping relation between the power flow variables. Then, the data-driven power flow model is established to fit the relationship using a neural network.

### 2.1 Analysis of variable function relations in power flow constraint

To build a data-driven power flow model, it is necessary to find the unique mapping relations among the power flow variables. Given some known power flow variables, this mapping relationship is used to derive other unknown power flow variables (Lyu et al., 2022).

In an LVDN with  $m$  nodes,  $2m$  power flow constraint functions can be established. The relationship between active power  $P$ , reactive power  $Q$ , voltage  $V$ , and phase angle  $\theta$  is expressed in polar coordinates:

$$\begin{cases} f_1 = P_1 - V_1 \sum_{k=1}^m V_k (G_{1k} \cos \theta_{1k} + B_{1k} \sin \theta_{1k}), \\ \vdots \\ f_m = P_m - V_m \sum_{k=1}^m V_k (G_{mk} \cos \theta_{mk} + B_{mk} \sin \theta_{mk}), \\ f_{m+1} = Q_1 - V_1 \sum_{k=1}^m V_k (G_{1k} \sin \theta_{1k} - B_{1k} \cos \theta_{1k}), \\ \vdots \\ f_{2m} = Q_m - V_m \sum_{k=1}^m V_k (G_{mk} \sin \theta_{mk} - B_{mk} \cos \theta_{mk}), \end{cases} \quad (1)$$

where  $V_i$ ,  $P_i$ , and  $Q_i$  are the voltage, active power, and reactive power of node  $i$ , respectively;  $G_{ij}$  and  $B_{ij}$  are the conductance and susceptance between node  $i$  and  $j$ , respectively; and  $\theta_{ij}$  is the phase angle difference between node  $i$  and node  $j$ ,  $i, j \in \{1, 2, \dots, m\}$ .

Since the Jacobian matrix is invertible, a unique mapping relationship between the variables  $P$ ,  $Q$ ,  $V$ , and  $\theta$  can be obtained according to the implicit function theorem. However, the value of  $\theta$  is difficult to measure. The mapping relationship can be modified by removing  $\theta$ :

$$h(V_1, P_2, \dots, P_m, Q_2, \dots, Q_m) = [P_1, Q_1, V_2, \dots, V_m]. \quad (2)$$

### 2.2 Data-driven power flow model

Based on the aforementioned discussion, this paper uses a neural network to fit the complex and nonlinear mapping relationship between power flow variables. Compared with traditional models, neural networks can learn and fit nonlinear mapping relationships between variables better. Additionally, they are capable of processing

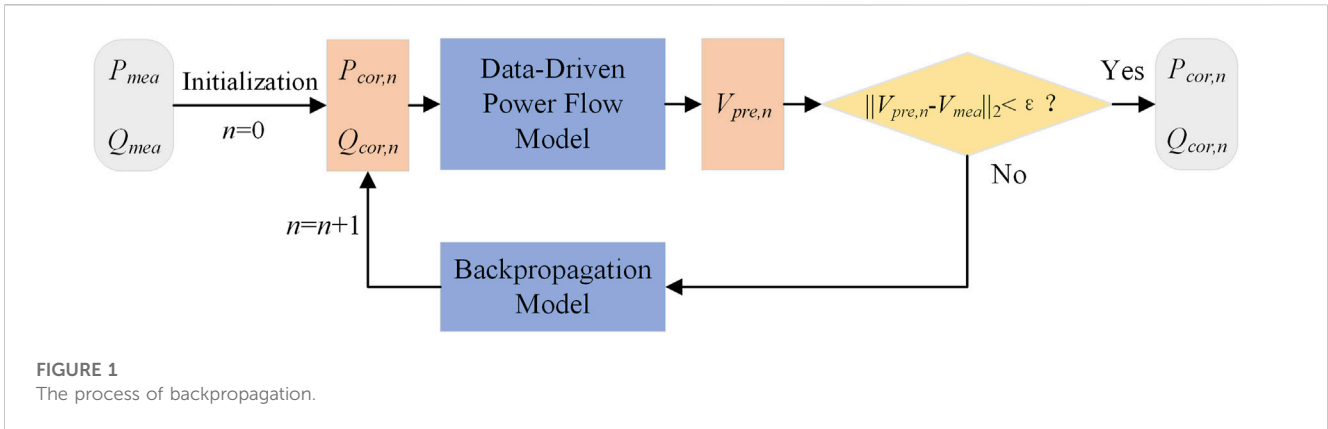


FIGURE 1 The process of backpropagation.

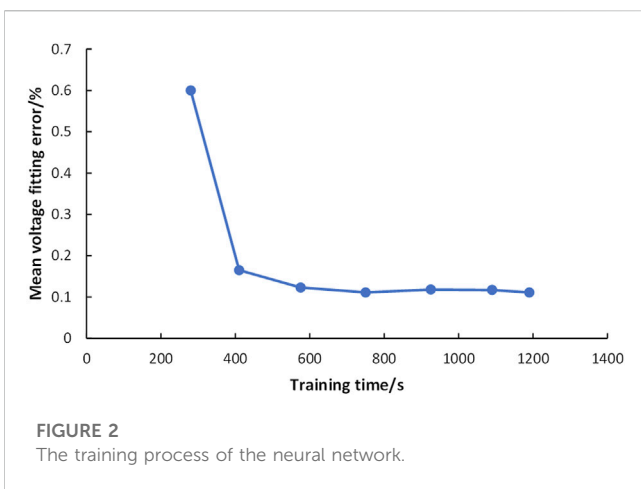


FIGURE 2 The training process of the neural network.

massive data in a short time by training for predictions. An  $L$ -layer neural network model can be divided into the following three layers:

$$\begin{cases} x = g^{(0)} = [V_1, P_2, \dots, P_m, Q_2, \dots, Q_m], \\ g^{(l)} = \max(0, W^{(l)}g^{(l-1)} + b^{(l)}) \quad l = 1, \dots, L, \\ Y = F(x) = W^{(L+1)}g^{(L)} = [P_1, Q_1, V_2, \dots, V_m], \end{cases} \quad (3)$$

where  $x$  is the input of the neural network and the number of input neurons is  $2m-1$ ;  $Y$  is the final output result and the number of output neurons is  $m+1$ ;  $g^{(l)}$  is the hidden layer in the middle;  $W^{(l)}$  is the weight matrix of the  $l$ th hidden layer; and  $b^{(l)}$  is the bias vector of the  $l$ th hidden layer. The mapping relationship between voltage and power can be obtained by fitting.

### 3 Traceability analysis considered abnormal line loss

#### 3.1 Analysis of the relationship between abnormal user and power flow constraint

Abnormal users might exhibit instances where the measured voltage or power diverges from the actual value (Chen et al., 2023). Traditional analysis methods use the power flow constraint to identify the characteristic. When an anomaly

occurs with a user, the measured power deviates from the actual value. Through power flow calculation, the calculated voltage is compared with the measured voltage. The user's abnormality is then determined based on the magnitude of the deviation. Because the line parameters and topology of LVDNs are unknown, this method cannot be used. Consequently, a data-driven power flow model is pursued to address this challenge.

However, when the abnormal measured power is used as an input to the data-driven power flow model, multiple voltages will deviate simultaneously, making the identification of the abnormal user challenging.

Therefore, this paper consistently uses voltage to correct the power through backpropagation. The abnormal users are judged by comparing the corrected power with the measured power.

#### 3.2 Backpropagation to correct the power

To keep the measured voltage constantly close to the calculated voltage, the power is constantly corrected by backpropagation. In this paper, FGSM (fast gradient sign method) is used to correct the power by calculating the difference between the voltage and the measured voltage without changing the parameters of the neural network (Duan et al., 2021; Li et al., 2022). The steps are as follows:

- 1) Select samples to be attacked: Select active and reactive power from the dataset as samples to be attacked, and these samples will be modified.
- 2) Calculate the loss function: Input the active and reactive power into the data-driven power flow model to calculate the loss function.
- 3) Calculate gradient: Calculate the gradient of the loss function with respect to the input sample.
- 4) Generate adversarial disturbance: Multiply the calculated gradient by the learning rate to obtain the disturbance vector in the direction of the fastest increase in the loss function.
- 5) Generate adversarial samples: Add the disturbance vector to the original sample.

The corrected formula is

TABLE 1 method comparison.

	Data-driven power flow model	Ordinary power flow method
$\alpha_{TPR}$	0.961	0.963
$\alpha_{FPR}$	0.001	0.001

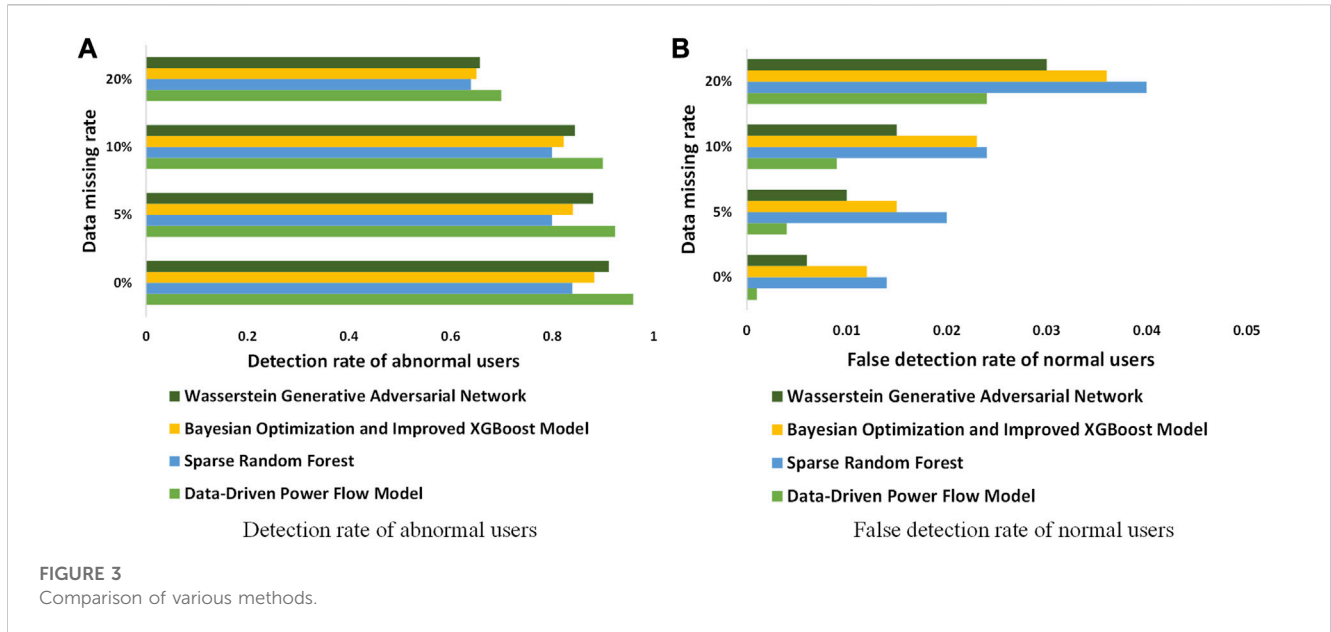


FIGURE 3 Comparison of various methods.

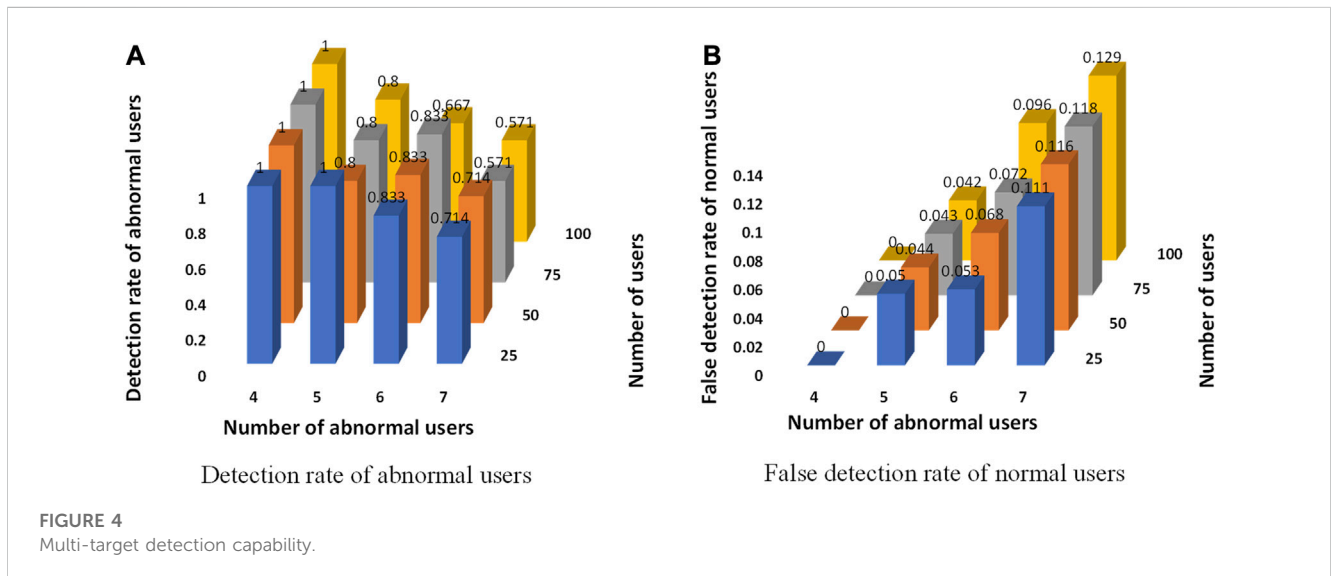


FIGURE 4 Multi-target detection capability.

$$\begin{cases} x_{n+1} = x_n - \gamma, \\ \gamma = \eta \nabla_x \Gamma(\lambda, x_n, V_{pre,n}, V_{mea}), \\ \Gamma(\lambda, x_n, V_{pre,n}, V_{mea}) = \|V_{pre,n} - V_{mea}\|_2, \end{cases} \quad (4)$$

where  $n$  is the number of updates;  $x_n$  is power after the  $n$ th update;  $\gamma$  is the disturbance value;  $\eta$  is the learning rate;  $\Gamma(\lambda, x_n, V_{pre}, V_{mea})$  is the loss function;  $\lambda$  is the neural network parameter;  $V_{pre,n}$  is the

voltage value calculated by the data-driven power flow model for the  $n$ th time; and  $V_{mea}$  is the measured voltage value.

The power is constantly corrected by continuous backpropagation. The power of abnormal users exhibits the most conspicuous changes during the initial iterations. Concurrently, the power of the remaining users exhibits minimal variation during the iteration process. Therefore, abnormal users can be detected by

examining the disparity between the corrected power and the measured power following iteration.

The process of backpropagation is shown in [Figure 1](#).

### 3.3 Line loss abnormal user detection standard

Use the average correction distance to find the abnormal user:

$$\begin{cases} d_{t,i} = |P_{cor}^{t,i} - P_{mea}^{t,i}| + |Q_{cor}^{t,i} - Q_{mea}^{t,i}| \\ d_i = \frac{\sum_{t=1}^T d_{t,i}}{T} \end{cases} \quad (5)$$

where:  $P_{t,i cor}$  and  $P_{t,i mea}$  are the corrected active power and measured active power of the  $i$ th user at time  $t$ , respectively;  $Q_{t,i cor}$  and  $Q_{t,i mea}$  are the corrected and measured reactive powers of the  $i$ th user at time  $t$ , respectively;  $d_{t,i}$  is the corrected distance of the  $i$ th user at time  $t$ ; and  $d_i$  is the average corrected distance of the  $i$ th user.

The calculated average correction distance of each user is compared with  $\delta$ . If  $d_i > \delta$ , it indicates that the  $i$ th user is the abnormal user.

## 4 Case studies

In this paper, data of an LVDN with clear ledger information in Zhejiang Province were selected. Some historical active power, reactive power, and voltage amplitude data were selected to train the model, 70% of which were training-set data and 30% of which were test-set data. Each sample includes active and reactive power injected by 32 user nodes and voltage amplitudes from distribution transformer nodes ( $1 \times 65$ -dimensional vector). Each label includes voltage amplitudes for 32 user nodes and active and reactive power injected by distribution transformer nodes ( $1 \times 34$ -dimensional vector). There are four layers in the neural network and 165 neurons in the hidden layer.

We also propose two evaluation indicators to verify the effectiveness of the proposed method. These are

$$\begin{cases} \alpha_{TPR} = \frac{P_{TP}}{P_{TP} + P_{FN}} \\ \alpha_{FPR} = \frac{P_{FP}}{P_{FP} + P_{TN}} \end{cases} \quad (6)$$

where  $P_{TP}$  is the number of abnormal users detected as abnormal;  $P_{FN}$  is the number of abnormal users detected as normal;  $P_{FP}$  is the number of normal users detected as abnormal;  $P_{TN}$  is the number of normal users detected as normal;  $\alpha_{TPR}$  is the precision of the method, representing the detection rate of abnormal users; and  $\alpha_{FPR}$  is the false-positive rate of the method, representing the false detection rate of normal users.

The training process of the neural network used in this paper is shown in [Figure 2](#).

[Figure 2](#) shows the relationship between the mean voltage fitting error and the training time of the neural network used in this paper during the training process. It can be seen that the neural network

rapidly converges after 300 s, and the mean relative error between the neural network and the actual voltage measurement value drops to 0.165%, and that it takes 410 s to complete the training.

The traceability results of the data-driven power flow model in an LVDN with unknown constitutive parameters and the traceability results of the ordinary power flow method in the network with known parameters are shown in [Table 1](#).

From [Table 1](#), the data-driven power flow model proposed in this paper is similar to the calculation results obtained by the ordinary power flow method, which proves the feasibility of the method used in this paper.

Under different data missing rates, the proposed indicators are used to compare the effectiveness of the proposed method with other methods.

From [Figure 3](#), under different data missing rates, the detection rate and false-positive rate of the method used in this paper are superior to other methods, reflecting its effectiveness. When the missing data rate rises, its accuracy declines accordingly. When the missing data rate is 10% or less, the method maintains high accuracy.

To test the detection ability of the method for multiple abnormal users, this method is used to detect an LVDN with a different number of users and abnormal users.

From [Figure 4](#), regardless of the number of users, this method accurately detects anomalies in an LVDN containing four abnormal users. Furthermore, the method achieves a zero false-positive rate. In the LVDN with five or six abnormal users, most of the abnormal users are detected by this method. The false-positive rate is also low. However, the precision and false-positive rate of this method are poor for seven abnormal users.

## 5 Conclusion

Given that it is currently difficult to obtain topology information and line parameters accurately and in a timely manner in LVDN, this paper proposes a data-driven traceability analysis approach to identify the specific end-user responsible for the anomaly in line loss. The proposed approach integrates the advantages of state estimation and data-driven methods. The main contributions of this paper are:

- 1) A practical traceability analysis approach is proposed to identify the specific end-user responsible for the anomaly in line loss for LVDN with incomplete topology and line parameters.
- 2) A data-driven power flow model based on a neural network is established to capture the power flow mapping relationship without topology and line parameter information.
- 3) A backpropagation algorithm is presented to correct the actual power consumption data according to the measured voltage data. By comparing the actual power consumption data with the measured power data, users with abnormal behavior can be accurately identified and tracked.

This method is suitable for anomaly tracing in most LVDNs. However, in cases where there are too many abnormal users in one LVDN, it is not able to accurately identify them and needs further improvement.

## Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

## Author contributions

ZS: writing—original draft. YX: data curation and writing—original draft. YH: writing—original draft. ZC: data curation and writing—original draft. JZ: writing—review and editing.

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## Conflict of interest

Authors ZS and YX were employed by the Hangzhou Power Supply Company of the State Grid Zhejiang Electric Power Company, Author YH was employed by the State Grid Corporation of China, and Author JZ was employed by the State Grid Zhejiang Electric Power Company Ltd.

The remaining author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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