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Online capacity detection of distribution transformers based on zero-sequence impedance curve matching

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Unauthorized tampering with distribution transformer nameplates poses significant economic and operational risks to power utilities, while conventional offline capacity detection methods require power outages and existing online short-circuit impedance approaches often lack sufficient engineering accuracy; therefore, this paper proposes a fully online capacity detection method based on zero-sequence impedance-capacity curve matching. First, parameter data of multiple transformer series (S7, S9, S11) covering capacities from 6.3 kVA to 1600 kVA were collected, and MATLAB/Simulink models were established to calculate zero-sequence impedance under three-phase unbalanced conditions, from which a reference curve relating zero-sequence impedance to rated capacity was constructed. During field application, secondary-side voltage and current data are acquired online, the zero-sequence components are extracted via symmetrical component decomposition, and the zero-sequence impedance is calculated; to enhance reliability, a BP neural network-based cyclic data cleaning method is introduced to automatically eliminate abnormal monitoring samples before impedance estimation. Simulation results demonstrate that zero-sequence impedance is predominantly determined by transformer structural parameters and rated capacity and remains essentially unaffected by load levels (30%–80% of rated capacity), confirming its suitability as a stable capacity indicator. Field validation on a 315 kVA Dyn11 distribution transformer shows that, after data cleaning, the calculated zero-sequence impedance matches the reference curve with errors within $\pm 10\%$, meeting engineering accuracy requirements. The proposed method enables accurate, non-intrusive, outage-free capacity verification within the practical range of 6.3–1600 kVA, providing an effective technical solution for online detection of nameplate tampering and supporting secure and intelligent operation of modern distribution networks.

KEYWORDS

capacity detection, datacleaning, distribution transformer, online detection, zero-sequence impedance

1 Introduction

Distribution transformers, as key power equipment for electric energy transmission and voltage transformation, directly supply power to end users and are crucial components in distribution networks. Their operational stability directly determines

the safety and reliability of the entire power system (Zhang et al., 2019; Chi et al., 2023).

The capacity of a distribution transformer refers to the product of its voltage and current, expressed as apparent power. This capacity reflects the transformer's ability to transmit electrical energy and is typically determined by power utilities based on users' electricity demands, while also reserving a certain margin for safety and ensuring economic operation of the power system (Hong et al., 2025; An et al., 2019). In recent years, the problem of tampering with transformer nameplates has become increasingly severe, posing significant threats to the safe and stable operation of power systems. There are two main types of nameplate tampering: (1) "overrating a larger unit as smaller," where users illegally replace the nameplate of a high-capacity transformer with that of a lower-rated one to reduce basic capacity charges; and (2) "underrating a smaller unit as larger," where some manufacturers falsely label small-capacity transformers as large-capacity units during bidding processes for profit, later secretly upgrading their capacity. If utilities plan operations based on the falsified nameplate capacity, transformers may operate continuously under either overloaded or lightly loaded conditions (Zhang et al., 2021; Yongjian et al., 2020). This increases energy losses in the power system, and prolonged overloading can degrade insulation, potentially leading to transformer burnout and serious safety incidents, thereby severely compromising the security and stability of the power grid (Zhang et al., 2025; An et al., 2020). Therefore, accurately verifying the rated capacity of distribution transformers is of great significance.

Currently, practical engineering methods for detecting distribution transformer capacity fall into two categories: offline and online approaches. Offline methods primarily include the loss comparison method, impedance voltage method, and three-parameter method. The loss comparison method requires shutting down the transformer to perform short-circuit and no-load tests, measuring actual short-circuit and no-load losses, and comparing them with national standard values to estimate capacity. However, relying solely on loss data leads to large errors in practice. To address this, the impedance voltage method was introduced, which calculates the percentage impedance voltage from short-circuit test data and uses it alongside loss data for capacity identification. The three-parameter method further combines both loss comparison and impedance voltage approaches, simultaneously considering short-circuit loss, no-load loss, and short-circuit impedance to improve accuracy compared to the previous two methods (Hong et al., 2016; He et al., 2010). Nevertheless, all these offline methods share a critical drawback—they require the transformer to be taken out of service for testing. In today's context of ever-increasing demands for power supply reliability, such outages reduce utility reliability and disrupt users' daily life and production activities, greatly limiting the feasibility of offline detection.

To address the challenge of non-interruptible capacity testing, Wu Xihong's team proposed an online capacity detection method based on short-circuit impedance. This approach derives online calculation formulas for short-circuit impedance tailored to different transformer winding configurations, validates feasibility through simulation, and integrates transformer loss data for capacity estimation (Li et al., 2024; Li et al., 2013). Li Xia's team developed a method that first computes short-circuit impedance using a transformer simulation model and then performs linear regression

between impedance, voltage, and current to determine capacity (Zhang et al., 2019). Although these methods center on short-circuit impedance and demonstrate theoretical feasibility in simulations, their practical application suffers from limited reference data and large errors, failing to meet engineering accuracy requirements (Wu et al., 2024; Li et al., 2021; Ren et al., 2004; An et al., 2018). Hence, there is an urgent need for an accurate and truly online capacity detection method.

In response, this paper proposes a novel online capacity detection method based on zero-sequence impedance versus capacity curves. First, parameters of distribution transformers from various manufacturers and series are collected. Transformer models are then built in the MATLAB/Simulink simulation platform to compute their zero-sequence impedances, and a reference curve mapping zero-sequence impedance to transformer capacity is established. For field measurements, secondary-side voltage and current data under unbalanced load conditions are acquired via voltage and current transformers. Using symmetrical component decomposition—a standard technique for analyzing unbalanced operation in power systems—the zero-sequence voltage and zero-sequence current are extracted from the measured data. The zero-sequence impedance is then calculated, and by referencing the pre-established zero-sequence impedance–capacity curve, the actual capacity of the transformer under test can be accurately identified.

2 Online capacity detection method for distribution transformers

2.1 Zero-sequence impedance of dyn distribution transformers under three-phase unbalanced conditions

Based on the fault characteristics of the cable joints, common issues that occur during the manufacturing of intermediate joints were selected as the research objects. In the laboratory, three types of real intermediate joint defects were set for 10 kV XLPE cables used in power systems. These defects include the outer semi-conductive layer-tip, main-insulation scratch, and stress-cone misalignment defects. Defect creation simulates the actual cable-installation process and industry conditions, ensuring that the defects are as close as possible to those encountered in industrial production, as shown in Figure 1. A 4-m-long defect-free cable was divided into two 2-m segments, which were connected using a CSS-1733J-8.7/15 kV cold-shrink joint. The test cable model was ZH-YJV with a cross-sectional area of 185 mm² and a rated voltage of 8.7/15 kV.

For distribution transformers, when the secondary side experiences asymmetric loading, zero-sequence components will be generated in the system. Figure 1 shows the equivalent circuit diagram of a Dyn connected distribution transformer. In this figure, R_1 and X_1 represent the resistance and reactance of the primary winding; R_2' and X_2' are the referred values of the secondary winding resistance and reactance on the primary side; R_m and X_m denote the magnetizing resistance and reactance, respectively. Since the primary side is connected in delta (Δ), zero-sequence currents can only circulate within the three-phase windings and cannot flow out, making the zero-sequence impedance viewed from the primary side infinitely large. On the secondary side, which is

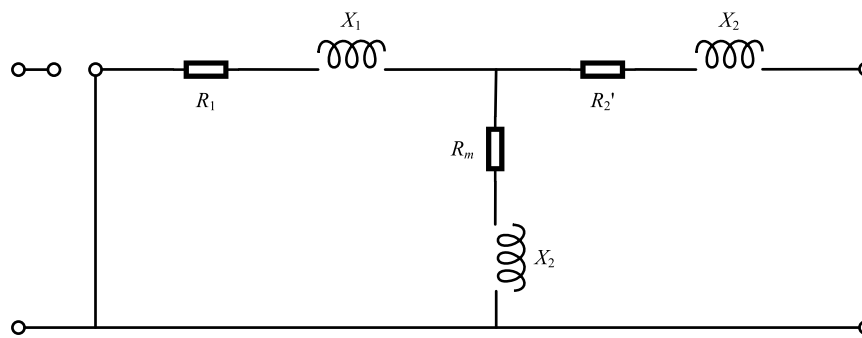


FIGURE 1
Dyn-connected distribution transformer equivalent circuit diagram.

connected in wye with neutral (y_n), zero-sequence currents can form a zero-sequence loop through the neutral point, resulting in a finite value for the zero-sequence impedance as seen from the secondary side (Qian et al., 2020).

When a distribution transformer operates under three-phase unbalanced conditions on the secondary side, zero-sequence components are generated in the system. Taking a Dyn-connected distribution transformer as an example, the primary side adopts a delta (Δ) connection, which prevents zero-sequence currents from flowing into the external system; instead, the zero-sequence currents can only circulate internally within the transformer windings. In contrast, the secondary side is connected in a grounded wye (y_n) configuration, allowing zero-sequence currents to form a closed loop through the neutral point. Consequently, from the perspective of the secondary side, the transformer exhibits a finite and observable zero-sequence impedance.

Under three-phase unbalanced operating conditions, the acquired voltage and current signals contain positive-sequence, negative-sequence, and zero-sequence components simultaneously. By applying the symmetrical components method, the zero-sequence voltage and zero-sequence current can be extracted from the measured data, and the zero-sequence impedance of the transformer can be calculated accordingly. The zero-sequence impedance is mainly determined by the transformer's structural characteristics and rated capacity, and is only weakly affected by load variations.

Therefore, without requiring power interruption, as long as a certain degree of load unbalance exists during transformer operation, the zero-sequence impedance can be calculated using secondary-side voltage and current monitoring data. This provides a practical basis for the online identification of distribution transformer capacity.

2.2 Online transformer capacity detection based on a capacity–zero-sequence impedance reference curve

Online capacity detection of distribution transformers primarily consists of four stages: data acquisition, data cleaning, zero-sequence impedance calculation, and capacity determination. As shown in Figure 2, it is a flowchart of online detection of distribution transformer capacity. First, under normal operating conditions, three-phase voltage and current data are continuously collected in real time via voltage and current transformers installed

on the secondary side of the transformer. When the three-phase loads are unbalanced—i.e., the magnitudes or phase angles of voltages or currents are inconsistent—zero-sequence components appear in the system, providing the necessary conditions for subsequent calculations. Next, the acquired operational data undergo cleaning and preprocessing to remove anomalies caused by sensor errors, external interference, or transient fluctuations, ensuring the validity and stability of the input data for computation. The cleaned data are then used to calculate the transformer's zero-sequence impedance. Specifically, the zero-sequence voltage and zero-sequence current are extracted using the symmetrical components method, and the zero-sequence impedance is obtained as the ratio of these two quantities. Finally, the computed zero-sequence impedance is matched against a pre-established reference curve that maps transformer capacity to zero-sequence impedance. By comparing the measured impedance with this curve, the actual capacity of the transformer is determined. If the detected capacity deviates from the nameplate rating, it indicates potential nameplate tampering or other anomalies, thereby enabling online identification and verification of the distribution transformer's true capacity.

3 Online data cleaning and capacity identification for distribution transformers

In the on-line detection of distribution transformer capacity, data cleaning is an important link to ensure the accuracy and reliability of the detection results. As the monitoring data comes from the voltage and current transformers at the operation site, the collection environment is complex, and the signal is easily affected by factors such as sensor accuracy error, electromagnetic interference, communication noise and user load mutation, which will lead to fluctuations or abnormalities in some voltage and current data, which will lead to inaccurate extraction of zero sequence voltage and zero sequence current, which will affect the capacity determination results and lead to misjudgment or deviation (Hou and Liu, 2024). Therefore, it is necessary to filter and correct the original monitoring data through data cleaning to eliminate the distorted samples caused by interference or fault (Zhao et al., 2021; Song et al., 2012; Gu et al., 2024; Dong and Dong, 2016). At

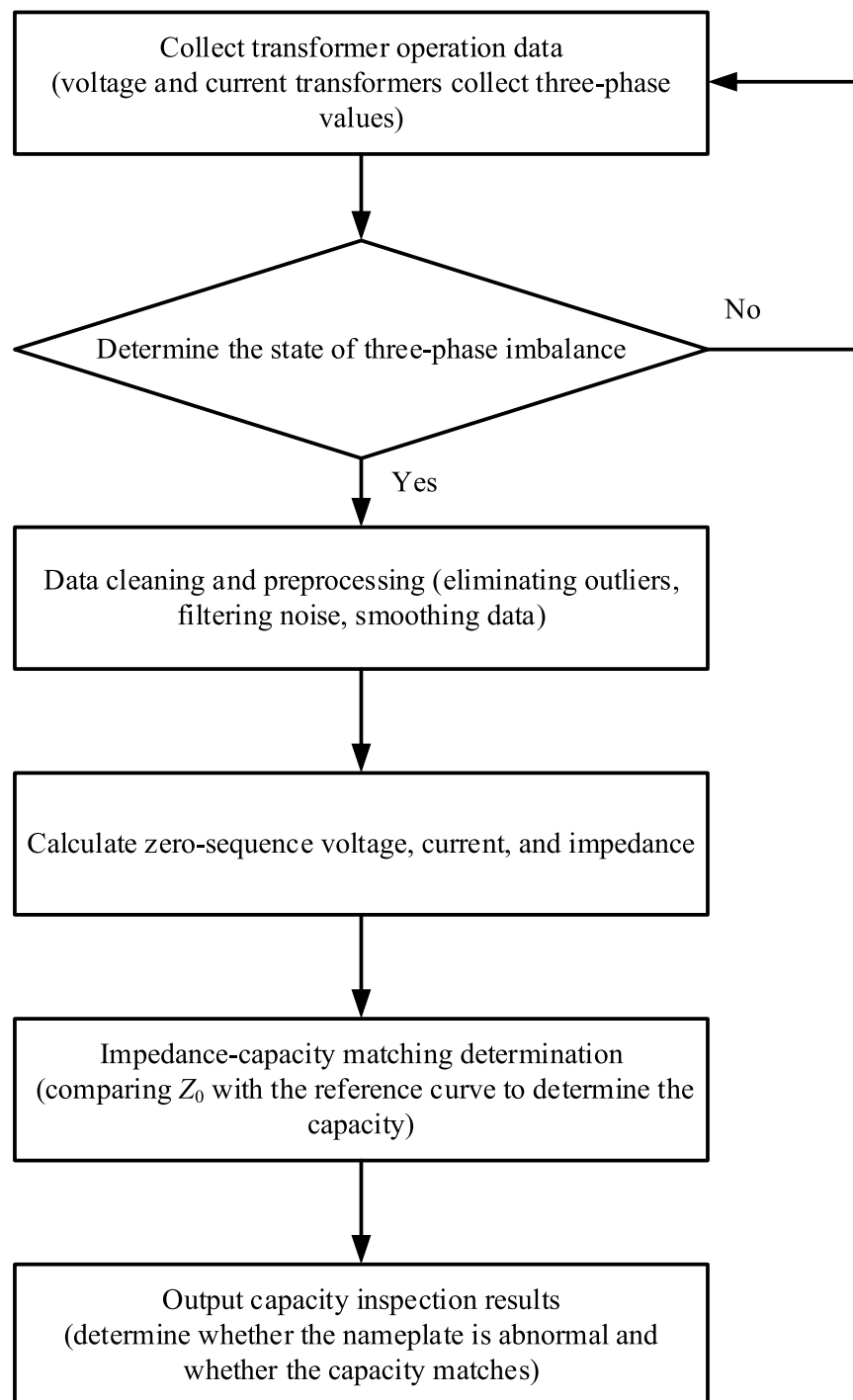


FIGURE 2
Online detection flow chart for distribution transformers.

present, the widely used data cleaning methods are mainly based on probability distribution, clustering and other algorithms to identify outliers in data, and to detect and process abnormal data by setting abnormal threshold. This kind of method belongs to supervised data cleaning, which usually requires manual participation in analyzing the internal relationship between statistical results or variables to determine a reasonable threshold standard (Jiang and Wenjian, 2022). However, this way of relying on prior knowledge

and human intervention is difficult to meet the needs of intelligent development of power grid system. In contrast, the unsupervised data cleaning method has more adaptability and automation advantages. Inspired by the idea of unsupervised learning in the fields of intelligent dialogue robot and sensitive word detection system, this paper proposes a cyclic data cleaning method based on BP neural network. This method uses the historical operation data to independently train the BP model, constructs the cycle cleaning

mechanism, and realizes the automatic identification and cleaning of abnormal data without manually setting the threshold.

3.1 Zero-sequence impedance neural network model

According to the symmetrical component method:

$$\begin{bmatrix} \dot{U}_1 \\ \dot{U}_2 \\ \dot{U}_0 \end{bmatrix} = \frac{1}{3} \begin{bmatrix} 1 & a & a^2 \\ 1 & a^2 & a \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} \dot{U}_a \\ \dot{U}_b \\ \dot{U}_c \end{bmatrix} \quad (1)$$

$$\begin{bmatrix} \dot{I}_1 \\ \dot{I}_2 \\ \dot{I}_0 \end{bmatrix} = \frac{1}{3} \begin{bmatrix} 1 & a & a^2 \\ 1 & a^2 & a \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} \dot{I}_a \\ \dot{I}_b \\ \dot{I}_c \end{bmatrix} \quad (2)$$

The zero-sequence components of voltage and current can be obtained from Equations 1, 2, and then the zero-sequence impedance of the distribution transformer can be calculated using Equation 3.

$$Z_{(0)} = \dot{U}_0 / \dot{I}_0 \quad (3)$$

Where, $Z_{(0)}$ is the zero sequence impedance of the transformer. Substituting Equations 1, 2 into Equation 3 yields:

$$Z_{(0)} = \frac{\dot{U}_a + \dot{U}_b + \dot{U}_c}{\dot{I}_a + \dot{I}_b + \dot{I}_c} \quad (4)$$

In Equation 4 \dot{U}_a , \dot{U}_b , and \dot{U}_c are the three-phase voltages on the secondary side of the transformer; \dot{I}_a , \dot{I}_b , and \dot{I}_c are the three-phase currents on the secondary side; and $Z_{(0)}$ is the zero-sequence impedance of the transformer. As seen from the equation, the calculation of zero-sequence impedance depends only on the secondary-side voltage and current of the transformer. Parameters such as internal structure, turns ratio, and primary-side voltage remain constant during operation (Kang et al., 2016; Miao et al., 2022). Therefore, according to Equation 4, a regression relationship exists between the zero-sequence impedance $Z_{(0)}$ and the secondary-side voltage U_2 and current I_2 . Based on this, a BP neural network model can be constructed with input features $X = [U_2, I_2]$ and output feature $Y = [Z_{(0)}]$, as shown in Figure 3.

The dataset is processed through forward computation according to the network architecture shown in Figure 3. Each neuron in the hidden layers is denoted as l_i , where l_{1i} , l_{2i} , and b_i represent the input, output, and bias of the i th neuron, respectively. The number of hidden layers is set to five. The input layer is characterized by two neurons $[U_2, I_2]$, the output layer is $[Z_0]$, and the network structure is fixed in the "2-5-1" mode. The input and output of the output layer are denoted as O1 and O2, respectively. The network computation error Δe for each sample is given by Equation 5.

$$\begin{aligned} l_{1i} &= U_2 W_{U_i} + I_2 W_{I_i} + b_{1i} \\ l_{2i} &= \text{sigmoid}(l_{1i}) \\ O_1 &= \sum_{i=1}^5 l_{2i} W_{li} + b_o \\ O_2 &= \text{sigmoid}(O_1) \\ \Delta e &= \frac{1}{2} (O_2 - Z_{(0)})^2 \end{aligned} \quad (5)$$

where W_{U_i} represents the connection weight between the U_2 neuron in the input layer and the i th hidden layer neuron, W_{I_i} represents the connection weight between the I_2 neuron in the input layer and the i th hidden layer neuron, W_{li} represents the connection weight between the i th hidden layer neuron and the output layer neuron, b_o represents the bias of the output layer neuron, and sigmoid (\cdot) is the activation function used in the neural network (Huang et al., 2025). The model training adopts gradient descent method to update the weights, and the learning rate α is taken as the key parameter, which needs to be kept fixed in the training, taking 0.01.

3.2 Online data cleaning

This paper adopts a BP neural network-based data cleaning method, which mainly consists of two stages: the abnormal sample exclusion stage and the potential normal sample review stage.

3.2.1 Abnormal sample exclusion stage

The purpose of this process is to identify and remove abnormal samples that significantly deviate from the overall data pattern. The initial model is used to predict all samples, and the prediction error for each sample is calculated (Hou et al., 2025a; Hou et al., 2025b; Liu and Hou, 2023; Liu et al., 2025). An error threshold is first defined, and any sample whose error exceeds this threshold is flagged as an "unreliable sample" and excluded. The model is then retrained using the remaining samples, and the process is repeated iteratively until no further samples are removed, thereby progressively improving data quality.

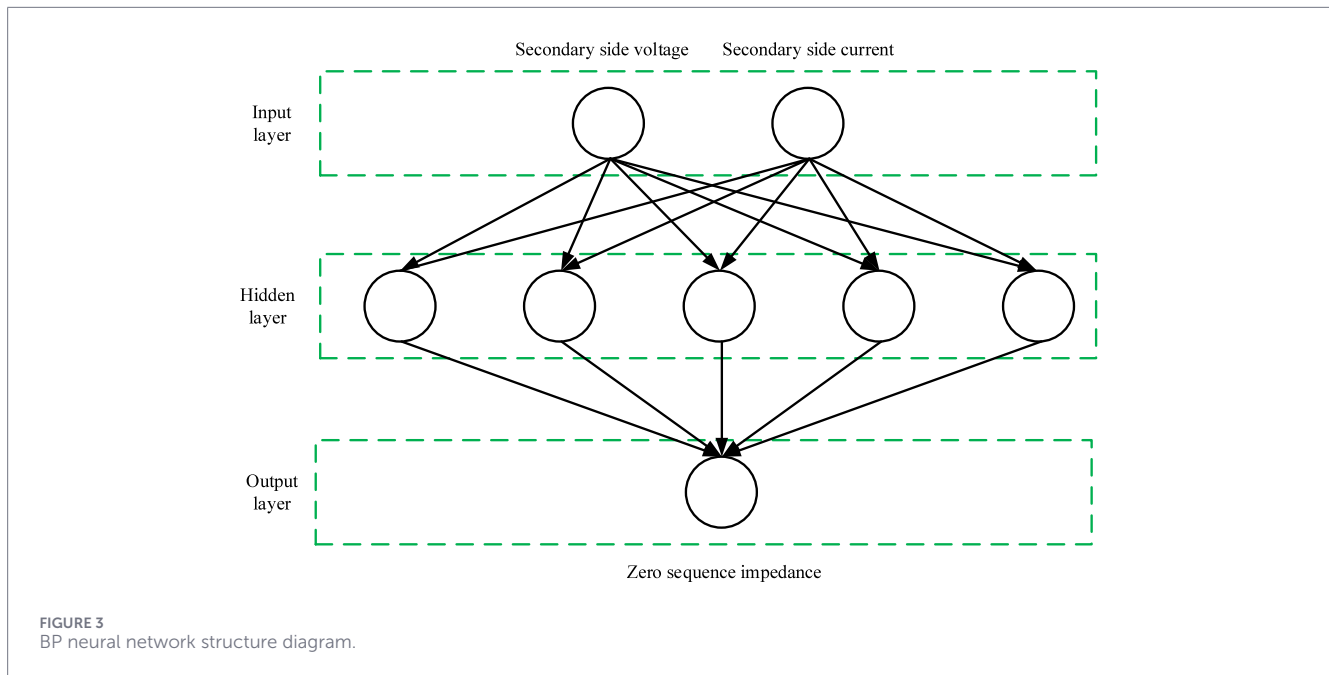
3.2.2 Potential normal sample review stage

This step checks for any normal samples that may have been mistakenly excluded in earlier stages and reintegrates them into the training set. The final trained model is used to make predictions on all original samples once again. Samples are then reselected based on their prediction errors, retaining only those that meet the error criterion. These selected samples undergo multiple rounds of testing and retraining to ensure model stability and to preserve as much genuine, valid data as possible.

3.3 Distribution transformer capacity identification procedure

As shown in Figure 4, the online capacity detection process for distribution transformers based on the zero-sequence impedance method with BP neural network-based data cleaning is as follows:

1. Obtain the rated parameters of distribution transformers with different capacities across various series, and use MATLAB/Simulink simulation software to calculate the zero-sequence impedance of each transformer under operating conditions. Based on these calculations, establish a reference curve that maps transformer capacity to zero-sequence impedance.
2. Perform preprocessing on the transformer's historical operational data and develop a final BP-based data cleaning model through an iterative cleaning process.



3. Input the real-time monitoring data into the BP cleaning model and calculate the prediction error of the model for each monitoring sample.
4. Evaluate the prediction errors, and if the error of a particular sample is significantly higher than the overall average error level, identify it as an abnormal sample and remove it.
5. Perform calculations on the remaining normal samples to compute the zero-sequence impedance, and then match this value against the simulated zero-sequence impedance–capacity reference curve to determine the actual capacity of the transformer.

4 Construction of zero-sequence impedance vs. capacity reference curve and verification of load independence based on MATLAB/Simulink

4.1 Construction of the reference curve relating zero-sequence impedance to transformer capacity

In this paper, a simulation model of distribution transformer operation is developed in MATLAB/Simulink, reflecting actual field operating conditions. The model comprises key components including a three-phase power source, a transformer, three-phase voltage and current sensors, and a load, as shown in Figure 5. The secondary-side phase voltages U_a , U_b , U_c and currents I_a , I_b , I_c are acquired from the transformer for subsequent calculation of zero-sequence impedance (Saeed et al., 2020).

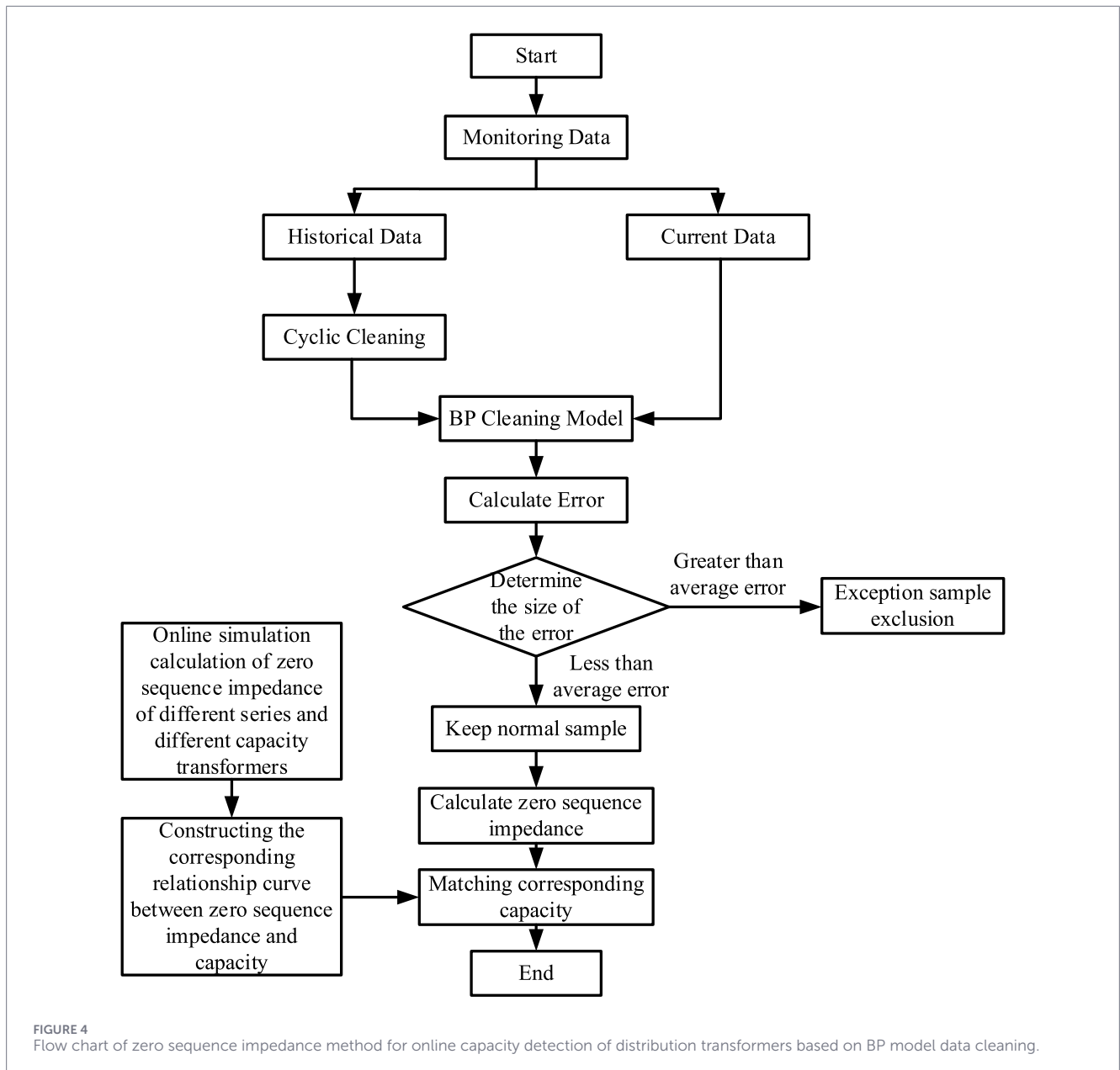
The three-phase voltage source is set to the rated primary-side voltage of the transformer. The transformer module is configured

according to the actual technical parameters of various series of distribution transformers. To induce zero-sequence components in the secondary-side voltage and current, the load is intentionally configured in a three-phase unbalanced condition. Since the zero-sequence impedance is an inherent property of the transformer itself, its value remains unaffected by the degree of load unbalance. In this study, a 10% current unbalance level is adopted for the load. The unbalance level is quantified using the current unbalance factor, as defined in Equation (7).

$$\frac{\max(|I_a - I_{\text{avg}}|, |I_b - I_{\text{avg}}|, |I_c - I_{\text{avg}}|)}{I_{\text{avg}}} \times 100\% \quad (6)$$

The method employed in this paper relies on the presence of zero-sequence current in the system, which arises only when there is a certain degree of three-phase load unbalance. Under ideal simulation conditions, even extremely low levels of unbalance can generate a resolvable zero-sequence current component, enabling accurate calculation of the zero-sequence impedance that closely matches the theoretical value. However, in practical engineering applications, factors such as the measurement accuracy of current transformers, the resolution of data acquisition systems, and background grid noise limit the detectability of weak zero-sequence signals. When the current unbalance falls below approximately 0.8%, the zero-sequence signal is easily overwhelmed by noise, leading to significant fluctuations and reduced stability in the impedance estimation. Based on field measurement experience, to ensure robustness and reliability, the proposed method is recommended for use in operating conditions where the three-phase current unbalance is no less than 1%.

In summary, a consistent 10 kHz sampling frequency was applied in both simulation and field testing, ensuring high-fidelity data acquisition and sufficient accuracy for practical engineering applications. This information has been added to the revised manuscript. In this paper, the calculation of zero-sequence

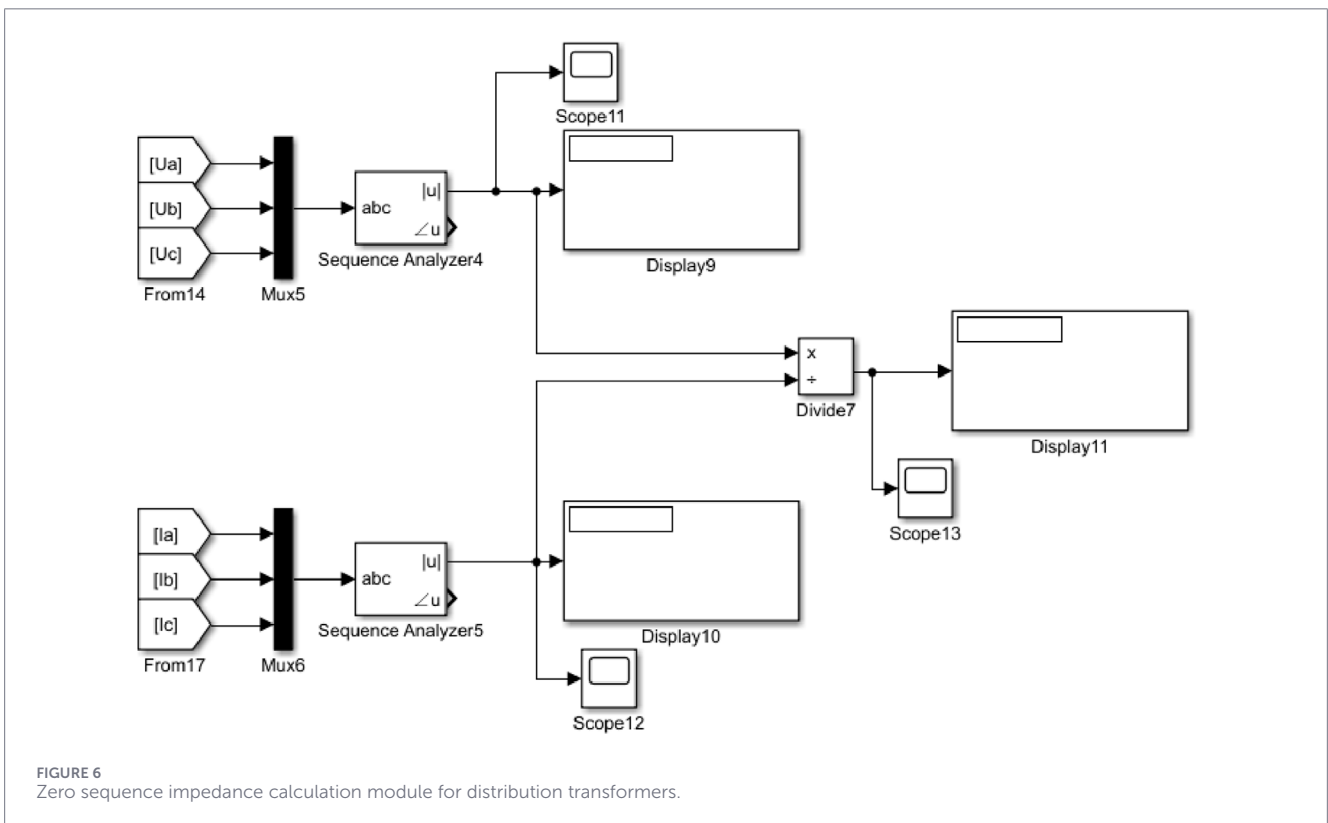
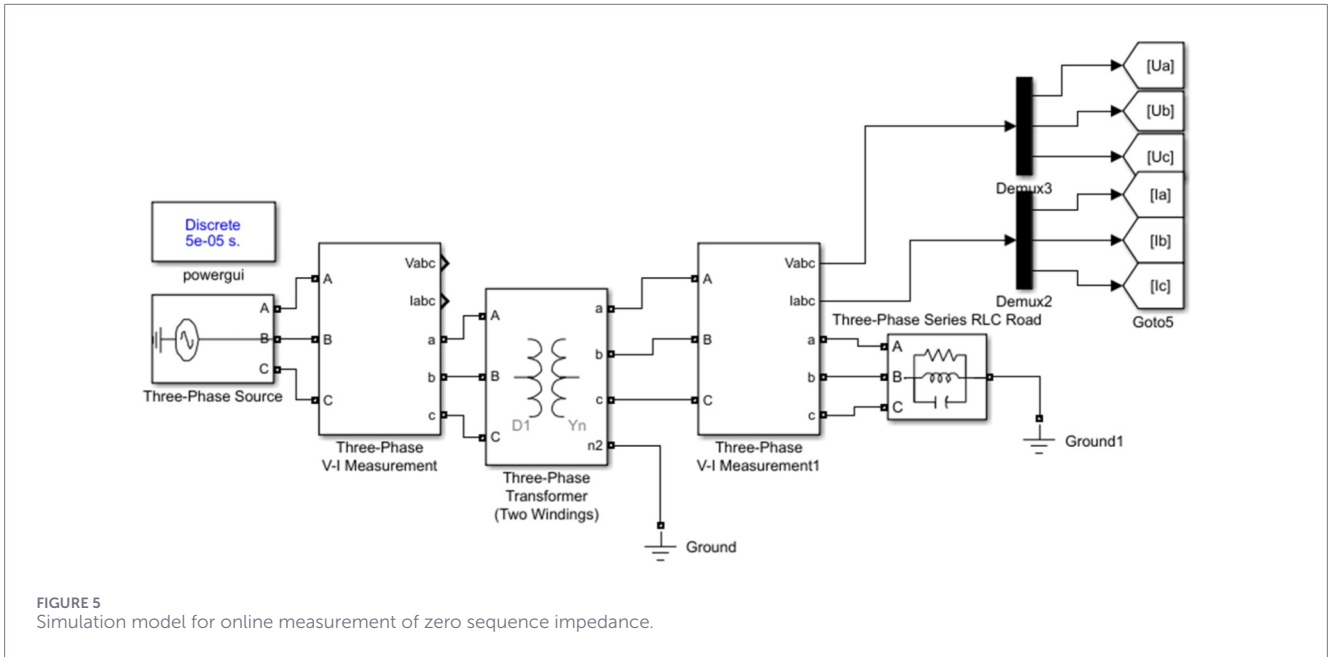


impedance is based on the symmetrical components method, which can be implemented in Simulink using the Sequence Analyzer block. Two Sequence Analyzer blocks are employed to separately compute the zero-sequence voltage and zero-sequence current. The zero-sequence impedance of the distribution transformer is then obtained by dividing the zero-sequence voltage by the zero-sequence current, as illustrated in Figure 6.

This paper considers the S7, S9, and S11 series of distribution transformers, with rated capacities ranging from 6.3kVA to 1600kVA, covering the common capacity classes of distribution transformers. The parameters of these transformers are incorporated into the simulation model to compute their respective zero-sequence impedances. Based on the results, a reference curve relating transformer capacity to zero-sequence impedance is constructed, as shown in Figure 7.

The applicable capacity range of the proposed method is determined comprehensively based on zero-sequence circuit characteristics and field signal measurability. Simulation studies covered typical distribution transformer models ranging from 6.3 kVA to 1,600 kVA, demonstrating that zero-sequence impedance values vary distinctly across this range, enabling reliable capacity discrimination.

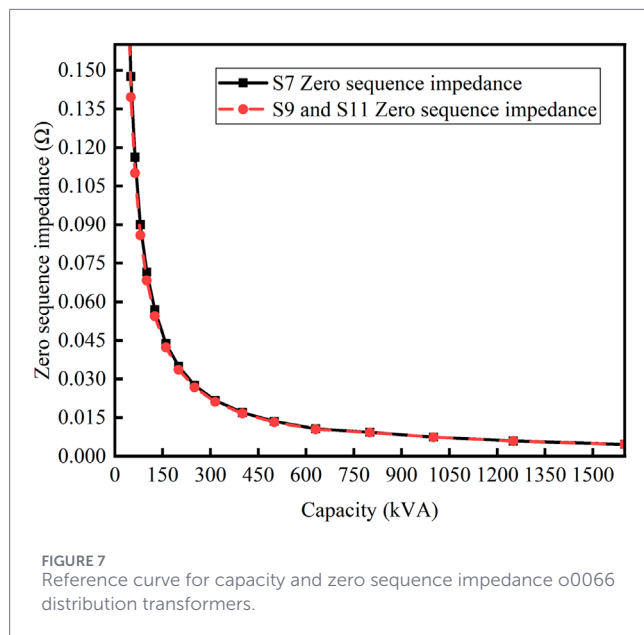
In practical applications, with the support of a local power supply bureau, we conducted field tests on 12 operating Yyn0-connected distribution transformers with rated capacities of 100 kVA, 200 kVA, 400 kVA, and 630 kVA. In all cases, the transformer capacity was successfully estimated from the measured zero-sequence impedance, with estimation errors within $\pm 10\%$, meeting the engineering requirements for applications such as anti-theft inspections.



When the transformer capacity exceeds approximately 1,600 kVA, the zero-sequence impedance typically drops below 0.01 Ω, resulting in an extremely weak zero-sequence voltage signal. Under such conditions, factors like grounding resistance, neutral conductor impedance, and measurement system noise can significantly interfere with the signal, leading to insufficient signal-to-noise ratio and reduced reliability of the assessment. Given the

capabilities of currently available standard power quality monitoring equipment, 1,600 kVA is considered the practical upper limit of the method.

Therefore, the proposed method is suitable for distribution transformers with capacities ranging from approximately 6.3 kVA to 1,600 kVA, which covers the vast majority of public distribution transformers in China.



Simulation results reveal that, for the same rated capacity, the S9 and S11 series distribution transformers exhibit identical zero-sequence impedance values; hence, they are represented by a single curve in the figure. As shown, the zero-sequence impedance of distribution transformers varies with capacity—specifically, it decreases gradually as the transformer capacity increases. Motivated by this monotonic relationship, this paper proposes an online capacity identification method: by using voltage and current transformers to acquire real-time operational voltage and current data from the distribution transformer, the zero-sequence impedance is computed and then mapped to the reference curve to determine the actual transformer capacity.

In the method proposed in this paper—estimating transformer capacity based on zero-sequence impedance measurement—the magnitude of the zero-sequence impedance is primarily utilized. Temperature affects the winding resistance and thereby indirectly influences the real part of the zero-sequence impedance. Specifically, as temperature increases, the DC resistance of copper windings rises, leading to an increase in the zero-sequence resistance component R_0 . In contrast, the zero-sequence reactance component X_0 is mainly determined by the transformer's magnetic circuit structure and core configuration, and remains essentially unaffected by temperature within normal operating ranges.

In practical measurements and engineering applications, we have observed that for most distribution transformers—particularly oil-immersed or dry-type three-phase units with three-limb or five-limb core structures—the zero-sequence impedance is predominantly reactive, typically satisfying $X_0 \gg R_0$. Reference (Jo et al., 2016) mainly analyzes the influence of transformer core configuration on zero sequence impedance characteristics, which supports the conclusion that structural parameters play a leading role. Although the temperature change may affect the winding resistance, since the zero sequence impedance is mainly determined by the structural configuration and magnetic coupling of the transformer, it is expected that the impact

of temperature change on the overall size of the zero sequence impedance is limited.

4.2 Simulation calculation of zero-sequence impedance of transformers under different load conditions

The zero-sequence impedance of a transformer reflects the equivalent flow path of zero-sequence current inside the transformer, and its value is mainly determined by the transformer's connection mode, winding structure, and magnetic circuit. Within the normal operating range, load variations do not alter the flow path of zero-sequence current or the structural parameters of the transformer. Therefore, the zero-sequence impedance is insensitive to changes in load level and exhibits excellent stability, which will be verified in the subsequent section.

The overall structure of the distribution transformer simulation model is illustrated in Figure 5.

In the actual operation process, the load level, power distribution, and degree of three-phase unbalance of distribution transformers vary with time. To verify whether the zero-sequence impedance is affected by load changes, this paper sets a variety of different loads in the simulation model to verify the zero-sequence impedance under different load levels and unbalanced conditions.

On the premise of keeping the transformer's structural parameters unchanged, this paper sets different operating capacities and three-phase unbalanced load conditions respectively. The different load levels are divided into 30%, 50%, and 80% of the rated capacity, with specific data shown in Table 1.

The simulation results show that in the simulation environment, the zero sequence impedance calculated by theory is consistent under different load levels and three-phase unbalanced operation conditions, while the structural parameters of the transformer remain unchanged. This shows that within the normal operation range, the zero sequence impedance is mainly determined by the structural parameters and rated capacity of the transformer, and is weakly related to the specific operating conditions.

5 Online verification of distribution transformer capacity detection based on field data

5.1 BP model-based data cleaning

In this paper, a total of 10,000 data samples are selected from the voltage and current data collected at one time from the secondary side as a data sample, using the continuous operation data of 1 month obtained by the on-line monitoring equipment of a distribution transformer in an enterprise in Yunnan. The number of hidden layers in the model is 5, the number of undisclosed neurons in each layer is 20, and the learning rate α is 0.01. The training algorithm uses gradient descent method and incremental iteration times. In this paper, 1-h granularity of primary and secondary side voltage and current data are used as samples to ensure the time continuity and consistency of the data. Each sample needs to contain the complete secondary voltage U_2 and secondary current I_2 . In the training process, 10^{-5} is used as the error threshold

TABLE 1 Transformer load under different operating conditions.

Three-phase load	30%		50%		80%	
	Active power/kW	Reactive power/kvar	Active power/kW	Reactive power/kvar	Active power/kW	Reactive power/kvar
A	6.5	4.5	11.0	6.8	18.0	11.1
B	8.5	5.3	14.0	8.7	22.0	13.6
C	10.5	6.5	17.5	10.8	28.0	17.3

Extract the corresponding zero-sequence voltage and zero-sequence current data, and calculate the zero-sequence impedance. The simulation results under various operating conditions are presented in Table 2.

TABLE 2 Zero-sequence impedance of transformers under different operating conditions.

Working condition	Load level	Zero sequence impedance/ Ω	Error/%
Condition 1	30%	0.06285	0
Condition 2	50%	0.06285	0
Condition 3	80%	0.06285	0

For each load class, the three-phase load distribution follows the configuration listed in Table 1.

between the actual value and the calculated value. When the average error after iteration decreases to near this threshold, the training convergence of the model is determined. The order of error is used as the judgment standard for abnormal samples: samples larger than the order of average error are judged as abnormal data. This rule runs through the process of sample exclusion and potential sample review.

In practical distribution systems, nonlinear loads generate so-called $3n$ th order harmonics, such as the 3rd, 9th, and 15th harmonics. These harmonics are of zero-sequence nature and accumulate in the neutral conductor or grounding path, producing additional zero-sequence currents. If left unaddressed, these harmonic components can interfere with the proposed method: directly using total current to compute zero-sequence impedance would lead to an underestimated result, thereby degrading the accuracy of transformer capacity estimation.

To address this issue, our method employs discrete Fourier transform in the signal processing stage to rigorously extract only the 50 Hz fundamental components of voltage and current. The zero-sequence impedance is then calculated exclusively from these fundamental components, effectively eliminating harmonic interference.

Simulation tests show that even under high harmonic conditions—with a total harmonic distortion of approximately 15%—the error in zero-sequence impedance estimation can be kept within 2% when the fundamental-component extraction strategy is applied. In contrast, without filtering, the error may exceed 10%. Therefore, as long as data processing focuses solely on the fundamental frequency component, the impact of harmonics on the proposed method remains limited.

Input historical data samples directly into BP model for training, which may contain abnormally large data and need to be cleaned), and screen the data samples according to the method proposed in Section 2.2. The initial training is set to 1,000 iterations, and the number of iterations increases by 1,000 each time a new model

is built. At the same time, the error tolerance between the actual value and the predicted value is set to 10^{-5} . After the model is built, the monitoring data is input into the BP model for cleaning. The statistical results show that there are six rounds of elimination operation in the whole sample elimination process, and no new samples are eliminated after the sixth round. Some data results are shown in Figure 8.

The results demonstrate that, after cleaning with the BP neural network model, anomalous data points in the monitoring dataset are effectively removed. This confirms that the proposed BP model-based anomaly detection and data cleaning approach is effective for preprocessing transformer operational data, thereby enhancing the accuracy of subsequent zero-sequence impedance calculations.

5.2 Capacity verification of the distribution transformer under test

The distribution transformer used in this case test is Dyn11 connection group, which belongs to the dyn connection category discussed in Section 2.1. In Dyn11 notation, the clock number only represents the phase displacement between the high-voltage winding and the low-voltage winding, and does not change the core structure of the transformer, the neutral grounding condition or the circulation path of the zero sequence current. Therefore, the zero sequence impedance characteristics and corresponding reference curves derived for dyn connected transformer are also applicable to Dyn11 transformer.

Export the cleaned voltage and current operation data to the table, and calculate the operation parameters at 10 time points, as shown in Table 3. Where φ_a , φ_B and φ_C are the phase angles of three-phase voltage respectively, and θ_a , θ_B and θ_C are the phase angles of three-phase current respectively. The basic parameters of the distribution transformer are shown in Table 4.

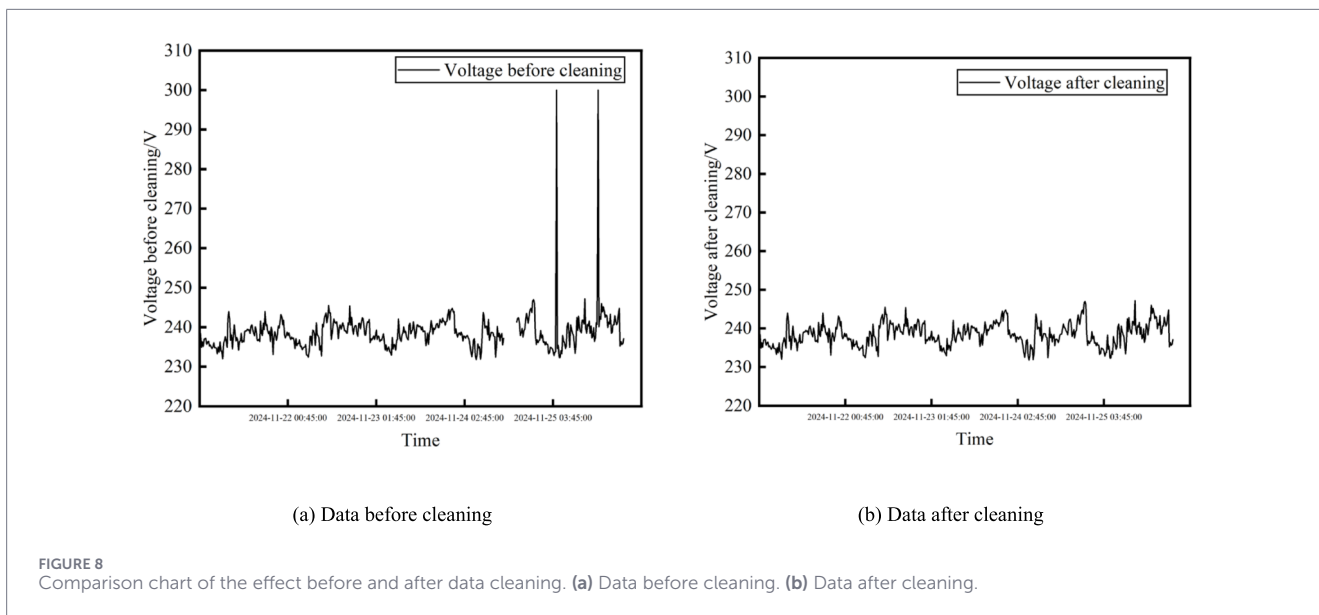


TABLE 3 Operation data of cleaned distribution transformer.

No.	1	2	3	4	5	6	7	8	9	10
U_a/V	229.8	229.9	229.5	229.7	230	229.9	229.6	229.5	229.3	229.7
U_b/V	229.2	229.4	229	229.1	229.4	229.4	229	229.1	229	229.3
U_c/V	228.7	228.7	228.3	228.6	228.8	228.7	228.4	228.4	228.3	228.6
φ_a	0	0	0	0	0	0	0	0	0	0
φ_b	120.2	120.2	120.2	120.2	120.3	120.2	120.2	120.3	120.2	120.2
φ_c	240.1	240.1	240.1	240.1	240.1	240.1	240.1	240.1	240.1	240.1
I_a/A	0.136	0.138	0.137	0.137	0.137	0.137	0.136	0.136	0.136	0.136
I_b/A	0.152	0.159	0.153	0.164	0.163	0.151	0.163	0.164	0.15	0.152
I_c/A	0.279	0.288	0.277	0.276	0.276	0.275	0.276	0.276	0.288	0.277
θ_a	313.6	314	314.2	313.9	313.9	314	313.6	313.7	314.1	313.9
θ_b	85.3	87.1	85.8	89.8	90.2	85.7	89.8	90.5	85.4	86.7
θ_c	215	215.2	214.4	214.3	214.4	214.4	215.9	215	216.9	215

TABLE 4 Basic parameters of distribution transformers.

Model	Connection group	Rated capacity/kVA	Short-circuit impedance/%	Rated voltage/kV
S11	Dyn11	315	4.18	10/0.4

It should be noted that the voltage phase angle listed in Table 3 represents the fundamental positive sequence voltage and is close to the equilibrium state. In this study, the existence of zero sequence component does not depend on the voltage phase imbalance. Zero sequence current is mainly introduced by unbalanced load conditions and neutral current path of transformer. Therefore, the phase angle of the balanced voltage shown in Table 3 does not contradict the existence or extraction of zero sequence impedance in the proposed method.

The sum of three-phase voltage and current phasors at the same time point in the table is not zero, so it is in three-phase unbalanced state, and there is zero sequence component, which can be used for zero sequence impedance calculation. The comparison and error between zero sequence impedance calculation results and zero sequence impedance capacity are shown in Table 5.

As can be seen from the data in the table, after data cleaning, the online-calculated zero-sequence impedance values closely match those obtained from the simulation-based reference

TABLE 5 Zero sequence impedance calculation results.

No.	Calculated Z_0/Ω	Reference Z_0 from curve/ Ω	Error/%
1	0.02042	0.02115	-3.45
2	0.02189		3.50
3	0.01947		-7.94
4	0.02233		5.58
5	0.02076		-1.84
6	0.02105		-0.47
7	0.02278		7.71
8	0.01994		-5.72
9	0.02162		2.22
10	0.02018		-4.59

curve. The calculated values agree well with the reference zero-sequence impedance values, with errors within 10%. Consequently, the transformer capacity can be accurately determined by locating the computed zero-sequence impedance on the reference curve, thereby fulfilling the requirement for online capacity detection.

In practical applications, the choice of data window length significantly affects the stability of zero-sequence impedance estimation. To accurately extract the zero-sequence component corresponding to the 50 Hz fundamental frequency, the selected time window must satisfy two conditions: first, it must contain an integer number of power-frequency cycles to avoid spectral leakage; second, it must be sufficiently long to effectively suppress background grid noise and minor operational fluctuations.

Comparisons of calculation results under different window lengths show that when the window is 20 milliseconds, the method is theoretically feasible but highly sensitive to transient disturbances, leading to large impedance estimation errors—exceeding $\pm 8\%$. When the window is extended to 200 milliseconds, the variation drops significantly, with errors confined within $\pm 3\%$. Further increasing the window to 1 s results in a well-converged zero-sequence impedance estimate with excellent repeatability, meeting the reliability requirements of engineering applications.

Therefore, considering both computational accuracy and response speed, this paper sets the minimum data window to 1 s in its field deployment strategy. It should be noted that in ideal simulation environments—where signals are noise-free and models are exact—even a 100-millisecond window or shorter can yield high-accuracy results. However, to ensure robust performance in real-world systems, a 1-s window is considered the most appropriate minimum practical length.

6 Conclusion

In certain regions, the unauthorized replacement of transformer nameplates in distribution networks has become a serious issue.

As the reliability requirements of power systems continue to rise, traditional offline capacity detection methods—which require power outages—are becoming increasingly impractical. This creates an urgent need for an effective online capacity detection approach. To address the insufficient accuracy of existing online methods based on short-circuit impedance, this paper proposes a novel online transformer capacity detection method that leverages the matching relationship between zero-sequence impedance and transformer capacity. Building upon extensive parameter data of various distribution transformer series (e.g., S7, S9, S11), a simulation model is established to compute the zero-sequence impedance for transformers across a wide range of capacities under unbalanced operating conditions. A reference curve mapping zero-sequence impedance to rated capacity is then constructed. To enhance computational accuracy, a Backpropagation (BP) neural network-based data cleaning technique is introduced to preprocess field monitoring data, effectively removing outliers and noise. The cleaned voltage and current data are used to calculate the zero-sequence impedance of the transformer under test, which is subsequently matched against the reference curve to determine its actual capacity—enabling fully online, non-intrusive capacity verification. The main findings are summarized as follows:

1. After BP-based data cleaning, the calculated zero-sequence impedance values closely align with those from the reference curve, with errors consistently below 10%, demonstrating that the zero-sequence impedance can reliably indicate transformer capacity.
2. The proposed zero-sequence impedance–capacity matching method enables accurate, online capacity detection without requiring power interruption, significantly improving operational efficiency and enhancing the reliability of power supply in distribution networks. This approach provides a practical and robust solution for detecting nameplate tampering and unauthorized capacity modifications, supporting the intelligent and secure operation of modern distribution systems.

Data availability statement

The original contributions presented in the study are included in the article/[Supplementary Material](#), further inquiries can be directed to the corresponding author.

Author contributions

BL: Writing – original draft. Y-XL: Writing – original draft. M-MZ: Writing – original draft. Y-HL: Writing – review and editing. R-JG: Writing – review and editing. M-GY: Writing – review and editing. X-DZ: Writing – review and editing.

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Conflict of interest

Authors BL, Y-XL, M-MZ, and Y-HL were employed by Yunnan Power Grid Co., Ltd. Electric Power Science Research Institute.

Author R-JG was employed by Yunnan Power Grid Co., Ltd.

Authors M-GY, X-DZ were employed by Yunnan Power Grid Co., Ltd. Lincang Power Supply Bureau Kunming.

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The author(s) declared that generative AI was not used in the creation of this manuscript.

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Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fenrg.2026.1751246/full#supplementary-material>

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