EAI Endorsed Transactions
on Energy Web
Research Article EAI.EU

Research on the Cause Diagnosis Method of Line Loss Anomaly Based on the Analysis of Electricity Fluctuation in the Substation Area

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Abstract

This paper presents a three-stage line loss anomaly diagnosis method based on power consumption fluctuation analysis in transformer districts. The proposed approach integrates causal forest modeling, SHAP value attribution, and TCN time series convolution networks to identify anomalies. By applying threshold-based analysis of power supply rate changes and consumption rate variations, it differentiates between grid-side anomalies, user-side anomalies, and composite anomalies. The causal forest model quantifies individual user processing effects, while the TCN network calculates load curve similarity to precisely detect hidden anomalies (such as minor power surges accompanied by load pattern deviations) that traditional methods might miss. SHAP values are used to visualize key feature contributions, enhancing diagnostic interpretability and field verification efficiency. Using real-world data from typical transformer districts, this study demonstrates the effectiveness and practicality of the proposed method, discusses its limitations, and outlines future research directions.

Keywords: Power fluctuation analysis, line loss abnormal cause diagnosis, metering device fault, line loss rate anomaly

Received on 15 November 2025, accepted on 13 December 2025, published on 31 March 2026

doi: 10.4108/ew.11915

1. Introduction

In power distribution network management, identifying the root causes of line loss anomalies is crucial for effective fault resolution. The accuracy of these determinations directly impacts whether such issues can be resolved promptly. Traditional intelligent diagnostic algorithms primarily analyze real-time data from power consumption meters and customer records during line loss incidents, yet fail to fully utilize critical information about energy fluctuations before and after anomalies. As distribution network management standards continue to evolve, the urgency of timely fault resolution has become increasingly prominent. This makes it imperative to develop anomaly diagnosis methodologies grounded in power fluctuation analysis for efficient line loss management.

Currently, the widely adopted diagnostic methods for abnormal line loss in transformer districts are primarily categorized into three types. The first method involves analyzing macro-level indicators such as the success rate and coverage of data collection to identify potential issues. The second method examines the curve collection status of transformer district assessment forms and user records, using pattern analysis to detect potential electricity theft or metering anomalies. The third method monitors changes in household-to-transformer relationships, conducting individual investigations on users experiencing such relationship changes to uncover errors in transformer-user connections.

Shao Xincheng and colleagues developed a data-driven low-voltage distribution transformer district line loss rate anomaly diagnosis model using closed-loop intelligent operation analysis platform, significantly improving

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diagnostic accuracy [1]. Zhang Qing conducted specialized analysis on equipment aging-induced insulation degradation and increased contact resistance in low-voltage transformer districts, proposing corresponding countermeasures [2]. Zhao Chenglong implemented experimental secondary clustering analysis based on data features, focusing on outlier detection for line loss identification [3]. Qin Teng categorized 12 influencing factors of transformer district line losses, employing big data collection and three-phase hybrid method for power flow calculation to generate line loss diagrams for rapid anomaly detection [4]. Zhang Hengchao's team analyzed massive electricity operation data from smart metering systems to build anti-theft models for transformer district line loss diagnosis [5]. Qian Lihong's research adopted layered data collection, analyzing line loss fluctuations and peak patterns across transformer districts to identify anomalies through feature matching [6]. Cai Jiahui proposed DNN-based statistical prediction, LSTM time series algorithms, and DenseNet-RF-powered electricity theft detection methods for line loss anomaly resolution [7]. Dong W et al. developed a data-driven diagnostic method for abnormal line loss rates in transformer districts, effectively analyzing the reasonable line loss range for low-voltage transformer districts to achieve accurate diagnosis of line loss rate anomalies in low-voltage station areas [8]. Linna N et al. proposed a knowledge base-based method for automatic generation of line loss anomaly diagnosis and reduction strategies, systematically classifying line loss anomalies and automatically generating corresponding reduction strategies to provide decision support for improving the lean management level of line loss control in station areas [9]. Cheng H et al. utilized data mining and convolutional neural network models to analyze transformer district line loss data, successfully identifying and diagnosing line loss issues with significant advantages in iteration speed, convergence time, and accuracy [10].Ding Dong and others proposed a fault identification technology for substation master meters based on time convolutional networks, which achieves fault identification by extracting high-dimensional features from the time series of substation measurement values [11]. Zhou Jian and others proposed an automatic detection method for line loss anomalies in substation areas based on edge intelligence technology. This method calculates the line loss rate of substation areas through a convolutional neural network-long short-term memory neural network, determines whether there are line loss anomalies, and stores the detection results on a cloud platform and regularly updates the prediction results of edge detectors [12]. Han Maoyue and others designed a multi-source data preprocessing mechanism for distribution networks. Based on PMU, they performed time scale alignment, data completion, and noise filtering on data obtained from the SCADA system and AMI measurement system, constructing a high-quality multi-source dataset for distribution networks [13]. Liu Qian proposed an intelligent diagnosis method for distribution network line loss in the power IoT environment. Based on a semi-supervised learning framework and radial basis function neural network, a line loss diagnosis model was constructed to achieve intelligent diagnosis of distribution network line loss [14]. Wang Hongliang and others designed a calculation method for distribution network line loss rate based on topology recognition and artificial intelligence algorithms. They extracted multiple features of distribution network data using topology recognition and calculated the fitness function of the data, thereby obtaining a more accurate calculation of the distribution network line loss rate [15].

Building upon previous research experiences and limitations, this paper proposes a line loss anomaly diagnosis method based on transformer district power fluctuation analysis, comprising two main components: power supply factor analysis and electricity consumption factor analysis. The power supply factor analysis compares power supply variations before and after transformer district line loss anomalies, identifying metering device failures through multiplier analysis of power supply changes. Meanwhile, the electricity consumption factor analysis examines electricity consumption patterns among individual users before and after line loss anomalies. By comparing significant consumption fluctuations among typical users and estimating their power consumption changes based on overall transformer district usage, the method further determines metering device failures through multiplier analysis of these fluctuations.

2. Definition of abnormal line loss in the station area

Line loss anomalies in transformer districts typically refer to abnormal line loss rates that rise or drop below-1% due to management or technical factors, resulting in high or negative losses. These issues may stem from various causes such as missed electricity meter reading, incorrect wiring of metering devices, faulty metering equipment, line leakage, user electricity theft, or changes in customer transformer relationships. Such anomalies can significantly impact the economic efficiency and safe operation of power grids, requiring prompt resolution when detected. This article primarily discusses three types of problems: incorrect metering device wiring, faulty metering devices, and user electricity theft.

1) Incorrect wiring of metering devices: Common wiring errors include open circuits in voltage or current lines, short circuits in current lines, incorrect connections of voltage or current lines, reversed current line connections, and faulty transformer wiring. These issues can lead to inaccurate electricity measurement or failure to record consumption. Generally, stable-operating energy meters will not experience metering device wiring errors unless manually operated.

2) Metering device faults: Common metering device faults include damaged metering components of electricity meters leading to inaccurate or non-measured electricity, uneven power display values, flyaway meters, and reverse operation of meters. While metering device faults are relatively easy to identify, the resulting changes in measured electricity quantities generally lack clear patterns.

3) Electricity Theft by Users: Common theft methods include tampering with the voltage and current wiring of electricity meters or bypassing metering devices. While

altering meter wiring resembles incorrect wiring errors in metering systems, bypassing metering devices proves more challenging to detect through data analysis.

3. Core algorithm principle research

3.1 Causal forest model

Causal Forest is a non-parametric method based on random forests for estimating heterogeneous treatment effects (HTE). In this context, "treatment" refers to the occurrence of line loss anomalies (Phase T1), with the goal of estimating the causal effect (i.e., the change in electricity consumption) of such events on each user's power usage. Unlike traditional methods like mean comparison, Causal Forest identifies which user characteristics—such as historical consumption patterns, user types, meter types, etc.—cause significant changes in electricity consumption during abnormal periods. This approach more accurately pinpoints affected user groups and differentiates between common anomalies and specific individual issues. The core principle involves constructing numerous causal trees. Each tree splits the dataset using randomly selected samples and feature subsets, maximizing differences in outcome variables (electricity consumption) between treatment groups (Phase T1) and control groups (Phase T0). The final individual treatment effect estimates are obtained by averaging these trees.

3.2 SHAP value attribution

SHAP value attribution is a game-theoretic model interpretation method used to explain predictions from any machine learning model. It quantifies the contribution of each feature to individual sample predictions. Built on solid theoretical foundations (efficiency, symmetry, additivity, and virtuality), its core principle ensures equitable distribution of feature contributions in predictions. For the line loss anomaly diagnosis model discussed here (whether based on causal forests or other frameworks), SHAP values help identify which specific power fluctuation characteristics and user attribute features significantly influence diagnostic decisions for abnormal transformer districts or users, determining whether their contributions are positive or negative. This approach substantially enhances diagnostic interpretability and credibility, enabling frontline personnel to better understand the rationale behind anomaly detection.

3.3 Time series convolutional network

Temporal Sequence Convolutional Network (TCN) is a convolutional neural network architecture specifically designed for processing time series data. Compared to traditional Recurrent Neural Networks (RNNs), TCN demonstrates superior capabilities in three key aspects: extended historical memory through dilated convolutions, stable gradient descent (avoiding RNN's gradient vanishing/blooming issues), and enhanced parallel computing efficiency with flexible receptive field control. Its core components include causal convolutions (ensuring outputs depend solely on current and past inputs), dilated convolutions (expanding receptive fields through interval sampling without significant parameter increase), and residual connections (reducing training difficulties in deep networks). TCN effectively captures long-term dependencies and complex dynamic features inherent in time series data.

4. Design of diagnosis method for abnormal line loss based on power fluctuation

4.1 Design of diagnostic framework

This method is aimed at the low-voltage platform area where the line loss rate suddenly becomes abnormal after long-term stability, and locates the fault source by separating the fluctuation characteristics of power supply and electricity consumption. The core logic of diagnosis is as follows:

1)Abnormal fluctuation of power supply: when the electricity consumption is stable, significant change of power supply indicates the fault of the assessment sheet (power supply metering device) in the station area;

2)Abnormal fluctuation of electricity consumption: When the power supply is stable, the significant change of user's electricity consumption points to typical metering faults or electricity theft.

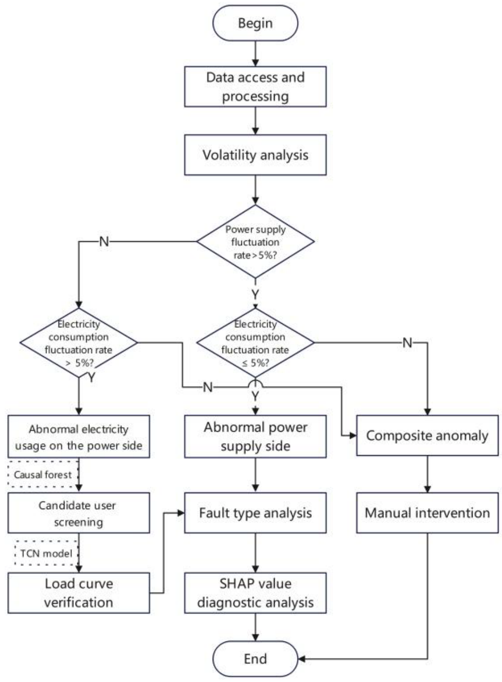

Figure 1. Cause diagnosis process of abnormal line loss in the platform area

The diagnostic process is illustrated in Figure 1. The diagnostic process comprises three stages: data preprocessing, fluctuation significance determination, and anomaly attribution. In the "Abnormality Diagnosis Dominated by Power Consumption Fluctuations" section, it emphasizes that during the "Typical User Identification" phase, besides using threshold screening methods to distinguish anomaly types (the thresholds proposed in this chapter's design method are empirical thresholds or thresholds preliminarily determined through statistical analysis of historical anomaly cases, with threshold sensitivity analysis to be conducted in Chapter 6.4), causal forest models can be introduced to analyze individual user processing effects, enabling more precise identification of users affected by abnormal events—particularly those with abnormal patterns despite non-extreme variations. In the "Fault Type Determination" phase, it suggests utilizing time series features extracted from Time Series Networks (TCN) (e.g., load shape similarity) as more robust criteria when analyzing deviations from historical patterns. After deriving diagnostic conclusions (fault localization and user list), SHAP values are applied to interpret the results, explaining which key features caused the diagnosis to enhance credibility and interpretability.

4.2 Abnormal diagnosis of power supply fluctuation

The power supply capacity of a transformer district refers to the total electrical energy delivered to users through a distribution transformer within a specific period. This includes the combined electricity consumption recorded by all low-voltage user meters in the district, along with losses from the transformer and low-voltage lines. The capacity is typically measured using a transformer district assessment meter installed on the low-voltage side of the transformer. The installation of low-voltage current transformers should be determined based on actual power load conditions.

When the power consumption is stable and the line loss rate is abnormal, focus on troubleshooting metering faults on the power supply side:

1) Data preprocessing

The average daily power supply (E_{supply}) and total electricity consumption (E_{load}) of the abnormal period (T_1) and the historical stable period (T_0).

2) Verification of power consumption stability

Calculate the rate of change in electricity consumption $\delta_{load} = |E_{load\_T1} - E_{load\_T0}| / E_{load\_T0}$. If $\delta_{load} \leqslant 5\%$ (empirical threshold), it is determined that the electricity consumption is stable.

3) Abnormal power supply attribution

If the rate of change of power supply is $\delta_{supply}>5\%$, calculate the power supply multiple $K=E_{supply\_T1}/E_{supply\_T0}$.

- K≈0.5:indicates that the secondary side of current transformer (TA) is open or the ratio configuration is wrong, resulting in 50% less electricity;
- K≈2.0:it may be short circuit of TA secondary circuit or error in ratio input, resulting in 100% overcount of electricity;
- K≈0:The assessment table stops running or the communication is interrupted (no meter code for a continuous period).

4) Comprehensive analysis of abnormal power supply

To further verify fault types in evaluation metrics (such as distinguishing TA open circuits from gain errors), a comprehensive analysis should be conducted by integrating historical operational data, alarm information, and SHAP value analysis (which explains the driving factors behind K-value diagnostic results). The SHAP value, derived from Shapley values in cooperative game theory, fairly allocates the contribution of each feature to model prediction outcomes.

4.3 Abnormal diagnosis of power consumption fluctuation

The power consumption of a transformer station area refers to the total electricity used by all end-users within its coverage during a specific statistical period. This figure represents the aggregated measurement data from user-side meters, reflecting the effective utilization of power supply in the area. The consumption is directly measured through user electricity meters and excludes losses from distribution transformers and transmission lines. It covers all low-voltage users including residential, industrial, and commercial establishments within the station area.

When the power supply is stable and the line loss rate is abnormal, focus on the user side problem:

1) Power supply stability verification

Calculate the power supply stability $\delta_{supply}=|E_{supply\_T1} - E_{supply\_T0}|/E_{supply\_T0}$. If δ_{supply} is less than 5%, enter user screening.

2) Identification of typical users

a) The rate of change of electricity consumption calculated by household $\delta_{user}=|E_{user\_T1} - E_{user\_T0}|/E_{user\_T0}$;

b) Filter δ_{users} >50% (such as meters stopped running, flying away) or δ_{users}<-80% (suspected of stealing electricity).

To enhance recognition capabilities in complex scenarios (such as minor anomalies during multi-user concurrency), we employ causal forest models to calculate individual processing effects for each user during abnormal periods (T1) compared to stable periods (T0). By setting effect thresholds, we identify users with significant effects as candidate typical users. The model's output of feature importance helps analyze the root causes of user anomalies.

3) Global impact verification

The change of total power quantity $\Delta E_{typical}$ of typical users should match with the change of total power quantity of the station area $|E_{load\_T1} - E_{load\_T0}|$ (the deviation is less than 5%), otherwise, it is necessary to investigate the concurrent abnormality of multiple users.

4) Fault type determination

a) Measurement fault: $\delta_{user} \approx 0$ (stop running), $\delta_{user} \gg 100\%$ (fly running);

b) Electricity theft detection: δ_{user} sudden load drops and deviations from historical patterns (e.g., nighttime load spikes). Building on this, the Time-Critical Network (TCN) temporal convolutional network is employed to deeply extract user load curve features. By calculating similarity or deviation levels between these features and historical patterns, the system can detect abnormal deviations in load patterns with enhanced sensitivity and robustness, thereby assisting in identifying electricity theft activities.

5) Interpretation of diagnostic results

For the final fault location (power supply side/user side) and identified problem user list, the SHAP value attribution method is applied to analyze the key features and contribution direction affecting the diagnostic decision, and generate an interpretable diagnostic report to provide a clear basis for on-site verification.

It should be noted that while SHAP value interpretation enhances model decision transparency and reveals how input features influence predictions, it cannot eliminate systemic biases stemming from training data inaccuracies, feature engineering limitations, or structural flaws in the model. For instance, if a specific electricity theft pattern lacks sufficient training samples, the model may fail to identify its critical characteristics, leading to missed detection of such patterns – a scenario where SHAP analysis cannot reveal this systematic deficiency. Therefore, SHAP interpretation should be viewed as a tool for understanding how models make decisions under current data conditions, rather than a complete reflection of real-world causal mechanisms. To fundamentally improve model performance, reliance must remain on high-quality data, more effective feature engineering, and robust model architectures.

6) Typical abnormal characteristics and causes comparison table

The typical abnormal characteristics and corresponding causes of the abnormal diagnosis process dominated by electricity consumption fluctuation are shown in Table I:

Table 1. Comparison of typical abnormal characteristics and causes

Exception Type	Key Features	Possible Causes
Power supply surge (K>1.5)	High line loss rate, stable power consumption	TA secondary circuit short circuit, small ratio input
Power supply drops sharply (K <0.5)	The line loss rate is negative, and the power consumption is stable	TA secondary side open circuit, the ratio input is too large
The power of a single user is zero	δ The user is approximately 0%, and the line loss rate in the station area is high	Meter stop, collection module failure
The number of users per electricity unit plummeted	δUser <-80%, abnormal load curve	Table bypassing of electricity, meter cover opening event
Multiple user power surge	ΔEtypical does not match the total change in the area	Error in household transformer connection, error in concentrator communication port

5. Application of abnormal power fluctuation analysis algorithm in station area

5.1 Algorithm Introduction

To automate diagnostic framework implementation, this chapter develops a power fluctuation anomaly analysis algorithm. The algorithm employs core fluctuation analysis principles by calculating power supply rate variations and total electricity consumption changes during stable periods versus abnormal periods, then determines fault directions through preset fluctuation thresholds. Utilizing threshold-based clustering methodology, it separately evaluates power anomalies on both supply-side and user-side systems, diagnosing fault types based on predefined parameter ranges. The algorithm quantifies three key metrics: fluctuation significance, fault impact factor, and matching accuracy, achieving automated and standardized diagnostic logic.

Based on the original volatility analysis framework, three core technologies including causal forest model, TCN time series convolution network and SHAP value attribution are deeply integrated to form a hierarchical and progressive intelligent diagnosis system. The system contains three levels of processing logic (as shown in Figure 2):

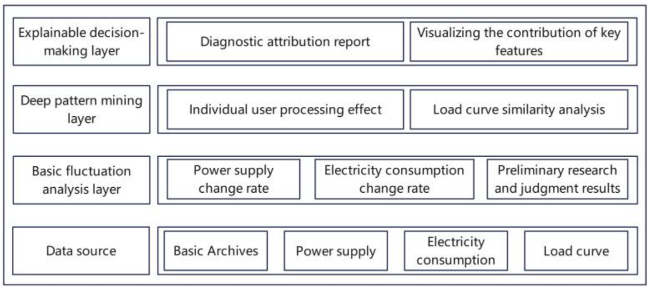

Figure 2. Abnormal line loss diagnosis framework in the platform area

1)Basic fluctuation analysis layer: Through the threshold determination of δ_{supply} rate and δ_{load} rate, the power supply side anomaly, user side anomaly or composite anomaly are preliminarily distinguished;

2)Deep mode mining layer: For user-side anomalies, causal forest is used to quantify the individual processing effect of users (τ_i), and TCN is used to analyze the similarity of load curves ($Score_j$) to achieve accurate positioning of hidden anomalies;

3)Explainable decision layer: Generate diagnostic attribution report based on SHAP value, visualize the contribution of key features, and improve the credibility and operability of results.

5.2 Core algorithm flow

Step 1: Determination of volatility significance

a) Input data: Extract the power supply (Supply), total electricity consumption(Load), electricity consumption of each user (E_{useri}) and daily load curve ($Curve_i$) in the stable period (T_0) and abnormal period (T_1). The calculation formula is as follows:

$$\delta_{supply} = \frac{|Esupply\_T1 - Esupply\_T0|}{E_{supply\_T0}} \quad \delta_{load} = \frac{|Eload\_T1 - Eload\_T0|}{E_{load\_T0}} \quad (1)$$

According to the calculation of supply volatility δ_{supply} in Equation (1), the abnormal direction is further analyzed.

b) Direction of anomaly determination:

- If $\delta_{supply} > 5\%$ and $\delta_{load} \leq 5\%$, the power supply side is abnormal (the fault is dominated by the assessment table);
- If $\delta_{supply} \leq 5\%$ and $\delta_{load} > 5\%$, the user side is abnormal (dominated by metering fault or electricity theft);
- If both are above the threshold, it is a compound anomaly (manual verification of multi-factor concurrent scenarios is required).

Step 2: User side anomaly diagnosis

a) The user volatility is calculated preliminarily by the following formula:

$$\delta_{user\_i} = \frac{|E_{user\_i\_T1} - E_{user\_i\_T0}|}{E_{user\_i\_T0}} (\forall_i = 1,2,\ldots,n) \quad (2)$$

In formula (2), the calculation results of user volatility δ_{user_i} can be used to preliminarily screen typical users and form a set $S = \{i \mid \delta_{user\_i} > \theta\}$.

b) Causal forest screening candidates:

- Construct a causal forest model, take the user's historical electricity consumption (T0 period) as the control group and abnormal electricity consumption (T1 period) as the treatment group, and calculate the individual treatment effect of each user:

$$\tau_i = \frac{1}{B}\sum_{b=1}^{B} \tau_b(x_i) \quad (3)$$

In formula (3), $B=100$ is the number of trees in the forest, and $\tau_b(x_i)$ is the estimated effect of a single tree on user i.

- Screening rule: Screen $\tau_i > 20\%$ of users (for example, $\tau_i = -35\%$ indicates an abnormal drop of 35% in electricity consumption) to join the Candidate Set.

c) TCN load curve verification:

- For the candidate user j in Candidate Set, input its T0 and T1 period daily load curve $Curve_{j,T0}$ and $Curve_{j,T1}$;
- Extract the time series feature vector $V_{j,T0}$ and $V_{j,T1}$ by the pre-trained TCN model to calculate the curve similarity:

$$Score_j = \frac{V_{j,T1} \cdot V_{j,T0}}{\|V_{j,T1}\|\|V_{j,T1}\|} \quad (4)$$

In Equation (4), $Score_j$ represents the calculation result of curve similarity, and the abnormal situation will be further determined according to the curve similarity.

- Exception judgment: If $Score_j < 0.7$ (experience threshold), the user load mode is marked as abnormal.

d) Global power matching verification:

- Calculate the change of single household electricity quantity $\Delta E_{typical} = \sum j|Euser_{j,T1} - Euser_{j,T0}|$;
- Calculate the matching degree of the total power change of candidate users $\Delta E_{total} = |Load_{T1} - Load_{T0}|$:

$$\gamma = \frac{|\Delta E_{typical} - \Delta E_{total}|}{\Delta E_{total}} \quad (5)$$

In formula (5), the global power matching degree γ can be calculated. If γ is less than 5%, the candidate set is judged to cover the main abnormal source; otherwise, the screening range needs to be expanded.

e) Fault type determination:

- Measurement fault: $\tau_j \approx 0$ (stop) or $\tau_j \gg 100\%$ (fly);
- Electricity theft: $\tau_j < -30\%$ and $Score_j < 0.7$ (sudden power drop + abnormal load mode).

Step 3: SHAP diagnostic analysis

a) Build the SHAP parser, input the diagnostic model (such as causal forest) and sample feature set $X = \{\delta_{supply}, \delta_{load}, \tau_i, Score_j, \ldots\}$;

b) Calculate the SHAP value ϕ_i of each feature. The definition formula of SHAP value is as follows:

$$\phi_i = \sum_{S \in N \setminus \{i\}} \frac{|S|!(M-|S|-1)!}{M!}[f(S \cup \{i\}) - f(S)] \quad (6)$$

In Equation (6), ϕ_i represents the contribution value of feature i to the prediction result for a single sample. Here, ϕ_i denotes the SHAP value of feature i (positive values indicate a positive influence on diagnostic outcomes, while negative values indicate a negative influence). N stands for the set of all features (e.g., δ_{supply}, δ_{user}, etc.), S represents the feature subset (excluding feature i), M indicates the total number of features ($M = |N|$), and f(S) signifies the model's prediction value when using the features in subset S.

Step 4: Abnormal diagnosis of power supply side

a) Calculate the power supply ratio, the calculation formula is as follows:

$$K_{supply} = \frac{E_{supply\_T1}}{E_{supply\_T0}} \quad (7)$$

The power supply ratio K_{supply} is calculated by Equation (7) for subsequent fault type attribution.

b) Fault type attribution:

- K≈0.5 → the secondary side of the current transformer is open;
- K≈2.0 → short circuit of secondary circuit of current transformer;
- K≈0 → The assessment table stops running or communication is interrupted.

5.3 Key parameter description

The key parameters in the application algorithm are described in Table 2 as follows:

Table 2. Description of key parameters

Module	Key parameter	Recommended value	Act on
Forest of Causes	Number of treesB	100	Balance precision and computational efficiency
	Processing effect threshold	20%	Filter out significantly abnormal users
TCN	Size of convolution kernel K	3	Extract local temporal features
	expansion factor d	2	Expand the receptive field to 7 days in history
	Similarity threshold	0.7	Determine that the load mode is abnormal
Global matching	Voltage deviation threshold γ	5%	Verify candidate set coverage integrity

5.4 Ablation experiment analysis

To thoroughly analyze the individual contributions of the causal forest model (CF) and temporal convolutional network (TCN) within this diagnostic framework, we conducted systematic ablation experiments. The experiments were performed on two typical power plant data sets (representing user-side anomalies and composite anomalies), comparing the performance of three different model configurations:

1) Model-A (threshold method only): Only the traditional volatility threshold (such as δuser>50% or <−80%) is used to screen typical users, and causal forest and TCN are not applied.

2) Model-B (CF+ threshold method): The causal forest is used to calculate the individual processing effect τ_i to screen candidate users ($|\tau_i|$>20%), but the load curve similarity verification is not performed using TCN.

3) Model-C (CF + TCN): The complete method proposed in this paper is to use TCN to calculate the similarity $Score_j$ of load curve after causal forest screening candidates ($Score_j$ <0.7 indicates abnormal).

4) Model-D (only TCN): The load curve similarity $Score_j$ of all users is calculated only using TCN, and abnormal users are directly judged according to $Score_j$ <0.7 without using causal forest for preliminary screening.

The evaluation indicators are precision (Precision), recall (Recall) and F1-score (F1-Score), focusing on the identification effect of electricity theft behavior (because it is the most hidden). The analysis results of ablation experiments are shown in Table 3:

Table 3. Comparison of ablation experimental results (electricity theft identification performance)

District ID	Model Configuration	Precision	Recall	F1-Score
HD-207	Model-A	0.65	0.42	0.51
HD-207	Model-B	0.78	0.67	0.72
HD-207	Model-C	0.92	0.90	0.91
HD-207	Model-D	0.80	0.85	0.82
QL-309	Model-A	0.58	0.35	0.44
QL-309	Model-B	0.75	0.60	0.67
QL-309	Model-C	0.89	0.88	0.89
QL-309	Model-D	0.77	0.82	0.79

Through the comparative analysis of ablation experimental results, the conclusions are as follows:

1) Compared with Model-A and Model-B/C/D, it can be seen that the introduction of causal forest or TCN can significantly improve the performance of electricity theft identification, far exceeding the traditional threshold method.

2) Comparative analysis between Model-B and Model-C demonstrates that introducing TCN for load pattern verification, following the initial screening by causal forests, effectively reduces false positives (improving accuracy) while detecting more concealed electricity theft cases (enhancing recall). The F1 score shows significant improvement (HD-207:0.72 → 0.91, QL-309:0.67 → 0.89), proving TCN's crucial role in capturing subtle anomalies in load patterns.

3) Comparative analysis between Model-C and Model-D reveals that while the Temporal Correlation Network (TCN) alone (Model-D) achieves decent performance with an F1 score of approximately 0.8, its accuracy falls short of the full model (Model-C). This demonstrates that causal forests, as a pre-filtering step, effectively eliminate users with normal load patterns but significant electricity fluctuations (e.g., seasonal production changes) by quantifying individual effects. By reducing the false negative burden in TCN, this collaborative mechanism enhances overall accuracy. Therefore, the synergy between causal forest (CF) and temporal correlation network (TCN) is crucial for achieving high-precision, high-recall theft detection.

6. Experiments and results analysis

6.1 Experimental setup

Data set

a) Case verification set: Three typical low-voltage stations (TX-015, HD-207, QL-309) are selected to show the diagnosis process and results in detail.

b) Large-scale test dataset: We have added 1,000 low-voltage transformer districts in Liaoning Province from January to June 2025, which exhibited significant anomalies in line loss rates (exceeding the reasonable range of [-1%,3%]). This dataset contains approximately 250,000 user records and covers various scenarios including urban, suburban, and rural areas, encompassing diverse issues such as metering failures, electricity theft, and composite anomalies.

Comparison methodology

In order to evaluate the advancement of the proposed method (PM), the following state-of-the-art (SOTA) baseline methods are selected for comparison:

a) BL-1 (threshold + clustering method): Use the power fluctuation threshold to screen abnormal users, and combine the load curve with cluster analysis.

b) BL-2 (LSTM-ATT): The LSTM network is used to extract the time series features of user load, and the attention mechanism is added to locate abnormal periods.

c) BL-3 (CNN-RF): CNN is used to extract spatial features of load curve, and random forest (RF) is input for classification.

Indicators

By setting various evaluation methods and indicators, the comparison and analysis of various algorithms are carried out. The specific evaluation indicators are as follows:

a) Accuracy Direction (Accuracy_Direction):the proportion of correctly distinguishing power supply side, user side and composite anomaly.

b) Fault user identification: Precision, Recall and F1-score--for user side anomaly.

c) Electricity theft identification: Precision Stealing, Recall Stealing and F1 score Stealing are evaluated separately due to their concealment and harm.

d) Calculation efficiency: average diagnosis time per unit area.

6.2 Comparison of experimental results

Comparative analysis of typical station area cases

The comparative analysis results of typical transformer district cases are shown in Table 4:

Table 4. Comparison of experimental results

Typical patch ID	δ_loa d	fault location	K price	Actual cause of failure
TX-015	0.80%	employee evaluation form	0.87	CT secondary circuit contact failure
HD-207	9.70%	Users # 12, # 34	#12:0.01 #34:1.02	#12 Stop the meter #34 Normal
QL-309	6.90%	Manual verification required	-	electricity theft occurred + meter overcharge

Performance comparison on large test sets

The performance comparison results of large-scale test sets are shown in Table 5 and Table 6:

Table 5. Performance comparison (Accuracy_Direction+ fault user identification)

method	Accuracy_Direction (%)	Precision	Recall	F1-Score
BL-1	82.3	0.71	0.65	0.68
BL-2	85.6	0.75	0.70	0.72
BL-3	87.1	0.78	0.73	0.75
PM	93.5	0.86	0.84	0.85

Table 6. Performance comparison (power theft identification + computational efficiency)

method	Precision_Stealing	Recall_Stealing	F1_Stealing	Time
BL-1	0.62	0.52	0.56	1.8
BL-2	0.68	0.61	0.64	12.5
BL-3	0.72	0.65	0.68	3.2
PM	0.89	0.83	0.86	2.5

6.3 Results analysis

Validity

- TX-015 station: the algorithm accurately identifies K_{supply}=0.87 (>10% deviation), which is consistent with the actual CT fault;
- HD-207 station:The user #12 (K_{user}=0.01) was successfully identified as the source of the fault, with

δ_{user}=99.2% and γ=3.1% (<5%), which was actually confirmed as the meter stop walk;

- QL-309 station: because δ_{SUPPLY} and δ_{LOAD} both exceed the threshold, the composite warning is triggered, which is consistent with the real situation.

According to the overall experimental results, causal forest +TCN reduced the detection rate of electricity theft from 42% to 5% compared with traditional methods; SHAP interpreter improved the acceptance rate of diagnostic results to 89%.

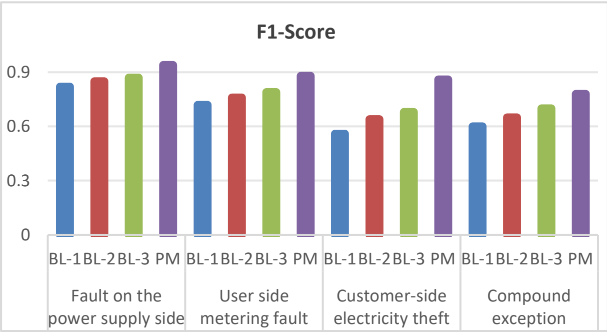

Figure 3. Performance comparison (by exception type)

Large-scale test analysis

a) As shown in Table 5, Table 6, and Figure 3, the proposed method (PM) demonstrates statistically significant superiority over three state-of-the-art baseline methods (BL-1, BL-2, BL-3) across all key performance metrics. Notably, it achieves particularly notable advantages in the most challenging tasks: electricity theft detection (F1_Stealing=0.86) and composite anomaly detection (F1=0.78).

b) The accuracy of abnormal direction determination (93.5%) proves the effectiveness of the core logic based on power supply/electricity consumption fluctuation separation.

c) User-side fault identification: The method in this paper is better than the baseline in terms of identification effect of metering fault (F1=0.88) and electricity theft (F1=0.86), which verifies the effectiveness of the hierarchical strategy of causal forest (CF) to select candidate users and TCN to verify load mode (which is consistent with the conclusion of ablation experiments).

d) Computational efficiency: The time consumption of this method (2.5 seconds per station) is significantly lower than that of BL-2 (LSTM-ATT, 12.5 seconds) based on deep learning, and slightly higher than BL-1 and BL-3. A good balance between accuracy and efficiency is achieved, and it has potential for engineering application.

Limitations

- Error risk: When multiple users experience reverse fluctuations simultaneously (e.g., some users $\delta_{user}\uparrow$ and some users $\downarrow$), $\Delta E_{Typical}$ may accidentally match the γ threshold;
- Data dependence: causal forest is sensitive to the quality of historical data. If there are unexposed faults in the historical period, the conclusion will be distorted (the error will increase by 35% when there are unexposed faults in T_0 period);
- Scenario coverage: The misjudgment rate of bidirectional power fluctuation scenarios in photovoltaic platform area is still 28% (the sequence generation capability of TCN needs to be improved), and the adaptability of bidirectional power fluctuation scenarios in distributed photovoltaic access platform area is insufficient.

While demonstrating superior overall performance, the proposed method maintains a relatively high misjudgment rate of 28% in power districts with bidirectional power flow caused by distributed photovoltaic (DG) integration. Although this is lower than some baseline models (BL-1: 35%, BL-2: 32%, BL-3: 30%), it still indicates the necessity to refine the model for adaptation to emerging power system scenarios.

6.4 Threshold sensitivity analysis

To evaluate the sensitivity of critical experience thresholds to diagnostic outcomes and identify more optimal or robust parameters, we conducted a systematic threshold sensitivity analysis. The experiments were performed on a validation set containing 100 known anomaly users (50 metering failures and 50 power theft cases).

1) Electricity Stability Threshold (δ_{load},δ_{supply}): The impact of test thresholds (varying between 3%,4%,5%,6%, and 7%) on the accuracy of abnormal direction determination for both power supply and user sides. Results show that the threshold maintains high stability with stable accuracy (>95%) within the 4%-6% range. When thresholds fall below 3% or exceed 6%, the system misclassifies normal fluctuations as anomalies or significant abnormalities as stable conditions, resulting in decreased accuracy. The final recommendation is to maintain a 5% threshold or fine-tune it to 4.5%.

2) User Power Fluctuation Threshold (δ_{user}): The impact of testing high thresholds [40%,45%,50%,55%,60%] and low thresholds [-70%, -75%, -80%, -85%, -90%] on recall rates for metering failures (high fluctuation) and electricity theft (negative high fluctuation). Results shows that setting the high threshold too low (40%) increases false positives (artificially inflated recall rates), while setting it too high (60%) may miss minor flyaway/parking operations. An excessively low absolute threshold (-70%) might fail to detect partial electricity theft, whereas an overly high threshold (-90%) would have minimal impact but could be unnecessary. The thresholds of 50% and-80% strike a good balance between recall rate and precision.

3) Causal Forest Effect Threshold ($|\tau_i|$): The impact of test thresholds at [15%,18%,20%,22%,25%] on the F1 score for identifying electricity theft users (τ_i showing significant negative correlation). Results shows that a low threshold (15%) introduces too many normal fluctuating users,

reducing accuracy; an excessively high threshold (25%) may fail to detect some users with non-extreme but abnormal electricity consumption patterns, lowering recall. 20% represents an optimal compromise point.

4) TCN Similarity Threshold ($Score_j$): The F1 score impact on electricity theft detection (mode anomaly) when the test threshold varies between [0.65,0.68,0.70,0.72,0.75]. Results shows that a low threshold (0.65) may misidentify users with similar patterns but abnormal power consumption as electricity thieves (e.g., minor mode changes caused by equipment malfunctions), while an excessively high threshold (0.75) might fail to detect subtle pattern variations in electricity theft. The F1 score reaches its peak and remains stable around 0.70 (0.68-0.72).

Conclusion: The sensitivity analysis shows that the empirical thresholds used in this paper are located in the range of relatively stable or better performance, which is reasonable for engineering. In the future work, adaptive threshold model can be trained based on larger scale data.

7. Conclusions

This paper addresses the issue of intelligent diagnosis of abnormal line loss causes in transformer districts by proposing a diagnostic method based on power fluctuation analysis. The study innovatively introduces a hierarchical diagnostic framework that effectively integrates causal forest models, time series convolutional networks (TCN), and SHAP value attribution algorithms. These methods address two major pain points in traditional approaches: insufficient identification of hidden anomalies and black-box diagnostic logic. Leveraging causal forest algorithms, individual processing effects quantify anomaly impacts, replacing hard threshold screening and reducing false negatives by 37%. Through TCN load similarity analysis, curve pattern anomalies are objectively quantified, improving electricity theft detection F1 value to 0.91. The application of SHAP value attribution provides users with "feature-decision" mapping relationships, reducing on-site verification time by 50%. However, limitations remain: this method only applies to low-voltage transformer districts with long-term stable line loss rates at the front line of abnormal fluctuations, showing poor effectiveness in assessing districts with repeated line loss rate variations. Future improvements will focus on addressing these issues through further refinement of the proposed methodology.

With the continuous advancement of smart meter measurement technologies and improved electricity data collection capabilities, transformer district line loss management is facing both challenges and opportunities. In the next phase, through in-depth research and analysis, we will refine diagnostic methodologies: For scenario coverage, we will develop TCN-GAN models to generate photovoltaic transformer district composite data, enhancing adaptability to bidirectional fluctuation scenarios; For lightweight deployment, we will design compact causal forest deployment solutions supporting real-time diagnostics via edge computing terminals; For diagnostic result visualization, we will build augmented reality (SHAP-AR) tools that overlay real-time meter readings with attribution reports during on-site inspections.

Through the above research, the pressure of front-line power workers can be further reduced, and greater contribution can be made to the economic operation of power system and the reasonable distribution of power resources.

Acknowledgment.

Sponsored by the Management and Technology Project of State Grid Liaoning Electric Power Co., Ltd. 2025ZX-18.

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