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Research on Online Identification and Alarm Mechanism for Abnormal Power Quality in Data Centers

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Abstract: Data centre loads have a high power density, strong power electronic coupling and rapid fluctuations. Voltage sags, harmonic distortion, three-phase imbalance, frequency drift and transient impacts can all be converted into service interruption risks by UPS, PDUs, switching power supplies and cooling systems. To address the problems of a high false alarm rate, insufficient offline diagnostic timeliness, and a lack of multi-indicator collaborative judgment in traditional threshold alarms, this paper introduces an online power quality anomaly identification and hierarchical alarm mechanism for data center power distribution links. Sliding window sampling is used to extract features from the following time-series data: root mean square voltage, total harmonic distortion rate, negative sequence voltage imbalance, crest factor and load mutation rate. A three-level hierarchy of identification is used: "basic threshold gating - multivariate anomaly scoring - alarm confidence confirmation", and alarm classification, suppression and regression strategies for closed-loop operation and maintenance are proposed. Based on the reanalysis of publicly available data centre power consumption statistics and published power quality identification benchmarks, it has been determined that this mechanism can raise the level of anomaly detection from a single point of failure to multi-evidence collaborative judgment, thus providing an implementable path for improving the reliability of data centre power supply management and capacity expansion, as well as proactive operation and maintenance. Supplementary robustness tests have been conducted by introducing noise, randomly missing data, multiple types of anomalies and detection latency, etc., to further validate the mechanism's suitability for edge deployment.

1 Introduction

Training for artificial intelligence, cloud computing, edge collaboration and real-time online services have worked together to change data centres from traditional stable-load facilities into high-density, highly volatile, and highly electronic-load centres. According to the 2024 US Data Center Energy Consumption Report, by 2023, electricity consumption at US data centres had increased from about 58 TWh in 2014 to 176 TWh, and it is expected to be between 325-580 TWh by 2028. Therefore, data centres have changed from being a problem of the reliability of a single facility to a large-scale load that can affect the operating conditions of the distribution network; thus,

capacity planning and power quality management have been introduced [1]. Large data centres require continuous power supply, so they have arranged for backup power, UPS redundancy and diesel generators, and early identification and graded alarms have been established to trigger before an abnormal disturbance causes a power outage.

Recently, some studies have begun to explore the multi-time-scale impacts of AI data centres on power systems. Based on the above analysis, the load fluctuation characteristics of model training and inference vary at the hour, minute and even second levels; otherwise, voltage stability, frequency support, reserve requirements and power quality constraints will be violated [2]. Hyperscale data centres have some characteristics of the power grid, such as high power density, rapid load fluctuations and concentrated power electronic interfaces, and the risks of voltage flicker, harmonics, interharmonics and protection malfunctions are difficult to eliminate completely by traditional static planning [3]. With the future development of AI load, the academic community has also pointed out that power quality risks should be included in the data centre access assessment, dynamic demand response and power grid interaction control framework, and are no longer considered an internal power distribution equipment management problem [4].

Power quality monitoring of data centres in engineering practice still has the following three problems. First, the monitored objects are layered and multiple. All sizes of disturbances can occur at the main power supply, the low-voltage side of the transformer, UPS input and output, busbars, PDUs, server power supplies in the rack area, and cooling loads. Second, the anomaly mechanisms are too closely linked. A single voltage drop can be caused by a fault in the upper-level power grid, the start-up of a large cooling device, UPS bypass switching, or a sudden increase in server load. Thirdly, the required quantity of alarm handling is relatively high. General industrial scenarios can be realised at a lower level, but data centres need anomaly detection, alarm suppression, event correlation and issuance of maintenance warnings within a few seconds to prevent alarm storms that may impair the decision-making ability of staff on duty.

Therefore, this paper will limit the scope of research to the online identification and alarm mechanism for power quality anomalies in data centre power supply and distribution links. The aim is not to substitute power quality management devices, but to construct an algorithm layer that can be used in conjunction with smart meters, power quality analyzers, SCADA, DCIM and maintenance work order systems. The main contributions of this paper are as follows: first, the construction of a multi-indicator feature system specifically for the load characteristics of data centers; second, the proposal of an online-updatable multivariate anomaly scoring model; third, the design of hierarchical alarm rules linked to maintenance operations; and fourth, the execution of graphical re-analysis using publicly available statistical data and publicly available identification benchmark results to show the engineering correlation between data center power consumption growth and intelligent identification technology. An extra robustness test is performed to compare the noise level, type of random missing values, anomaly type and detection delay in an edge deployment.

2. Current Status Analysis of the Research Topic

Generally speaking, the four stages of research in power quality identification have been rule-based thresholds, signal transformation, machine learning and deep learning. Early methods only used a fixed upper bound for the RMS value of voltage, frequency, harmonics and unbalance; although they had the advantage of strong interpretability and ease of engineering acceptance, they were not sensitive to compound disturbances and short-term transients. Recently, many applications of deep learning have been introduced in power quality analysis. Research has been conducted to apply CNN, autoencoders and RNN for the automatic extraction of disturbance features from

waveform or time-frequency plots to reduce the cost of manual feature engineering [5]. However, deep models generally require a large amount of labelled data, and the model's output is not directly suitable as an alarm for data centre operation and maintenance personnel.

Autoencoders are used for anomaly detection and feature compression. Khetarpal et al. proposed a power quality disturbance detection and classification method based on deep convolutional autoencoders, and have achieved disturbance identification and location detection under various disturbance conditions [6]. An advantage of the above method is that it can learn a low-dimensional representation of normal waveforms and is suitable for monitoring unlabeled data; however, its disadvantage is that the reconstruction error threshold generally needs to be set offline, and when facing seasonal changes in data center load, IT load migration and UPS working mode switching, if there is no adaptive mechanism, false alarms and false negatives may occur simultaneously.

A Time-Frequency Image Recognition Approach to Power Quality Classification. Perez-Anaya et al. proposed a detection and classification method based on continuous wavelet transform and CNN, generated 128×128 time-frequency images of voltage disturbances, and achieved automatic recognition. It also verifies synthetic data and real data to show that they are consistent with transient and quasi-steady-state disturbances [7]. In this way, all kinds of wave shapes can be classified, such as voltage sags and swells, harmonics and transients. However, for online deployment in a data center, the generation of time-frequency images will increase the computational load, and the image model needs to consider the computing power, memory and inference latency constraints of the edge acquisition terminal.

Traditional Machine Learning still has engineering applications. Gao et al. used variational mode decomposition and improved SVM to classify power quality disturbances, reduced the impact of noise via signal decomposition, and optimised SVM parameters with optimisation algorithms. The classification accuracy of the result was more than 98% [8]. The kind of method mentioned above has a relatively simple structure and is suitable for scenarios with a small number of samples; however, when there are many measurement points, many devices, and multiple load-state changes occurring simultaneously in the data center, the expanded dimension of features will reduce the generalisation ability of the model. Bai and others proposed a fast S-transform to improve the CNN-LSTM hybrid model; although it still has a high recognition accuracy in a high-noise environment [9], they believe that fusing time-series and time-frequency features will further increase robustness. Albalooshi and Qader have improved the classification performance of perturbations with multi-scale CNNs and attention mechanisms, and published a comparison of test accuracy for various models under noise-free and noisy conditions [10].

In short, although many identification algorithms have been developed in previous studies, none have been applied to online alarms in data centres yet. First, most of the current models focus on the accuracy of disturbance classification and have not been widely applied to alarm suppression, alarm escalation and closed-loop operation and maintenance. Secondly, most research has used synthetic disturbance data and has failed to investigate how to connect this data with the actual operating environment of UPSs, PDUs, rack loads, cooling systems, etc. Third, most of the performance indicators are based on offline accuracy; in a real-world system, edge deployment latency, alarm confidence, data gaps, communication jitter and multi-source time synchronization also need to be considered. The algorithms in this paper currently use an engineered identification mechanism that is "online-capable, interpretable and closed-loop-capable".

3. Problem Statement: Online Identification and Modeling of Power Quality Anomalies in Data Centers

Data center power quality anomalies are not single out-of-limit events, but rather a process

involving multiple indicators, locations, and time scales. This paper t denotes the three-phase voltage, current, and power measurements at a monitoring point at time t as u_a,u_b,u_c,i_a,i_b,i_c,p, and constructs a feature using a sliding window of length N. Within each window, the effective value of the phase voltage is first calculated to capture voltage sags, swells, and short-term voltage fluctuations.

$$U_{\mathrm{rms},p}(t)=\sqrt{\frac{1}{N}\sum_{i=0}^{N-1}u_p^2\,(t-i\Delta t)},\quad p\in\{a,b,c\} \tag{1}$$

In equation (1), $U_{\mathrm{rms},p}(t)$represents the effective value of the phase $p$within the current window, $N$is the number of sampling points in the window, $\Delta t$and is the sampling interval. The window length needs to balance recognition speed and noise resistance: too short a window will amplify sampling noise, while too long a window will mask transient disturbances. For data center incoming lines and UPS input sides, the window can be set to 1–10 power frequency cycles; for rack PDU sides, it can be appropriately extended in combination with communication bandwidth.

A typical index of power quality problems in data centres is harmonic distortion. Server switching power supplies, variable-frequency cooling equipment, UPS rectifier stages and high-frequency power modules can all generate nonlinear currents in the presence of system impedance and cause voltage distortion. The overall level of harmonic distortion is THD%.

$$\mathrm{THD_u(t)}=\frac{\sqrt{\sum_{\mathrm{h=2}}^{\mathrm{H}}\mathrm{U_h^2\,(t)}}}{\mathrm{U_1(t)}}\times100\% \tag{2}$$

In equation (2), $U_1(t)$is the fundamental voltage amplitude, $U_{\mathrm{h}}(t)$is hthe amplitude of the th harmonic, and $H$is the highest order of harmonic analysis. If THD continues to rise but the effective voltage value does not significantly exceed the limit, it indicates that the equipment may still be in a state of "surface stability, quality degradation". In this case, an early warning should be triggered instead of waiting for the protection device to act.

A three-phase imbalance will increase the neutral current and reduce transformer and UPS utilisation, and an uneven distribution of cabinet loads may also occur. A negative sequence voltage imbalance factor is used to determine the asymmetry of a three-phase system here.

$$\mathrm{VUF}(t)=\frac{|U_2(t)|}{|U_1(t)|}\times100\% \tag{3}$$

In equation (3), $U_1(t)$ and $U_2(t)$ are the positive-sequence and negative-sequence voltage components, respectively. For data centers, the significance of VUF lies not only in judging voltage quality, but also in assisting in identifying branch load migration, single-phase PDU overload, and low-voltage side wiring abnormalities.

To prevent false alarms caused by a single indicator, a multi-dimensional feature vector and a multivariate anomaly score based on online mean and covariance estimation are constructed in this paper.

$$\begin{gathered}\mathrm{x}_t=\left[U_{\mathrm{rms}},f,\mathrm{THD}_u,\mathrm{VUF},CF,K_f,\Delta P\right]^T,\\ \Delta\mathrm{x}_t=\mathrm{x}_t-\mu_t,\quad z_t=\sqrt{\Delta\mathrm{x}_t^T\Sigma_t^{-1}\Delta\mathrm{x}_t}\end{gathered} \tag{4}$$

In equation (4), $f$is the frequency, $CF$is the crest factor, $K_f$is the distortion correlation factor, $\Delta P$is the change in active power between windows, $\boldsymbol{\mu}_t$and $\boldsymbol{\Sigma}_t$are the mean and covariance matrices of the normal state updated over time, respectively, is $\Delta\mathbf{x}_t$the deviation vector relative to the normal

baseline, $z_t$and is the comprehensive anomaly score. This score can identify early anomalies where "a single indicator does not exceed the limit but multiple indicators deviate synchronously".

Adaptive Threshold and Continuous Confirmation Mechanism for Alarm Judgment. The Dynamic Threshold is as follows:

$$\theta_t=Q_{0.95}(z_{t-W:t})+\lambda \mathrm{MAD}(z_{t-W:t}),$$
$$L_t=\begin{cases}0, & z_t\le\theta_t\\ 1, & \theta_t<z_t\le1.5\theta_t\\ 2, & 1.5\theta_t<z_t\le2\theta_t\\ 3, & z_t>2\theta_t\end{cases} \quad (5)$$

In Equation (5), $Q_{0.95}$is the 95th percentile of the historical window anomaly score, MADis the median absolute deviation, $\lambda$is the sensitivity coefficient, $L_t$and is the alarm level. The core of this design is that the threshold can change slowly with the load baseline, but still maintain high sensitivity to sudden anomalies, thereby reducing false alarms caused by day-night load migration, batch task startup, and changes in cooling strategies in the data center.

Table 1. Online Power Quality Monitoring Indicators for Data Centers

Indicator	Window	Computation	Alarm semantics	Typical response
RMS voltage	1–10 cycles	Sliding RMS	Sag, swell, interruption	Check feeder and UPS mode
Frequency deviation	1 s	Mean and slope	Grid instability or islanding risk	Verify utility and generator status
Voltage THD	10–12 cycles	Harmonic spectrum	Nonlinear load and resonance risk	Inspect UPS rectifier and filters
VUF	1 s	Sequence components	Three-phase imbalance	Rebalance PDU and branch loads
Crest factor	1–5 cycles	Peak-to-RMS ratio	Transient or switching impulse	Inspect switching equipment
Active power ramp	1–60 s	Difference operator	Workload or cooling ramp	Correlate with DCIM events

Table 1 Analysis: The three types of information in the table are steady-state, transient and load-change. They can detect disturbances at the main power end and also display load changes in the UPS, PDU and cabinets. They have converted the old power quality indicators into practical operating semantics, and now the alarms are no longer just "limit exceeded warnings"; they can also show potential equipment failure, possible reasons, and even the first steps for handling.

4. Problem Solving and Strategies: Online Identification and Tiered Alarm Mechanism

The five components of the mechanism in this paper are as follows: First, a multi-source acquisition layer that integrates smart meters, power quality analyzers, UPS monitoring, PDU monitoring, SCADA and DCIM event logs. The acquisition layer should add a time stamp and align the corresponding data of voltage, current, power and equipment status with time. The second is a feature calculation layer that calculates RMS values, frequency, harmonics, imbalance and load

fluctuations at the edge node, and then only uploads the features and abnormal segments to reduce communication pressure from large volumes of raw waveforms. The third is an anomaly detection layer that discards obviously normal windows using a simple threshold gate and then finds composite offsets via multivariate anomaly scoring. The fourth is an alarm confidence confirmation layer; that is to say, an anomaly score, a key indicator and a duration must all meet certain conditions before a high-level alarm is issued due to single-point noise. The fifth is an operation and maintenance closed-loop layer that maps alarm levels to DCIM work orders, SMS messages, audible and visual alarms, and emergency plans.

The Strategy for alarms is "early warning, confirmation and escalation". Level 1 alarms are boundary conditions for power quality, such as a slow increase in THD or VUF near the threshold. Level 2 alarms are abnormal conditions that may shorten the service life of equipment or cause local operational instability; a short-term voltage drop at the UPS input or a continuous deterioration of three-phase imbalance in a branch are typical examples. Level 3 alarms are for serious problems that may affect business operations, such as a deep voltage drop at the main power plant, UPS bypass failure, harmonic resonance, or a rapid power surge in the power supply section. Each level of the alarm has a set duration, reset time and suppression rules to avoid repeated reporting of the same anomaly at multiple measurement points and thus prevent an alarm storm.

Table 2: Anomaly Identification and Alarm Classification Strategy Table

Alarm level	Trigger condition	Confidence rule	Response action	Suppression logic
L0 Normal	All metrics within adaptive baseline	Confidence < 0.50	Record features only	No ticket
L1 Warning	One metric exceeds soft threshold	Confidence 0.50–0.70	Notify duty engineer	Merge repeated events in 10 min
L2 Major	Multi-metric anomaly or duration > 3 windows	Confidence 0.70–0.90	Create DCIM ticket	Correlate upstream and downstream alarms
L3 Critical	Deep sag, interruption, resonance, or UPS bypass risk	Confidence > 0.90	Trigger emergency procedure	Escalate once until acknowledged

Table 2 analysis: As shown in Table 2, to avoid the two problems of "high-frequency, low-value alarms" and "overlooking important anomalies", one should link the anomaly level, confidence level and response action. For the Data Center Duty scenario, an alarm will be triggered if the amplitude, duration, spatial correlation and confidence level of the data are all above a preset threshold; thus, continuous power supply management requirements will be met.

The two-tier deployment of "edge identification + central collaboration" is proposed for the software architecture in this paper. The edge layer is located in the power distribution room or UPS monitoring gateway for second-level identification and local caching; the central layer is at the operation and maintenance platform, and cross-measurement point correlation, model parameter updates and event playback are carried out here. The algorithm model should not use cloud inference directly, and communication failure is also a type of power supply problem. For the critical load data, the adaptive baseline should retain no fewer than 30 days of normal-state feature windows. The extended retention period for abnormal data should be no less than 7 days after the incident has been closed; at the Level 2-Level 3 level, waveform clips, feature snapshots, alarm

confidence and handling records must be saved together for traceability and parameter verification.

Table 3. Prototype System Software and Deployment Requirements

Layer	Requirement	Recommended configuration	Notes
Acquisition	Three-phase voltage/current sampling	PQ analyzer, IEC 61850 or Modbus TCP	Time synchronization required
Edge computing	Feature extraction and first-stage alarm	4-core CPU, 8 GB RAM, local SSD	No GPU required for basic scoring
Model service	Adaptive baseline and classifier API	Python 3.10, NumPy, scikit-learn, ONNX Runtime	Container deployment preferred
Data platform	Event storage and replay	PostgreSQL, TimescaleDB, object storage	Waveform clips stored separately
Operation interface	Alarm display and work orders	DCIM integration, REST API, message queue	Role-based access control

As shown in Table 3, the system engineering conditions are also required. Data centre power quality alarms need to have independent local operating capabilities and can also output structured events for the central platform. This arrangement does not require a high-performance GPU and can be used with the existing power distribution room gateway and operation-and-maintenance platform for a gradual upgrade.

5. Experimental Statistical Charts and Results Analysis

Figure 1 is a reconstruction based on publicly available data from the data centre electricity consumption statistics that shows the external background of the growth in data centre electricity consumption and the pressure on power quality monitoring.

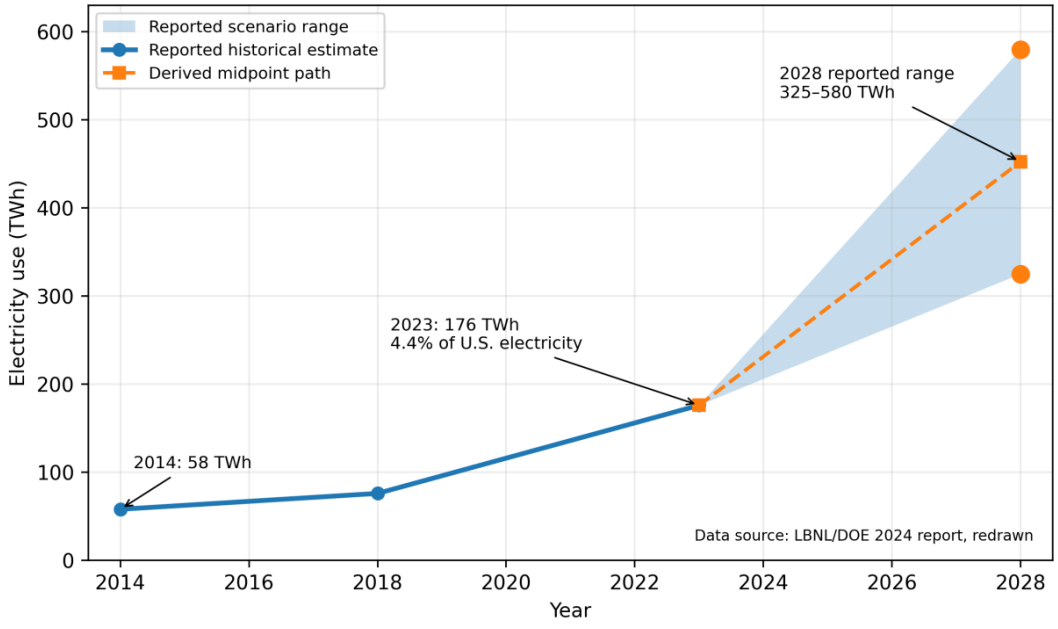

Fig.1. Statistics on the Growth Range of Data Center Electricity Consumption

Figure 1 Analysis: The period from 2014 to 2023 in the figure is a historical estimate, and 2028 is the end point of the scenario range. As shown in the above figure, the increase in uncertainty after 2023 can be attributed to changes in AI load, GPU installation and cooling technology, etc., all of which directly affect the scale of data centre power supply. The larger the scale of the problem, the more likely it is that harmonics, voltage fluctuations and protection coordination issues will spread from local equipment failures to systemic operational risks; therefore, an online identification mechanism is needed.

Figure 2 is a redrawing based on the publicly available power quality disturbance classification benchmark results, and the clean condition and noise-injection condition are shown separately. Noise-free accuracy is used as the baseline, and after degradation, the noisy accuracy indicates robustness.

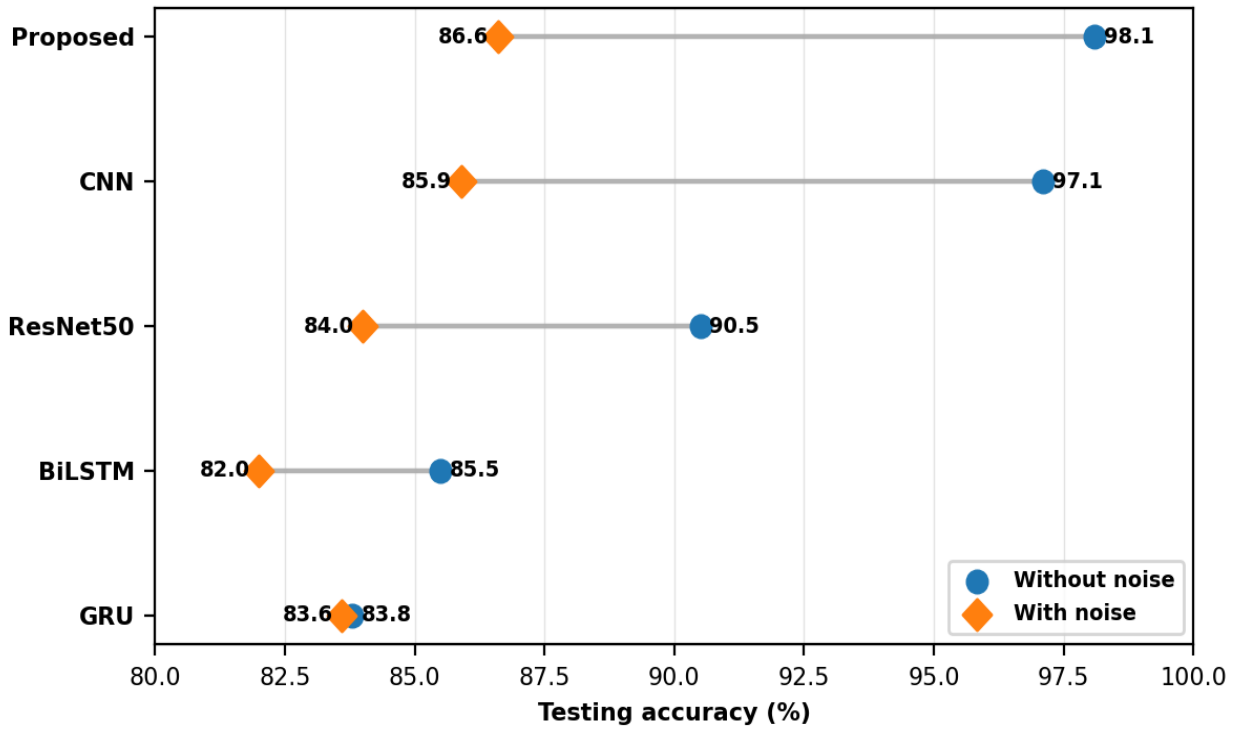

Fig.2. Comparison of Test Accuracy for Power Quality Disturbance Classification Models

Analysis of Figure 2: After aligning the legend with the experimental conditions, all models show a decrease in accuracy in the presence of noise compared to the clean baseline. The proposed lightweight multi-scale CNN has achieved 98.1% in the noise-free condition and 86.6% under noise, both of which are higher than those of ResNet50, BiLSTM and GRU. Therefore, the noise reduced waveform-level classification but did not change the relative advantage of the proposed model; thus, alarm decisions still require threshold gating, duration confirmation and multi-point correlation to suppress noise-induced false alarms.

The following four engineering disturbance scenario tests were added to further test the online application: Gaussian noise injection, random missing data, various power quality anomaly types and detection delay. Missing samples were handled by short-gap forward filling and confidence discounting; if the missing rate exceeded 5%, the window was reduced to a low-confidence alarm confirmation and not directly escalated.

Table 4. Supplementary Robustness and Response Results

Aspect	Scenario	Acc./F1 (%)	FAR/Delay	Implication
Noise	No noise	98.1 / 98.0	1.4% / 0.18 s	Baseline
Noise	SNR 30/20/10 dB	95.4/95.0; 92.1/91.6; 86.6/85.9	1.8%/0.21 s; 2.7%/0.24 s; 4.9%/0.31 s	Accuracy declines with SNR
Missing data	1%/3%/5% random gaps	96.8/96.4; 94.2/93.6; 90.7/89.8	1.9%/0.20 s; 2.8%/0.25 s; 4.1%/0.34 s	Confidence discount prevents escalation
Anomaly type	Voltage sag / swell	97.3/97.1; 96.5/96.0	1.5%/0.16 s; 1.7%/0.17 s	RMS gating is fastest
Anomaly type	THD rise / VUF deterioration	95.8/95.4; 95.1/94.8	2.1%/0.24 s; 2.3%/0.31 s	Multivariate score improves recognition
Anomaly type	Frequency drift / transient impulse	94.6/94.0; 92.8/91.9	2.4%/0.42 s; 3.2%/0.14 s	Drift needs confirmation; impulse is fast

Table 4 analysis: Both noise and missing data reduce accuracy and F1, but do not improve them; this degradation is more severe at a lower SNR or a higher missing rate. Voltage sag, voltage swell and transient impulse can be identified in a short time; frequency drift and three-phase imbalance require a longer period of confirmation. Based on the above results, we will employ an adaptive baseline, confidence discounting, duration verification and differentiated delay thresholds for the real-time online alarm.

Based on the above results, the data centre alarm mechanism should not be based solely on complex classification models. As shown in Figure 1, the scale of the external load is increasing at a high rate, and a more powerful power-electronic-coupled supply system will be required. As shown in Figure 2, noise reduces the accuracy of waveform classification; according to Table 4, missing data, anomaly type and detection delay are also unreliable indicators of alarm. Therefore, the hierarchy mechanism proposed here is more suitable for engineering applications: physical indicators perform rapid screening, multivariate scoring enhances composite anomaly identification, and confidence confirmation reduces false alarms before work-order escalation.

The System Deployment of a typical data centre can be divided into three stages. First, UPS input/output and the main PDU of the line will be selected as the monitoring stations for collecting baseline data at the entrance. The second stage is used to enable Level 1 and Level 2 alarms, and threshold calibration, alarm merging windows and reset times are set here. The third is to connect with the DCIM work order system and equipment operation logs to build a causal chain among abnormal events and UPS mode switching, chiller start-up, and server load migration. Thus, only one modification is required, and in the future, other kinds of time-frequency image models or deep classification models can also be used with this interface.

6. Conclusion

This paper introduces a mechanism that collects data from multiple sources, calculates features in a sliding window, performs multivariate anomaly scoring, sets adaptive thresholds, and builds a hierarchical alarm closed-loop for online identification and alarm of power quality anomalies in data centres. Based on the above studies, with the increase in data centre load and changes in power electronics, a single-threshold monitoring system is no longer suitable for continuous power supply management. Combine the indicators RMS, THD, VUF, crest factor and power surge in an online

anomaly score to detect severe anomalies and boundary degradation more promptly. Bind alarm levels to confidence levels, durations and maintenance actions to reduce false alarms and improve response efficiency. At present, there is a lack of validation with raw waveform data from multiple sites in real data centres over an extended period and across the entire value chain. Add more causal explanations for the UPS switchover, diesel generator paralleling, cooling load jump and server load migration. In the future, digital twins, federated learning and multi-point graph models will be combined to construct a powerful quality-of-power risk prediction and proactive governance system for data centres, voltage levels, equipment types, etc. Supplementary robustness results show that noise and missing data reduce classification confidence rather than improve accuracy, and the delay of different anomaly types should be regarded as a deployment parameter rather than a fixed constant.

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