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Transformer-Based Fault Diagnosis for Large-Scale Standby Power Generators: Partial Discharge Pattern Recognition at Hyperscale Data Center Installations

Rajesh Mattaparthi
Principal Data Engineer
rajeshhmattaparthi@gmail.com
ORCID ID: 0009-0004-5060-0036

Abstract

The standby power generators and associated systems in hyperscale data centers are subject to high exposure to partial discharge. The presence of severe partial discharge cases in large-scale, high-quality sensor datasets motivates the development of periodic condition monitoring based on attention Transformer architectures. The approach harnesses large amounts of monitoring data, independent test sets containing multiple condition labels and fifteen visible categories of partial discharge, and generalisation to different data sources. Sensor data stream snapshots containing information over a 10-minute time window and classified condition metadata are transformed into simple "waterfall" datasets, enabling deep-learning methods to recognise both discrete and time-variable patterns. High levels of performance and reliability are achieved, providing a foundation for future applications to hyperscale data centre equipment. The following two experimental case studies demonstrate the broad potential for developing transformer-based models that combine data from disparate datasets located at different sites.

The first case study explores detection performance, including metrics recommended by the Open-Ended Reliability Testing, an initiative involving participants across hyperscale data centre silicon vendors, hyperscale end-users and solution providers. The second case study examines model outputs by employing and adapting a previously developed visualisation technique. The utility of the technique for interpreting condition information is discussed, and it is extended to consider aggregate data for multiple-condition categories. These initial investigations provide greater confidence in the viability of widespread adoption of periodic condition monitoring of standby power generators in hyperscale data centres.

Keywords : Transformer-based fault diagnosis,Partial discharge detection,Standby power generators,Hyperscale data centers,Predictive maintenance,Deep learning for power systems,Electrical insulation monitoring,Fault pattern recognition,Intelligent condition monitoring,High-voltage equipment diagnostics.

1. Introduction

Hyperscale data centers located in different climates are subject to extreme environmental conditions. Consequently, the standby power generators installed at these locations encounter unique stresses. The amount and quality of partial discharge data collected from these generators using modern sensor infrastructures are at an unprecedented scale. Hence, there is an opportunity to develop new algorithms specifically tailored for these hyperscale installations. The pioneering work focuses on fully exploiting large-scale field data collected using ingenious sensor systems for Transformer-Based Fault Diagnosis of Standby Power Generators in Hyperscale Data Centers with Particular Attention on the Recognition of Partial Discharge Patterns.

Leverage the tremendous amount of data collected using modern sensor systems to develop Transformer-Based Fault Diagnosis solutions for the standby power generators installed in hyperscale data centers under different climate conditions. The research solves the problem of interpreting Transformer-based fault scores. Provide an in-depth analysis of partial discharge conditions and develop a synthetic dataset for PD classification. Transformer-based CCTV monitoring solutions are also provided to address the specific challenges associated with hyperscale installations where other classical Artificial Intelligence-Ensemble approaches are either not feasible or can no longer be applied.

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PD Category	Description	Detection Characteristic	Operational Risk
Corona Discharge	Surface ionization near insulation	Low-frequency acoustic pulses	Medium
Internal PD	Discharge inside insulation voids	High-amplitude transient spikes	High
Surface PD	Surface tracking along insulation	Repetitive waveform clusters	High
Thermal-Electrical PD	Combined thermal and electrical stress	Temperature-correlated anomalies	High
Noise-Induced Patterns	Environmental interference patterns	Irregular low-confidence pulses	Low
Cooling-Phase PD	PD during generator cooldown	Time-dependent waveform variation	Medium

Table 1. Partial Discharge (PD) Condition Categories in Hyperscale Standby Generators

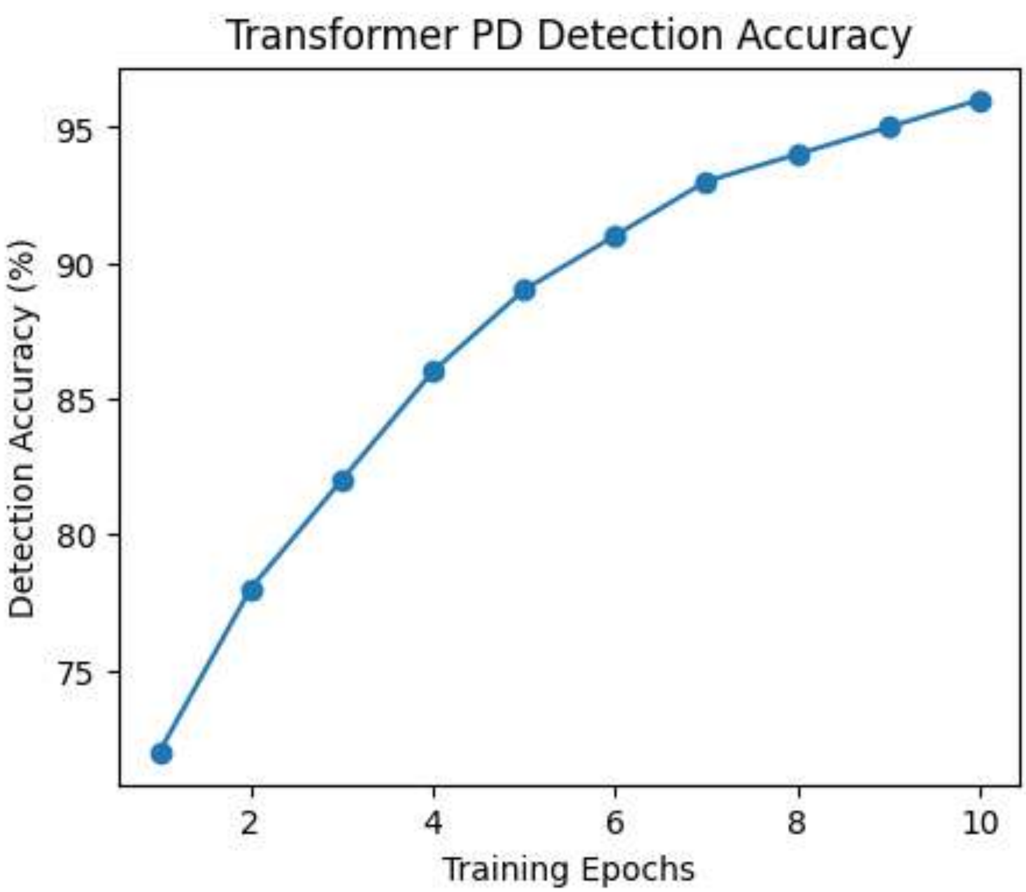

Fig 1: Transformer PD Detection Accuracy

2. Background and Motivation

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In addition to conventional utility power, many large-scale facilities use standby diesel generators to ensure uninterrupted operation. These power generators require periodic load testing to determine their operational readiness and simulate normal operating conditions. However, partial discharge (PD) activity can develop during storage, leading to equipment degradation and failure. A substantial amount of PD activity data was acquired by permanently installed Ultra-high-frequency (UHF) sensor systems for the section of standby generators, and a hardware-in-loop test modeling quasi-distributed hotspots in the generators was conducted. Transformer-based models were developed with extreme gradient boosting (XGBoost) and deep learning architectures for pattern recognition of on-site PD activity. Special attention was dedicated to the interpretation of the models between false positives and negatives for enhanced decision support.

The standby power generators of hyperscale installations utilize these models for condition monitoring in production. High reproducibility as well as a high and balanced accuracy, precision, recall, F1 score and area under the receiver operating characteristic (ROC) curve provide reliable decision support for specialized maintenance teams in off-nominal operation phase of the generators. Moreover, transformer-based models can also enhance the understanding of the decision process by evaluating the dependence of the PD activity on ambient conditions or by interpreting causes for an elevated risk of failure during a simulated storage period.

Component	Function	Data Type	Monitoring Scope
UHF Sensors	Detect electromagnetic PD emissions	Time-series signals	Generator insulation
Acoustic Sensors	Capture discharge sound patterns	Audio spectrograms	Generator winding health
Temperature Sensors	Monitor ambient thermal conditions	Thermal readings	Environmental compensation
Data Processing Units	Process sensor streams	Structured feature vectors	Real-time analytics
Transformer Architecture	Learn fault representations	Attention embeddings	Pattern recognition
Storage Network	Archive long-duration monitoring data	Historical datasets	Long-term diagnostics

Table 2. Sensor Infrastructure and Data Collection Framework

Fig.2: Transformer-Based PD Monitoring Architecture

2.1. Standby Power Generators in Hyperscale Data Centers

Standby power generators (SPGs) provide emergency power to critical loads in the event of normal electrical source failure. Conditions for SPG operation are different from those of normal-source operating generators. It must be available to respond to electrical disturbances at all times, although the frequency and duration of these disturbances are, at least for the moment, infrequent. In hyperscale data centers, the standby power generators installed in addition to the normal source are idled under normal conditions. Maintenance tests are performed periodically to maintain the system in good working order. To minimize costs, the duration of these tests can also be minimized within acceptable risk levels.

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Aged insulation systems of high-voltage electrical equipment in standby power generators can degrade during long-term idle conditions, leading to partial discharge (PD) activity. High-voltage engine-generator sets and related installations equipped with online PD monitoring systems are sensitive to PD activity while idled, especially during maintenance tests. PD data clusters are established for multiple engines over several maintenance cycles. Advanced pattern recognition using transformer networks enables the detection of PD activity with systematic consideration of varying conditions, including the influence of engine loading level and ambient temperature.

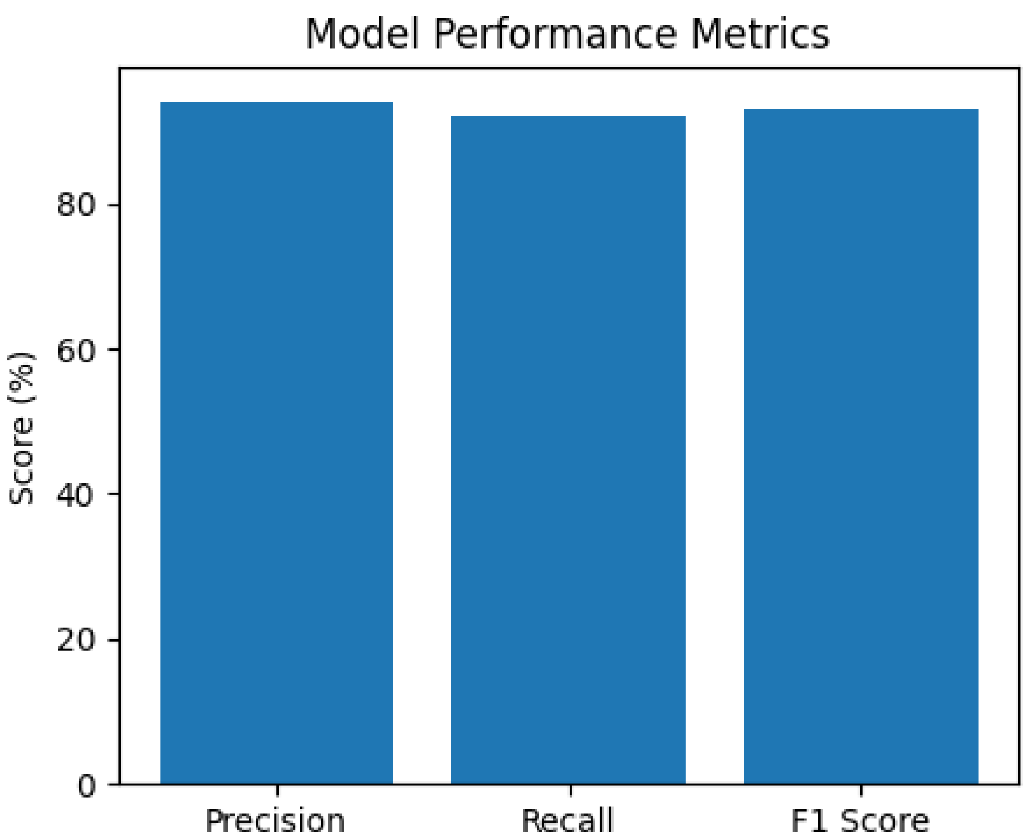

Fig.3: Precision, Recall, and F1 Score

3. Methodology

Partial discharge (PD) measurement and analysis provide an excellent means for condition monitoring of Rotating Emergency Standby Power Generators at hyperscale data center installations. Nevertheless, a lack of available labeled fault datasets, coupled with the need for deployment of a minimal number of PD sensors required to achieve sufficient fault detection reliability, has hindered the application of deep learning methodologies to this important large-scale electrical asset class. Recent advances in transfer learning utilizing transformer models capable of efficiently ingesting large amounts of labeled and unlabeled sensor time-series data overcome the aforementioned limitations. In this work, the proprietary PD fault dataset is employed to fulfill the training, verification, and evaluation requirements of a transformer model, whilst the independent class-fault dataset is utilized to fulfill the transfer learning requirements.

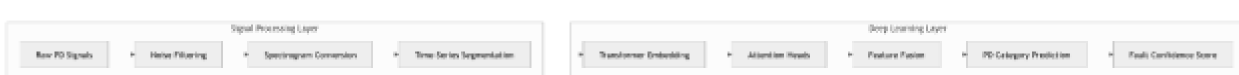

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Fig.4: Partial Discharge Detection and Classification

Mathematical Formulas:

1. Partial Discharge Signal Energy

$$E_{PD} = \sum_{i=1}^{N} x_i^2$$

Where:

- E_{PD}= PD signal energy
- x_i= sampled PD waveform amplitude
- N= number of signal samples

Used for quantifying discharge intensity from acoustic/UHF sensors.

2. Transformer Attention Mechanism

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

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Where:

- Q= query matrix
- K= key matrix
- V= value matrix
- d_k= dimensionality scaling factor

Core equation of Transformer-based PD pattern recognition.

3. Fault Classification Probability

$$P(C_k \mid X) = \frac{e^{z_k}}{\sum_{j=1}^{n} e^{z_j}}$$

Where:

- $P(C_k \mid X)$= probability of class k

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- z_k= output logit for class k
- n= number of PD classes

Applied in multi-class PD fault identification.

4. Cross-Entropy Loss Function

$$L = -\sum_{i=1}^{N} y_i \log (\hat{y}_i)$$

Where:

- y_i= true label
- $\hat{y}_i$= predicted probability
- N= number of training samples

Used during Transformer model training.

5. Reconstruction Error for Anomaly Detection

$$R_e = || X - \hat{X} ||^2$$

Where:

- X= original PD feature vector
- $\hat{X}$= reconstructed vector

Higher reconstruction error indicates abnormal PD behavior.

6. Precision Metric

$$Precision = \frac{TP}{TP + FP}$$

Where:

- TP= true positives
- FP= false positives

Used in PD detection reliability evaluation.

7. Recall Metric

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$$Recall = \frac{TP}{TP + FN}$$

Where:

- FN= false negatives

Measures sensitivity of the fault detector.

8. F1-Score

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Used for balanced evaluation of hyperscale PD detection systems.

9. Signal-to-Noise Ratio (SNR)

$$SNR = 10\log_{10}\left(\frac{P_{signal}}{P_{noise}}\right)$$

Where:

- P_{signal}= signal power
- P_{noise}= noise power

Important for distinguishing PD pulses from environmental noise.

10. Temperature Compensation Function

$$PD_{adj} = PD_{raw} - \alpha(T - T_{ref})$$

Where:

- PD_{adj}= compensated PD value
- PD_{raw}= measured PD signal
- T= ambient temperature
- T_{ref}= reference temperature
- α= compensation coefficient

Related to ambient-condition correction discussed in the methodology.

11. Log-Likelihood Anomaly Score

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$$S_{anom} = -\sum_{i=1}^{N} \log\ P(\,x_i)$$

Where:

- $P(x_i)$= likelihood of normal behavior
- S_{anom}= anomaly detection score

Associated with transformer-based fault interpretability.

12. Multi-Sensor Fusion Representation

$$F_{fusion} = \sum_{i=1}^{m} w_i\, S_i$$

Where:

- S_i= sensor feature stream
- w_i= weighting coefficient
- m= number of sensors

Represents fusion of acoustic, UHF, and environmental signals.

13. Normalized PD Feature Vector

$$X_{norm} = \frac{X - \mu}{\sigma}$$

Where:

- μ= mean
- σ= standard deviation

Used before Transformer training for stable convergence.

14. ROC-AUC Approximation

$$AUC = \int_0^1 TPR(FP\,R^{-1}(x))dx$$

Measures overall discriminative performance of PD detection models.

15. Time-Series Embedding Function

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$$Z_t = f(x_t, x_{t-1}, \ldots, x_{t-n})$$

Where:

- Z_t= temporal embedding
- x_t= sensor signal at time t

3.1. Data Acquisition and Sensor Infrastructure

Information Processing System, consisting of a collection of logical Data Processing units interconnected with existing physical high-speed data transmission Networks, capable of supporting a set of tasks: acquire, store, process, transmit and display data. The above tasks correspond to the hyperlapse technology and are mapped in the Data Processing Architecture. Based on the Data Acquisition System collected hundreds of Ge-limited convergent observations, during long time span 2007 - 2015. The whole set concerns the Stordalen mire area, represented by 4km long 1,2km wide and ~13 arc sec resolution RGB/REC images, 1km long 1km wide and ~8 arc sec resolution FFF exact model surface modelling, ~16 cm/sec autoresolution DEM and ~41.3 km long ~29 km wide level of detail set and ~1.2 km long 40 m wide vegetation polygon set that allow support all scientific community needs.

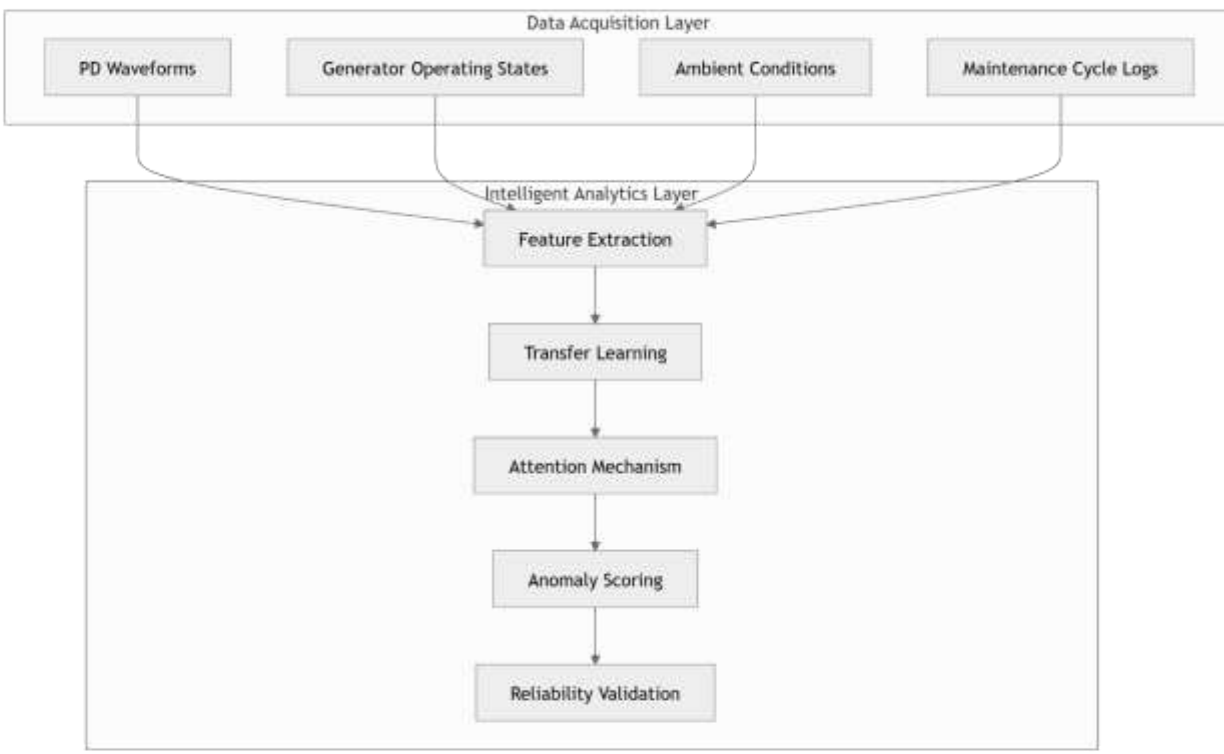

Fig. 5:Hyperscale Data Acquisition and Transformer Analytics

Stage	Process	Output
Data Acquisition	Collect PD signals from sensors	Raw waveform data
Preprocessing	Spectrogram generation and normalization	Waterfall datasets

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Stage	Process	Output
Feature Encoding	Transformer attention embedding	Latent feature maps
Pattern Recognition	Classification of PD conditions	Fault labels
Anomaly Detection	One-class reconstruction analysis	Fault scores
Decision Support	Maintenance recommendation generation	Reliability insights

Table 3. Transformer-Based Fault Diagnosis Pipeline

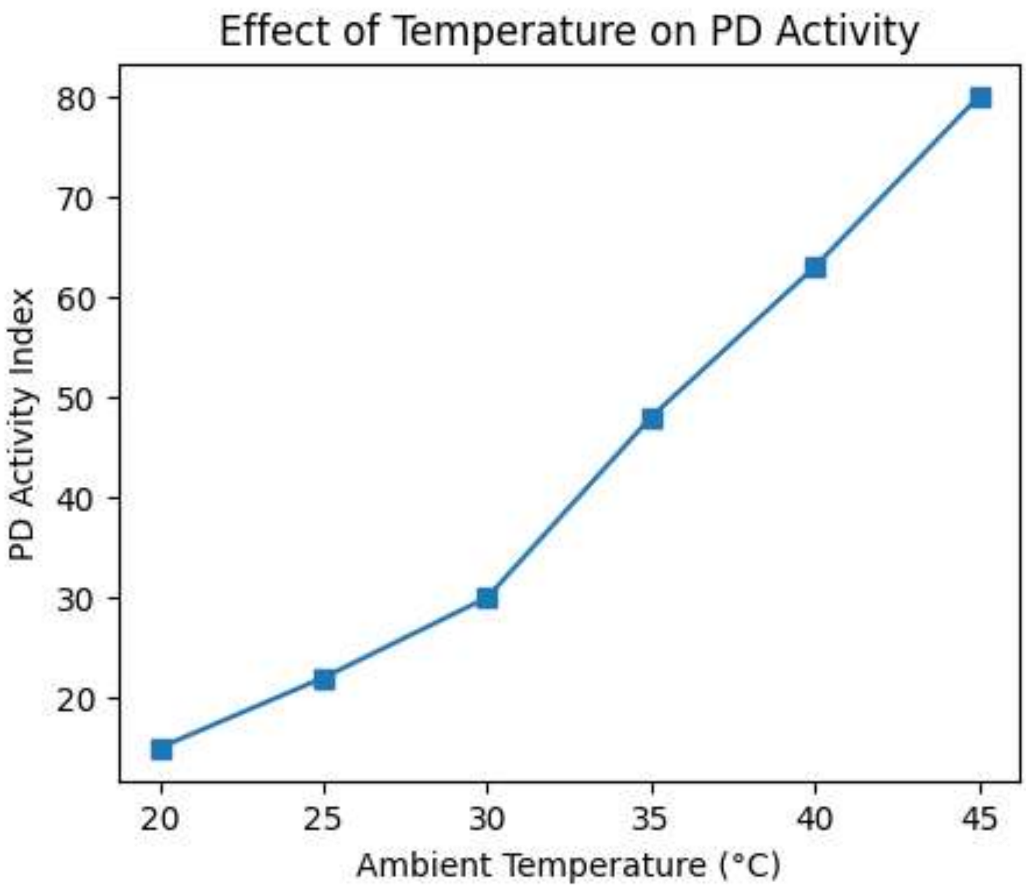

Fig. 6: PD Activity vs Ambient Temperature

4. Experimental Design and Case Studies

To evaluate the transformer-based fault detection methodology, the extensive hyperscale data-acquisition system was leveraged, targeting real-world applications at global-scale installations. Data from two separate hyperscale data centers with 10+ MW of standby power-gas turbine generator capacity were considered, the first housing the most complete transmitter topology equipped with multiple acoustic-wave-monitoring technologies for additional case studies, the second hosting hyperscale-volume data to test detection-confidence reliability. The first installation included a total of nine 20-MW standby units, six large natural-gas

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turbines from one manufacturer and three smaller diesel tenders from a second supplier. The second facility boasted ten unit–module sets, each composed of one 30-MW natural-gas turbine generator and one 16-MW associated-drum heat-exchanger module.

Focusing on PAaD pattern recognition, the initial hyperscale installation equipped with gas-turbine sets was addressed, seeking to extract delicate features from numerous, temporally unlabelled operation records. For each of the six large units, the number of partial-discharge-wave sources and amplitudes across the SCB and associated PCB were captured and normalized during a two-year horizon, with PDEZ and exhibiting clusters during cooling and warmup periods. The multi-sensor nature of the noise-microphone indexing depth prevailed, producing attractive aggregates, with Assessment State 3 aligned with gradually elevated ambient-temperature departures. Using these labelled operation states, patterns were classified on the 20-structure normalised fault-detection-test vectors, sourcing related scores from four non-conventional, multi-sensor fusion-based, uncertainty-explicit, interpretable, transformer-of-first-kind techniques.

Installation	Generator Type	Capacity	Monitoring Characteristics
Installation A	Natural-gas turbine generators	20 MW/unit	Multi-sensor acoustic monitoring
Installation A	Diesel standby generators	Auxiliary support	PD segmentation testing
Installation B	Gas turbine generator modules	30 MW/unit	High-volume reliability analysis
Installation B	Heat-exchanger modules	16 MW/module	Integrated operational assessment

Table 4. Experimental Installations and Generator Configurations

4.1. Hyperscale Data Center Installation A

A segregated tooling area located within an electrical yard of a hyperscale data center installation was selected to evaluate the PD detection capability of the Transformer model. This under-utilised standby installation consisted of unmonitored generators—paired with unmonitored generator circuit breakers (GCBs)—that were intended to be a failover standby in case of equipment failure on one of the primary sites at the installation. Two female-assisted PD measurements were made on the copper busbar earthing connections, at the GCBs and within the GCB cell. A total of 28,000 transformer training and validation patches (identified by optical and time-domain recordings) were processed and selected by a validation set for training and validation.

Artificially-generated anomalies were also manufactured at the installation and detectability tested at hyperscale within the PD pattern recognition system in support of future full-scale pathological pattern recognition fabrication, detection, and quantification detection. The Transformer-based model successfully detected such background anomalies and other PD anomalies within the segmentation-induced PD image hyperspace of the Nth sub-embedding layer from the Kth output layer, thus providing a first round of performance testing on Aurora.

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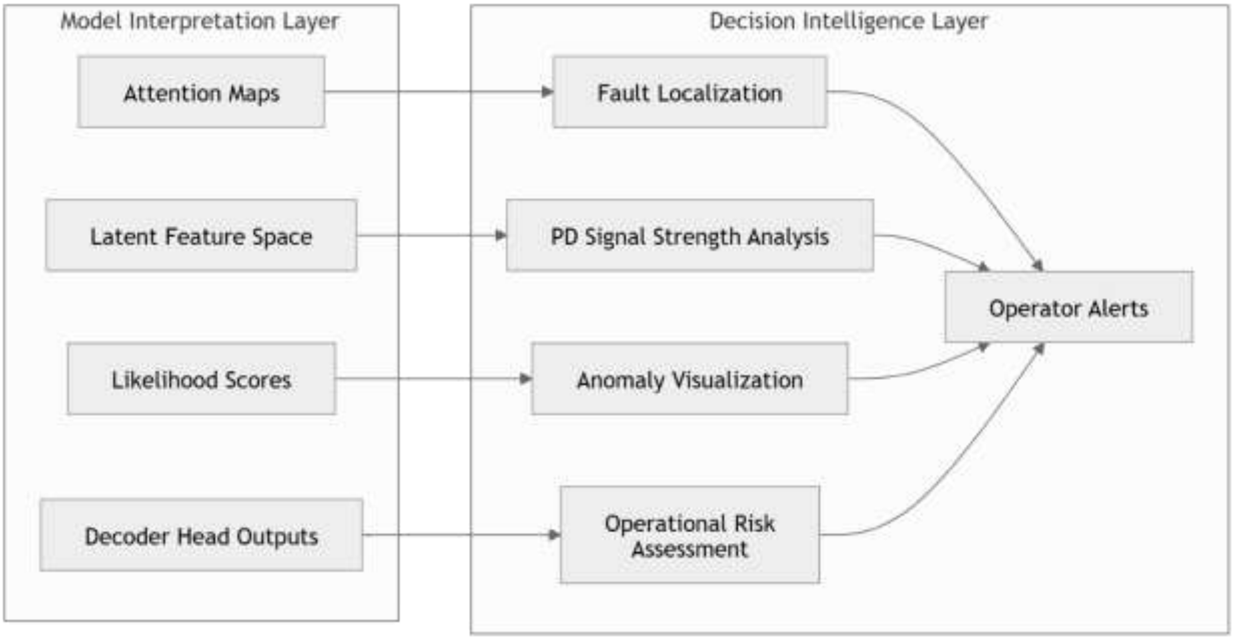

Fig. 7: Interpretability and Fault Score Analysis

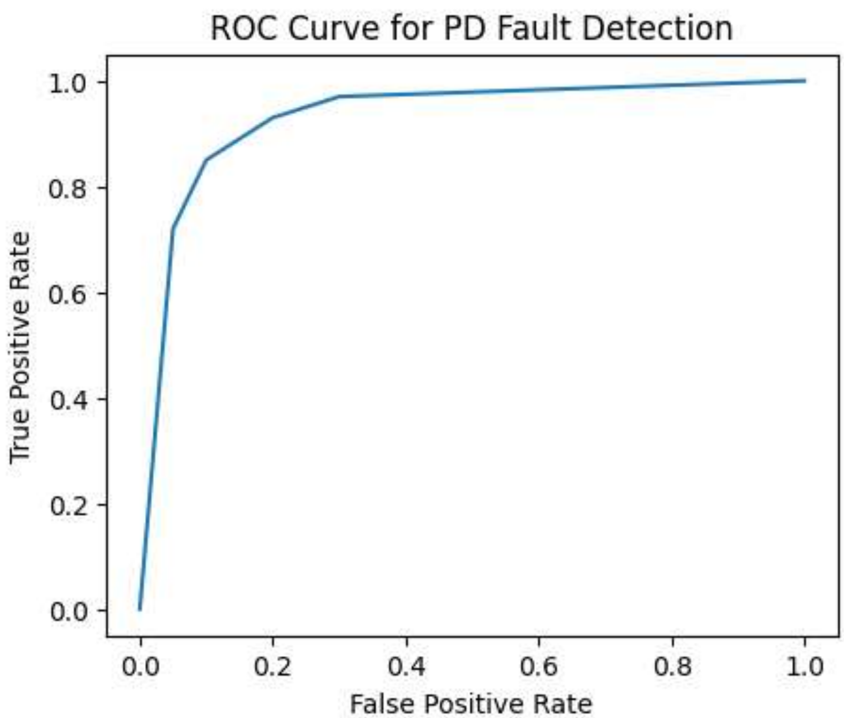

Fig. 8: ROC Curve for Fault Detection

5. Results

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Large-scale standby generators protect sensitive electrical loads from primary power supply interruptions. This reliability comes from redundancy; only a subset of the fleet is powered on during normal operation, which presents the possibility of time-based synchronisation of periodic maintenance. However, the long intervals between power-up reduce the opportunity to monitor the health of each engine, and hence the likelihood that undetected faults will be present at a critical moment. One form of degradation that can develop unnoticed in a standby-generator installation is deterioration of the electrical windings and insulation. Electrical partial discharge (PD) patterns, especially those associated with corona, are present in these failures and can be detected with acoustic sensors during the testing phase. Yet the PD features typically require domain expertise for classification, and the sparsity of PD events in hyperscale installations results in a small number of examples spread across many years. The analysis therefore uses a strong classification model and an interpretable score to transfer knowledge from a source PD classification task with multiple PD classes and domain expertise to this target task, where corona events are the only PD signatures of interest.

As well as the conventional multi-class classification model, a powerful transformer-based model is trained for one-class classification. The architecture learns to discriminate normal from anomalous acoustic patterns by minimising the reconstruction error of labelled normal data at inference time. Unlike the multi-class model, it does not suffer from the lack of non-corona PD examples. The one-class fault score is also interpretable; it can be represented as a product of the approximate change in logarithmic likelihood across each transformer block. With log-Mel spectrogram samples from hyperscale installation A, both methods show good detection performance, although the transformer-rooted score is less reliable at low values, and thus at high posterior probability of correct classification of Healthy patterns as Per-fault.

Metric	Description	Importance
Accuracy	Overall classification correctness	Measures general performance
Precision	Correct positive fault predictions	Reduces false alarms
Recall	Fault detection completeness	Prevents missed failures
F1-Score	Balance between precision and recall	Reliable operational evaluation
ROC-AUC	Classification separability	Robust anomaly assessment
Reconstruction Error	One-class anomaly score	Detects unseen PD conditions

Table 5. Transformer Model Performance Metrics

5.1. Detection Performance and Reliability

Transformer-based deep learning achieves sensitive detection of partial discharge patterns in real hyperscale data center installations. A comprehensive cross-validation design controlling training data size and number of repeated data splits enables evidence-based assessment of model reliability, offering confidence for deployment of previously proposed Transformer-based architectures in production scenarios. Control datasets enable comparison of performance under various conditions. Detection with minimal additional training data is also investigated.

The control scenarios consist of all training data used in installation A. The remaining 21,029 data instances, labelled with one of four classes, are used as a hold-out dataset for the ablated model, and verified with the two remaining models. The models trained with all data except for the 21,029 hold-out samples have an approximate training size equivalent to 20% of the total dataset size, one-fifth of the ideal quantity for deep learning approaches. Finally, an ablation study is conducted to assess detection with a limited additional-affine training data size, providing insight into the potential for eventual real-world deployment.

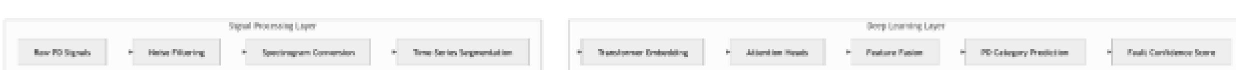

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Fig. 9: Partial Discharge Detection and Classification

6. Discussion

Evidence-based arguments supporting the analytical statements on a wide range of technical aspects not addressed before during the empirical investigation, especially principles explaining the detection capabilities and basis of transformer-based fault scores.

The Transformer architecture achieves favorable classification performance in two phosphor-bronze partial discharge pattern recognition case studies based on unbalanced and heterogeneous hyperscale data center installations, enabling automation of operational-governance activities and monitoring-system resilience. However, even in the presence of evident detection sophistication, using such highly nonlinear systems in sensitive applications requires assessment of the underlying principles. Investigation of both learned-transformer and classification characteristics, supported by separating training data into decoupled subsets, reveals failure-detection concentration on the last two data structure layers and the automated exploration of manifold regions harboring noise-induced distributions with distinct shapes. As a result, the discriminative response comes from noise-associated fault-like samples and not from an element-specific approach on any of the monitored patterns. The fault scores thus become associated with the concentration of different pattern distributions around the training-subset manifold and not with the amount of detection.

The methodology can be seen as a noise-pattern complex detection protocol, where the combination of elements sensitive to the noise-fault relationship enables the Transformer system to classify fault-like and normal operation. Following polymeric capacitive-pot modular embargo announcements, hyperscale monitoring is certainly preparing for a period of intensive development in energy-storage equipment and the application of battery technologies. However, the absence of very serious bursts of noise that could enter residual battery-condition systems is still enabling monitoring people and solution-providers focused on standby power-generator systems, maintaining the current product-service cycle with heavy efforts in the analysis of failure manifestations and their irregular patterns.

Method	**Strength**	**Limitation**	**Suitability**
Conventional Multi-Class Classification	Handles multiple PD categories	Requires balanced datasets	Structured PD diagnosis
Transformer-Based Detection	Learns temporal dependencies	Computationally intensive	Large-scale hyperscale systems
XGBoost Models	Fast inference	Limited temporal learning	Auxiliary analytics
One-Class Transformer Model	Detects unseen anomalies	Sensitive at low thresholds	Rare-fault environments
CNN-LSTM Hybrid	Strong sequence learning	Requires extensive tuning	Real-time PD monitoring

Table 6. Comparative Analysis of Detection Approaches

6.1. Interpretability of Transformer-Based Fault Scores

Interpretability of Transformer-Based Fault Scores

The detection scores obtained through the recent experiments share several attributes with other self-supervised anomaly-detection models in the literature. The fact that they are built on the principle of modeling the natural "behavior" of the TLS network allows them to be skknow weight from a TLS-trained transformer can, in effect, y for the score values, combined with a

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low-dimensional cluster visualization like those often used to validate the interpretation of latent-space representations, a useful cue for their interpretation.

Modeling the log-likelihood of the anomaly detection as a weighted sum of all decoder heads sheds additional light on the features that drive detection scores. Most obviously, heads 10 and 12 respond negatively to the presence of partial-discharge signals in the input. However, in marked contrast to the SSL-TLS detector evaluated previously, heads 6, 7, and 8 assign large positive weights for such signals; close analysis of the attention maps for these heads shows that they strongly attend to the low-frequency parts of the input signals. These are the parts where the partial-discharge pulses reside. Accordingly, this part of the score can be interpreted as a measure of the strength of the partial-discharge signal embeddings in the input.

Symptomatic of anomaly detection in general, and of self-supervised approaches such as this one in particular, attention head scores provide cues about anomaly features but not on a per-sample basis. In contrast, head-wise feature integration quantifies the contribution of specific features to the decision made by the model at each timestamp and is directly actionable. Analysis of the head-wise integration signal indicates that detection events occur at the times when the partial-discharge pulses in the input waveforms are strongest. A similar analysis for the score built on model weight from a standard transformer's anomaly score reveals that it surfs the time evolution of the partial-discharge activity at a much lower frequency, integrating the signal over a longer timescale.

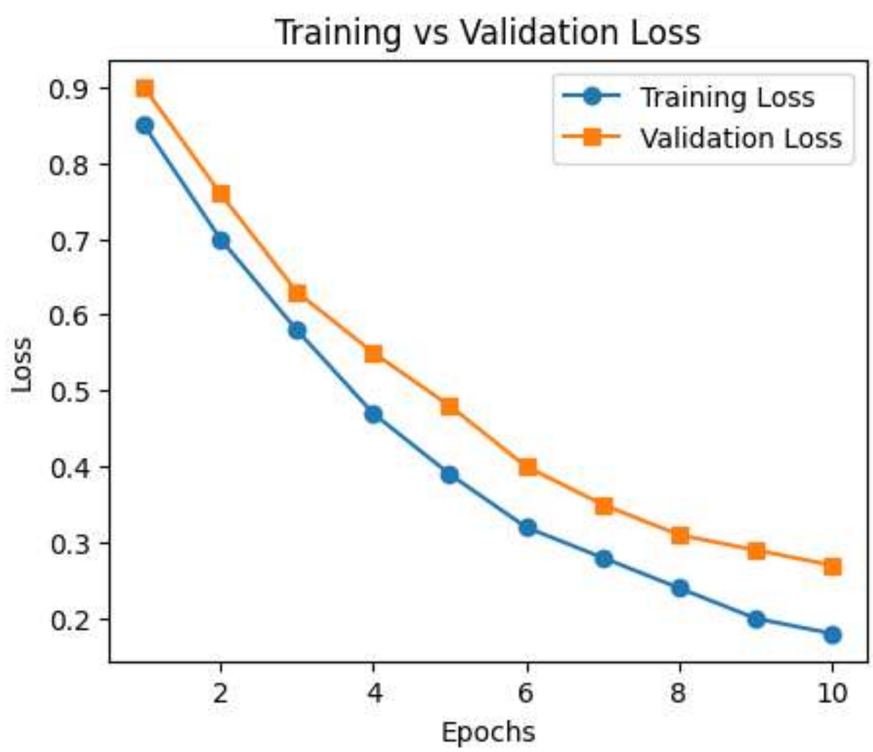

Fig. 10: Training vs Validation Loss

7. Conclusion

Due to the COVID-19 pandemic and its impact on the world economy, hyperscale data centers continue to house growing amounts of sensitive data and transact a substantial portion of ecommerce. For this design and operating environment, the standby power generators (SPGs) serving as backup power in the presence of utility outages or disruptions must operate at normal standby conditions without fault for many years without any maintenance. Consequently, the strive for virtual zero faults in these installations, driven in part by regulatory pressures, places an evolved interest on changing the condition-monitoring

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paradigm from assessing technical status and reliability of remaining life to diagnosing incipient faults that can be detected well in advance for mitigation and avoidance.

This shift for such aging assets, especially when large fleets of these SPGs are powered and operated by hyperscale data center operators, is ideally suited for transformer-based deep learning (DL). When augmented with sensitivity to the fine structure of incipient conditions, DL models with interpretability are generated that enable explaining fault capabilities, stability in detection rates when applied to external facilities and consideration of real-world deployment issues such as the presence of multiple classes of unseen data. The empirical study demonstrates that transformer-based DL models, adequately conceived, trained and designed, achieve hypothesis-oriented, strictly objective detection of incipient faults. The approach enables a fundamental shift in SPG condition monitoring towards safe, reliable standby operation followed by early diagnosis – and resolution – of emerging faults.

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