

Article

A Catboost-Based Machine Learning Approach for Fault Detection in VSC-Based Multi-Terminal HVDC Grid

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Abstract

High-voltage direct current (HVDC) transmission systems face protection challenges due to the absence of natural current zero-crossings and the rapid rise of fault currents. This paper proposes a hierarchical fault detection and classification framework for multi-terminal HVDC networks that combines transient feature extraction with gradient boosting decision trees. The proposed method utilizes traveling wave transients distinguish between internal and external faults across a range of fault resistances and noise levels. The three-stage architecture employs asymmetric loss weighting to maintain system security alongside dependability for high-impedance fault detection. When evaluated on a four-terminal VSC-HVDC benchmark network, the protection scheme achieved zero false trips against normal operational fluctuations and remote pole-to-ground disturbances, alongside 92.24% overall dependability across fault resistances up to 500 Ω and noise levels down to 20 dB SNR. For cumulative fault resistances up to 150 Ω , the dependability exceeded 99%. Furthermore, the framework demonstrates generalization across measurement noise and provides interpretability through feature importance analysis. The proposed framework offers a data-driven approach for HVDC protection that balances the requirements of relay security and dependability.

Keywords: High-Voltage Direct Current; HVDC protection; fault classification; gradient boosting; high-impedance faults; traveling waves; machine learning



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1. Introduction

The global shift toward low-carbon energy systems has led to rapid growth in large-scale renewable generation, particularly offshore wind, remote hydropower, and utility-scale solar plants. At the same time, climate policy commitments, including net-zero targets across Europe and other regions, have increased the demand for transmission systems capable of carrying large amounts of power over long distances and across national borders [1]. These trends highlight the limitations of conventional HVAC transmission, especially for submarine and underground cables, where reactive power losses and charging currents restrict practical transmission distances [2].

As a result, High-Voltage Direct Current (HVDC) transmission has regained importance in modern power systems. Although AC systems replaced early DC networks, advances in power electronics have made HVDC the preferred option for long-distance bulk power transmission, offshore grid connections, and interconnection of asynchronous power systems [3]. Early projects such as the Gotland link in Sweden and the Nelson River scheme in Canada demonstrated the technical viability of HVDC, while later thyristor- and IGBT-based converters enabled higher power ratings and more flexible operation [4,5].

In recent years, HVDC deployment has expanded rapidly to support renewable energy integration. In Europe, projects such as the BritNed interconnector between the UK and the Netherlands [6], the Shetland–Caithness HVDC link [7], and the NeuConnect interconnector between the UK and Germany [8] demonstrate the increasing role of HVDC in offshore wind integration and cross-border power exchange. Similarly, China and other regions have developed large HVDC corridors and multi-terminal systems to connect remote renewable resources to major load centres [9,10]. These developments show a shift from isolated point-to-point HVDC schemes toward more complex and interconnected DC networks.

Despite these benefits, HVDC systems present protection challenges that differ fundamentally from those in AC networks. The lack of natural current zero crossings, the rapid rise of DC fault currents, and the discharge of DC-link capacitors in voltage-source converters significantly reduce the time available for fault detection and isolation [11,12]. These challenges are more severe in cable-based and multi-terminal HVDC systems, where fault paths multiply and conventional AC protection principles are no longer directly applicable [13–15].

As HVDC networks continue to grow in size and complexity, fast and reliable fault detection becomes essential to maintain system security and availability. This drives ongoing research into advanced protection and monitoring methods suited to the unique electrical characteristics of modern HVDC grids.

To address these challenges, this paper presents a hierarchical three-stage fault identification framework evaluated on a standard four-terminal VDC-HVDC benchmark grid. The proposed scheme achieves reliable fault discrimination strictly within the first millisecond of inception, utilizing only single-ended measurements at one terminal. The specific contributions of this work are summarized as follows:

- a. Validation on a four-terminal HVDC grid to capture complex traveling wave reflections and attenuations.
- b. A cascaded classification architecture that routes specific feature subsets to distinct decision boundaries, utilizing a hybrid physics-ML security gate to decouple relay security and dependability.
- c. Reliable high-impedance fault detection while limiting the observation window to 1 ms.
- d. An out-of-distribution evaluation proving reliable generalization and strict security on unseen high-impedance faults (up to 500 Ω) and varying noise levels, despite training exclusively on low-impedance data.

2. Fundamental Technologies of HVDC Systems

HVDC transmission systems are mainly classified by the type of converter used at their terminals: line-commutated converters (LCC) and voltage source converters (VSC). These technologies differ in their commutation methods, controllability, interaction with AC networks, and fault response behaviour. These differences directly affect system performance, grid-support capability, and protection design [16].

Historically, Line-Commutated Converter High-Voltage Direct Current (LCC-HVDC) has been the dominant technology for long-distance bulk power transmission, particularly

in ultra-high-voltage applications. This is demonstrated by projects such as the ± 1100 kV, 12,000 MW Changji–Guquan scheme in China, which remains the highest-capacity HVDC link in operation [17]. In contrast, VSC-HVDC has become the preferred option for submarine cables, weak-grid connections, offshore wind integration, and urban power supply. Examples include the Trans Bay Cable project (± 200 kV, 400 MW, USA) [18] and the INELFE France–Spain interconnector (± 320 kV, 2×1000 MW), both implemented using modular multilevel converter (MMC) technology [19].

2.1. Converter Technologies in HVDC Systems

2.1.1. Line-Commutated Converter (LCC) HVDC

LCC-HVDC systems, often referred to as “HVDC Classic,” use thyristor valves whose commutation depends on the connected AC system. They are therefore classified as current-source converters (CSCs) [16]. As a result, LCC converters require strong synchronous AC networks for stable operation and do not have inherent black-start capability. Early installations, such as the Gotland HVDC link, required synchronous condensers to restore operation after AC disturbances, illustrating this dependency in practice [20].

Despite these limitations, LCC technology remains unmatched for ultra-high-power transmission. Modern schemes in China have achieved ratings above ± 800 kV and 10 GW, including the ± 1100 kV Changji–Guquan project [17]. These systems demonstrate the suitability of LCC-HVDC for long-distance bulk power transfer between strong generation regions and major load centres.

However, LCC converters consume large amounts of reactive power, typically 50–60% of rated active power, requiring extensive reactive compensation and harmonic filtering equipment [16]. They are also prone to commutation failures and temporary overvoltages during AC voltage dips and transient disturbances, which limits their application in weak or renewable-dominated networks [21–23]. Although capacitor-commutated converter (CCC) variants have been proposed to address these issues, their use remains limited due to increased control complexity and insulation requirements [24–26]. Figure 1 shows the single line diagram representation of typical LCC-HVDC system [27].

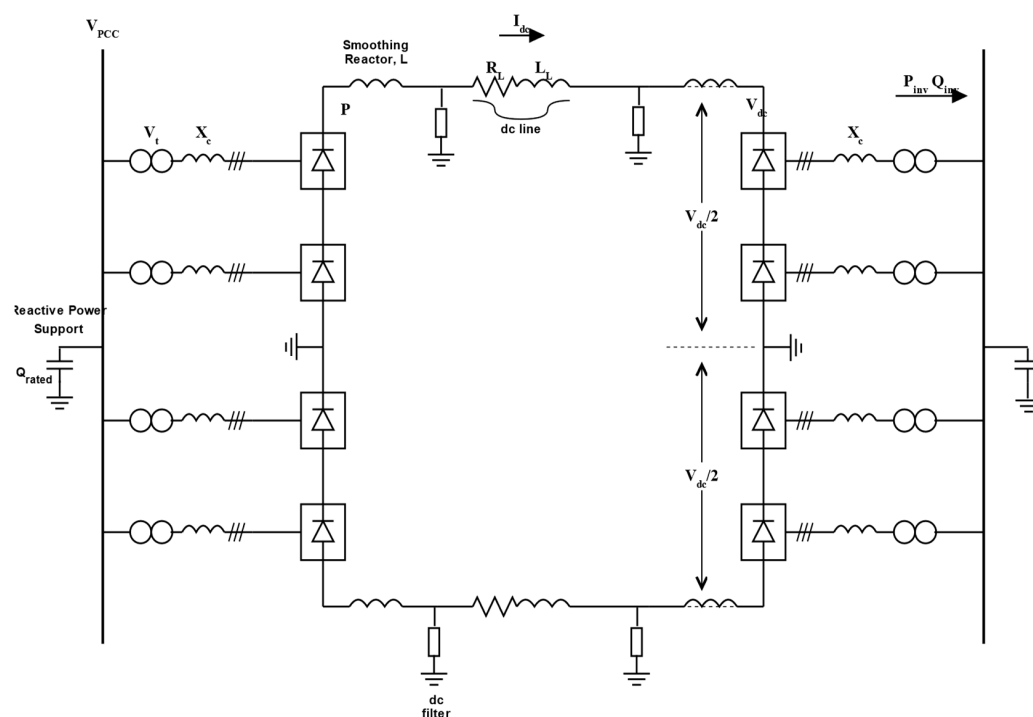


Figure 1. LCC-based HVDC system.

2.1.2. Voltage Source Converter (VSC) HVDC

VSC-HVDC systems use self-commutated power electronic devices, mainly insulated gate bipolar transistors (IGBTs), which allow fast and independent control of active and reactive power [28]. Unlike LCC systems, VSC converters do not depend on AC voltage for commutation and therefore provide black-start capability and stable operation when connected to weak or passive networks [20].

The first commercial VSC-HVDC link was commissioned in Sweden in 1997, and the technology has since developed rapidly. Projects such as Trans Bay Cable [18] and INELFE [19] have confirmed the suitability of VSC-HVDC for submarine cable transmission and inter-area interconnection. Today, modular multilevel converter (MMC) topologies dominate VSC applications due to their improved harmonic performance, reduced filtering needs, scalability to higher voltages, and higher efficiency compared with earlier two-level converters [29].

VSC systems reverse power flow by changing the direction of DC current while keeping the DC voltage polarity constant, which enables faster and more reliable transitions than the polarity reversal required in LCC systems. In addition, VSC stations can operate as STATCOMs during DC outages, providing voltage support and regulation to the connected AC networks [16]. These features make VSC-HVDC particularly suitable for offshore wind integration, urban infeeds, and emerging multi-terminal DC grids. Figure 2 shows the single line diagram representation of typical VSC-HVDC system [27].

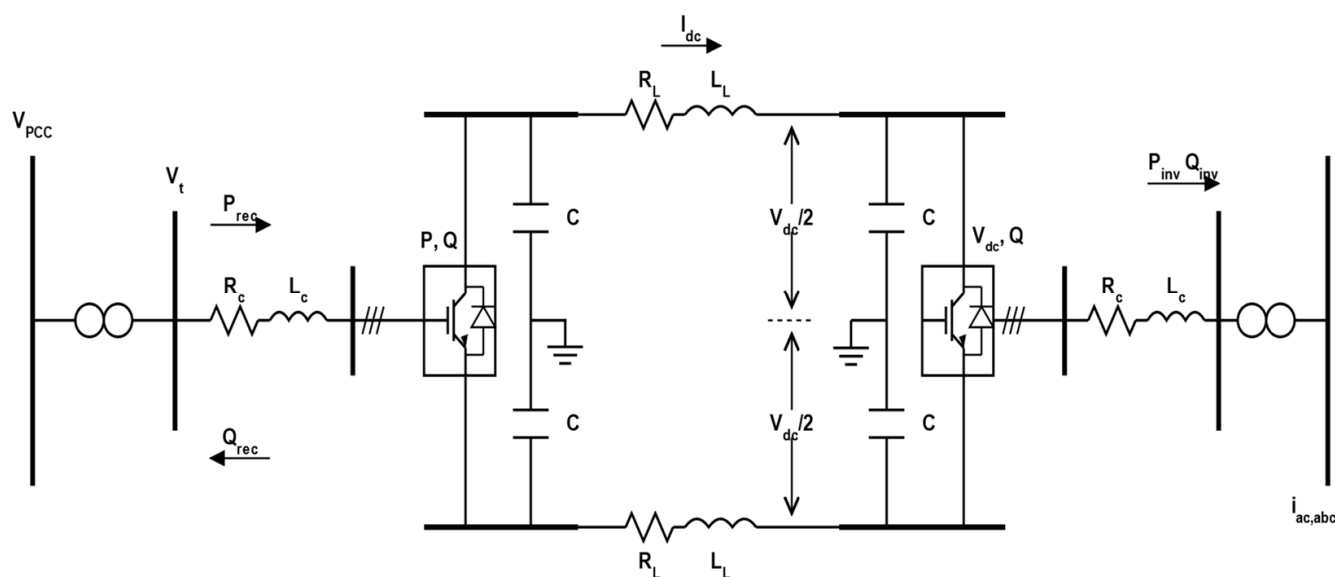


Figure 2. VSC-based HVDC system.

2.1.3. Comparison Between LCC and VSC Technologies

Although LCC-HVDC remains the preferred option for ultra-high-power bulk transmission because of its high efficiency and achievable ratings, VSC-HVDC is increasingly used for weak-grid interconnections, submarine cables, and renewable energy integration [28,30]. This trend is illustrated by the NEMO interconnector between the UK and Belgium, which was originally planned as an LCC scheme but was later implemented using MMC-VSC following improvements in converter performance and cost-effectiveness [31].

From a technical perspective, LCC systems depend on strong AC networks and are susceptible to commutation failures, whereas VSC systems offer black-start capability, independent reactive power control, and better dynamic performance during AC disturbances [32,33]. From an economic perspective, LCC remains more cost-effective

at very high power ratings due to the superior voltage and current capability of thyristors, while VSC stations require smaller footprints and avoid large reactive compensation equipment, especially in cable-based applications [16].

These complementary characteristics have led to the development of hybrid LCC–VSC schemes, particularly in China. In such systems, LCC stations are installed at generation sites for high-capacity transmission, while VSC stations are used at receiving ends to provide improved grid support and compatibility with weak networks [26,33,34].

3. Characteristics of Faults in HVDC Systems

A fault on the DC side of an HVDC system is a very fast event that produces a complex transient response. When a fault occurs, it creates a conductive path, causing the DC voltage to drop quickly and the DC current to rise sharply. Unlike AC systems, where fault currents drop to zero every half cycle, DC fault currents do not naturally decrease and continue to rise rapidly, limited by the system's impedance [35]. Because these currents reach dangerous levels in just a few milliseconds, the protection system must respond equally fast.

The fault also generates an impulsive disturbance that creates a traveling wave along the DC transmission line from the fault location. This wave contains high-frequency components and carries important information about the fault. As it moves, the wave is attenuated, distorted, and reflected at points like converter stations or smoothing reactors [36]. The combination of forward and reflected waves at measurement points forms a complex, non-stationary transient signal. These transient signals are the focus of this research. Traditional protection methods often filter out high-frequency components, which leads to loss of this critical information.

4. Detection and Classification of HVDC Faults

Fault detection in HVDC systems presents challenges that are fundamentally different from those encountered in AC networks. The absence of natural current zero crossings, the low line impedance, and the rapid rise of fault currents necessitate ultra-fast and highly reliable protection mechanisms. As a result, a wide range of fault detection and classification techniques have been investigated in the literature, evolving from conventional magnitude-based protection to transient-based and, more recently, to pattern recognition based on machine learning.

4.1. Magnitude-Based Protection Methods

Threshold-based protection methods detect faults by comparing measured electrical quantities with predefined limits. These schemes are attractive because they are simple, fast, and easy to implement. In HVDC systems, overcurrent and rate-of-change-of-current (di/dt) protection are commonly used, as DC faults cause a rapid rise in current [35,37].

However, their performance is strongly affected by fault conditions. Low-impedance faults close to the relay are usually detected reliably, but high-impedance or remote faults produce weaker transients that may not exceed the threshold, leading to missed detections [38]. In addition, fault current characteristics vary with operating conditions and system configuration, making it difficult to select thresholds that work well in all cases [39]. Normal switching events and sudden load changes can also cause false trips, reducing protection security.

Differential protection compares the currents at both ends of a line and operates when their difference exceeds a threshold. Although this method is highly selective for internal faults, its application in HVDC systems is complicated by line capacitance and charging currents, which can produce spurious differential signals. As a result, conventional schemes

often require intentional delays or compensation techniques [40]. Faster implementations reduce operating times to around 10–20 ms but depend on accurate system models, precise time synchronisation, and high-speed communication links [41], limiting their practical deployment in large HVDC networks.

4.2. Transient-Based Fault Detection Methods

Transient-based protection methods use the high-frequency voltage and current disturbances that occur immediately after a DC fault. These transients travel along transmission lines at near the speed of light and contain useful information about fault location and direction, allowing very fast detection [42,43].

Travelling-wave-based schemes analyse these disturbances by separating terminal measurements into forward- and backward-travelling components and using their polarity, energy, or arrival time to distinguish between internal and external faults. Both single-ended and double-ended approaches have been proposed in the literature. Single-ended schemes are easier to implement but are sensitive to threshold settings and signal attenuation, especially for high-resistance and remote faults. Double-ended schemes improve reliability but require high-speed communication and accurate time synchronisation between terminals [44].

Despite their speed, travelling-wave methods still rely on fixed thresholds, and their performance varies with system operating conditions and fault characteristics. Weak transients, particularly from high-resistance faults, can lead to misclassification. These limitations motivate the development of more adaptive and data-driven fault detection techniques.

4.3. Signal Processing and Data-Driven Fault Detection

HVDC protection is difficult because DC currents do not naturally cross zero, fault currents rise very rapidly, and system behaviour depends strongly on converter dynamics. These factors reduce the effectiveness of traditional impedance-based and travelling-wave protection methods, especially in VSC-based and multi-terminal HVDC systems. As a result, data-driven protection schemes have attracted growing interest, where fault characteristics are learned directly from transient voltage and current signals [45,46].

Recent studies show that machine learning models such as support vector machines (SVM), artificial neural networks (ANN), random forests (RF), and deep learning architectures can significantly improve fault detection speed and classification accuracy by exploiting patterns in high-frequency transient data [47–52]. Most of these approaches follow a common structure: first, raw signals are transformed into informative features, and second, a classifier is trained to detect and classify faults. This section reviews both stages in the context of HVDC systems.

4.3.1. Signal Representation and Feature Extraction

Accurate HVDC fault detection depends on converting raw voltage and current measurements into compact features that preserve fault-related information. Early studies mainly used time-domain statistical features, such as RMS values, standard deviation, and signal magnitude changes. For example, refs. [53,54] showed that RMS voltage and current variations and half-cycle statistical measures can enable fast fault detection using ANN and SVM classifiers.

However, time-domain statistics alone often fail to capture the high-frequency oscillations and sharp transients produced by HVDC faults. To overcome this limitation, time–frequency methods have been widely adopted. The discrete wavelet transform (DWT) is particularly popular because it provides good localisation in both time and frequency [55]. Extracted wavelet energy and entropy features for neural-network-based fault classification,

while [56] used wavelet packet decomposition and travelling-wave components to improve fault localisation accuracy. A three terminal conceptual grid was tested for HVDC fault detection using Symlet wavelet [57]. A standard four-node grid HVDC fault detection test using symlet was conducted in [58], and a more extensive comparative study of different wavelets with different cable lengths and noise levels, including hardware-in-the-loop (HIL) validation, was conducted in [59].

Other time–frequency techniques have also been explored. The authors of [60] used S-transform to extract multi-scale frequency components from fault traveling waves, while [52] applied the Hilbert–Huang transform to construct time–frequency energy matrices for CNN-based classification. These studies consistently report improved robustness to noise and fault resistance compared with purely time-domain approaches.

Despite their strong performance, complex feature extraction pipelines often require multiple measurements, extensive preprocessing, and higher computational effort. This limits their suitability for ultra-fast HVDC protection. Therefore, several studies recommend compact hybrid feature sets that combine simple statistical descriptors with wavelet-based features, achieving a balance between computational efficiency and classification accuracy [55,61]. Such representations are well suited to practical protection systems operating under tight time constraints and limited measurement availability.

4.3.2. Data-Driven Fault Detection

After feature extraction, fault detection and classification are usually treated as supervised learning problems. Early studies applied shallow classifiers such as SVMs, k-nearest neighbours, and feedforward neural networks. The authors of [53] reported SVM-based HVDC fault classification using statistical features, while [54] demonstrated ANN-based fault detection and localisation using RMS voltage and current measurements. These models are computationally efficient but often show reduced robustness under noisy conditions or changing operating points.

To improve performance and stability, optimisation-based learning frameworks have been introduced, where evolutionary algorithms such as particle swarm optimisation and ant colony optimisation are used to tune model parameters or select informative feature subsets [62–64]. These methods reduce sensitivity to irrelevant features and improve generalisation across operating conditions.

More recently, deep learning models such as CNNs, LSTMs, and hybrid CNN–LSTM architectures have been applied to HVDC and transmission system fault detection, achieving very high classification accuracy on benchmark datasets [47,51,65,66]. While these models can learn complex temporal patterns directly from raw signals, their high computational cost, training complexity, and limited interpretability create challenges for real-time protection deployment.

In response, ensemble learning methods have gained attention as a practical compromise between shallow classifiers and deep neural networks. The authors of [50] showed that ensemble-based models can achieve high accuracy while maintaining lower computational burden and improved robustness to noise and class imbalance. These properties are particularly attractive for HVDC protection, where fast decision-making, reliability across operating conditions, and tolerance to measurement uncertainty are essential.

Overall, existing research suggests that combining compact statistical and time–frequency features with reliable ensemble-based learning models provides a strong foundation for reliable HVDC fault detection. This trend also motivates the investigation of tree-based boosting frameworks, which naturally handle heterogeneous features, nonlinear relationships, and noisy data, and therefore align well with the objectives of this study.

The below Table 1 provides a summary of the comparison between the above mentioned fault detection methods.

Table 1. Fault detection methods summary.

Method	Principle	Advantage	Limitation	References
Threshold Based (Overcurrent/di/dt)	Fault detected when current exceeds predefined threshold	Simple and low computational cost	Sensitive to threshold selection	[37,38]
Differential protection	Current difference between line terminals	High selectivity	Requires communication link	[40,41]
Travelling-wave methods	Detect high-frequency fault transients	Very fast detection	Signal attenuation for remote faults	[42,44]
Wavelet-based methods	Time–frequency decomposition of transient signals	Effective for transient analysis	Computational complexity	[55,57]
Machine learning approaches	Pattern recognition using extracted features	High accuracy and adaptability	Requires training data	[53,54,63]

5. System Topology and Transient Simulation

5.1. MTDC Configuration and Boundary Conditions

In this study, a four-terminal ring-net topology was implemented, consisting of four active converter terminals interconnected through DC transmission links. The configuration was inspired by the Zhangbei ± 500 kV four-terminal HVDC demonstration project in China [67]. The modelled setup includes four active VSC converter stations and one passive DC load terminal, connected through frequency-dependent distributed parameter cables, designed entirely in MATLAB/Simulink (R2026b) as shown in Figure 3.

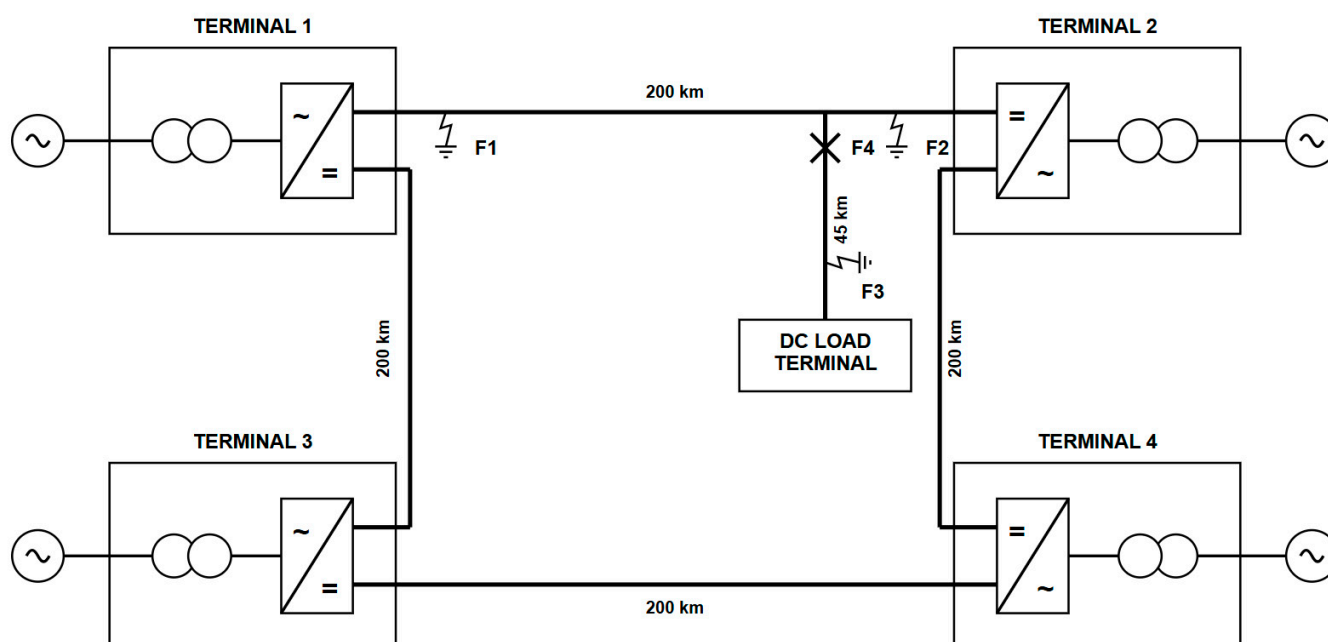


Figure 3. Model used in this research.

The DC network is rated at ± 100 kV with a nominal power of 200 MVA. Each VSC station employs a three-level Neutral Point Clamped (NPC) topology controlled through sinusoidal pulse width modulation (SPWM) switching. On the AC side, star-delta converter transformers, reactors, and passive filters are used to regulate voltage and suppress har-

monics, aligning with the established need for advanced harmonic detection, aggregation, and estimation to maintain converter stability and power quality in modern grids [68,69]. On the DC side, distributed parameter cable models are applied to represent resistance, inductance, and capacitance accurately. The converter stations are spaced 200 km apart, while the DC load terminal is connected through a 45 km cable. The cable parameters were adopted from [57–59]. Smoothing inductors and reservoir capacitors are incorporated to maintain voltage stability and reduce current ripples across the DC network.

Although Modular Multilevel Converters (MMCs) are widely used in modern commercial HVDC applications, a three-level Neutral Point Clamped (NPC) VSC topology was adopted in this study because of its relatively simple structure and computational efficiency. The selected configuration is also consistent with established benchmark models used in travelling-wave-based HVDC protection studies [57]. Since the proposed feature extraction is performed within a 1 ms observation window following wavefront arrival, the analysed transients primarily reflect transmission-line propagation and reflection characteristics.

5.2. Parameters Variations

The simulation environment utilized a multi-dimensional parameter sweep to generate a continuous spectrum of transient fault conditions. Fault resistance was varied to encompass both solid and extreme high-impedance faults. The training dataset utilized fault resistances of 0.01, 0.1, 1, 5, and 10 Ω . To rigorously test out-of-distribution generalization, the testing dataset introduced extreme high-impedance faults with resistances of 50, 100, 150, 200, 300, and 500 Ω , alongside intermediate values of 0.05, 0.8, 3, and 5 Ω .

Spatial and load conditions were systematically varied. Fault distances for line faults were swept across 10, 30, 50, 70, 100, 130, 160, and 190 km during the training phase. To evaluate spatial generalization, the testing phase utilized fault distances of 20, 87, 115, 142, and 175 km to capture non-linear spatial attenuation.

Fault inception times were systematically shifted to capture varying steady-state operating points. The training phase utilized inception times ranging from 0.10 s to 0.40 s in 0.05 s intervals. The testing phase introduced distinct inception times at 0.22, 0.28, 0.38, and 0.42 s to evaluate temporal generalization. Although 5 Ω is included in both resistance sweeps, the training and testing datasets remain strictly disjoint across all spatial and temporal dimensions.

The simulation encompasses four operational classes across the MTDC grid topology:

Normal: Normal steady-state grid operation.

PTG (Pole-to-Ground): Internal protected transmission line faults, encompassing faults near Terminal 1, Terminal 2, and sliding faults distributed across the connecting line.

PTP (Pole-to-Pole): Internal sliding pole-to-pole faults across varying distances of the primary transmission corridor.

External: A remote passive ground fault, specifically defined as a positive pole-to-ground fault located at the DC load terminal.

5.3. Measurement Constraints

Local voltage and current measurements were acquired exclusively at Terminal 1. The data extraction and processing were governed by two primary parameters:

Sampling Rate: Data was sampled at 50 kHz, yielding a sampling period of 20 μ s. This sampling frequency is selected in accordance with practical engineering constraints and international standards. The IEC 61869-9 standard stipulates that the maximum allowable sampling frequency for DC substations is 96 kHz [70], while typical HVDC projects employ sampling frequencies ranging from 10 kHz to 50 kHz [40,45,54,62–64]. The selected 50 kHz rate is a balance between capturing sufficient high-frequency transient components for

accurate fault discrimination and maintaining compatibility with commercially available measurement hardware.

Extraction Window: The transient analysis utilized a fixed 1 ms observation window immediately following the detection of the initial fault surge. This window duration is sufficient to capture the initial traveling wavefront before significant reflections arrive from remote terminals or busbars, while providing adequate data points for reliable feature extraction.

5.4. Transient Wavefront Synchronization and Windowing

Accurate classification of HVDC faults relies on capturing the initial high-frequency travelling-wave arrival at the local terminal before significant contamination from reflections and steady-state components. To ensure consistent feature extraction, the analysis window is time-aligned to the estimated arrival of the wavefront at Terminal 1 as shown in Figure 4.

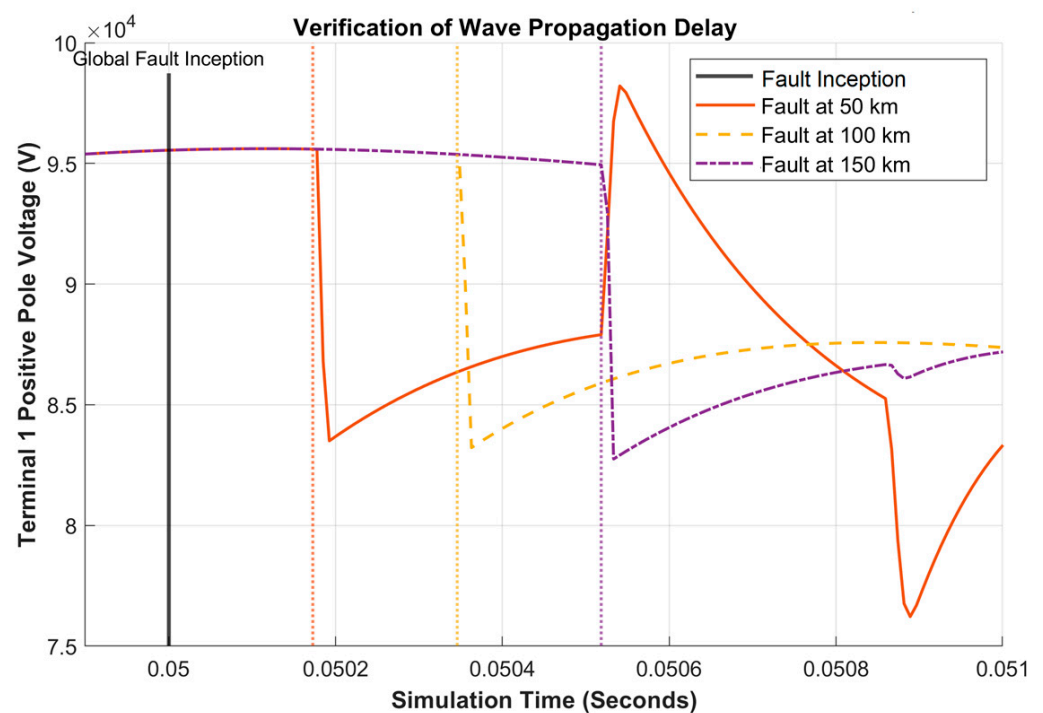


Figure 4. Wave Propagation Delay.

Electromagnetic wave propagation in DC transmission cables occurs at a finite velocity, resulting in a spatial–temporal delay between fault inception and local observation. This propagation delay (Δt) is proportional to the fault distance (d):

$$\Delta t = \frac{d}{v}$$

For dataset generation, the arrival time of the wavefront at the local terminal is computed from the simulated fault inception time (t_{inc}) and the propagation delay. A small pre-trigger buffer ($t_{buffer} = 0.02$ ms) is kept to account for discretization and timing uncertainties to ensure that the initial transient is fully captured. The feature extraction window is then defined as:

$$t_{start} = \left(t_{inc} + \frac{d}{v} \right) - t_{buffer}$$

The observation window was extracted from this synchronized start time. This equation is strictly applicable for offline simulated data slicing only, not in real time online

application, as the global parameters such as fault inception time, and fault distance are unknown in real time.

5.5. Transient Waveform Analysis and Physical Constraints

Designing a reliable protection scheme requires understanding the physical behaviour of VSC-HVDC transients during the critical first millisecond of a fault. Figure 5 displays the incremental terminal voltage and current waveforms measured at Terminal 1 across four specific scenarios: a $10\ \Omega$ low-resistance internal pole-to-ground fault, a $10\ \Omega$ low-resistance internal pole-to-pole fault, a $0.01\ \Omega$ low-resistance external fault, and a $500\ \Omega$ high-resistance internal pole-to-ground fault.

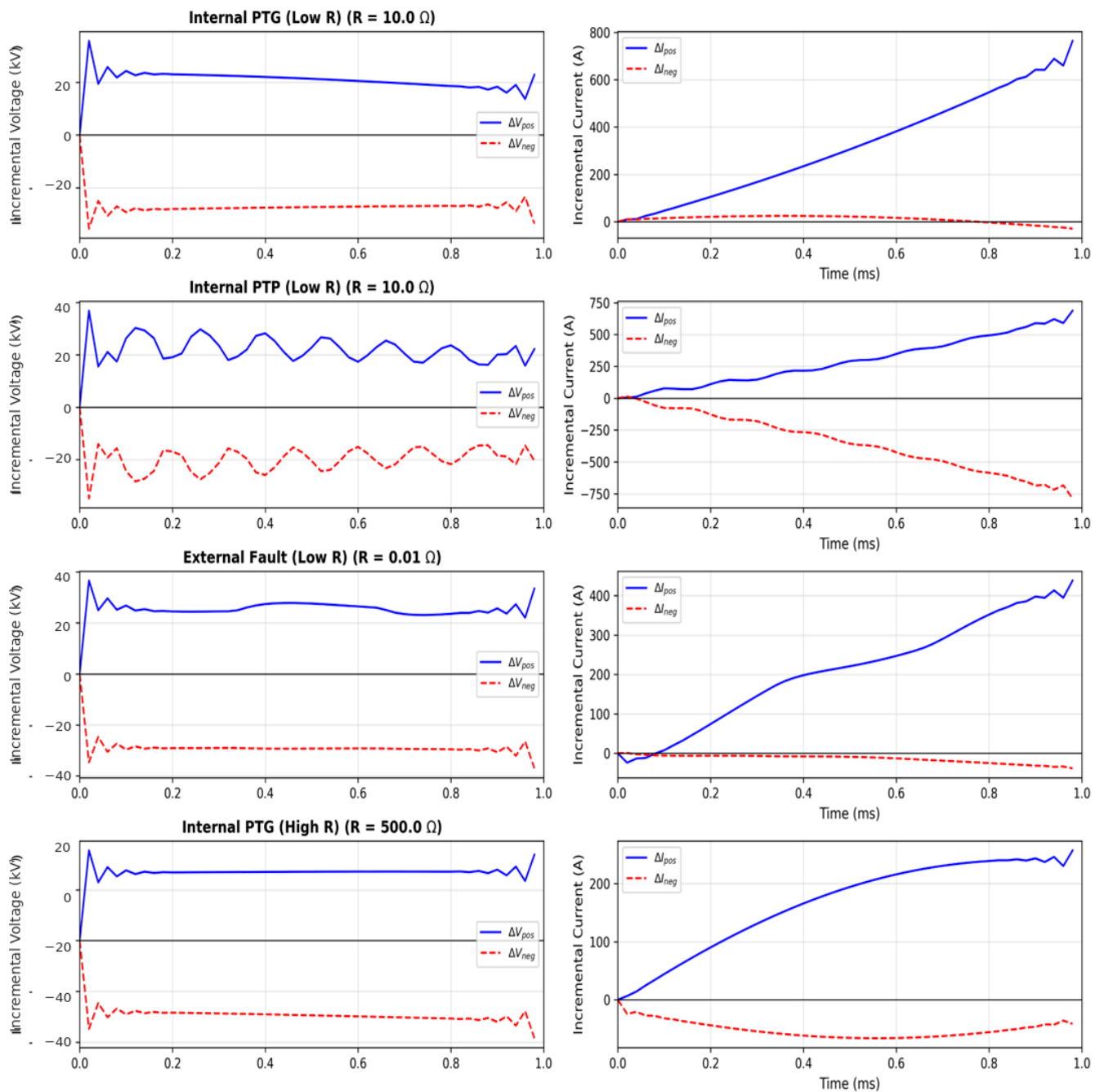


Figure 5. Incremental voltage and current during faults.

Different fault types exhibit a clear physical asymmetry, which is governed by the fault loop impedance. An internal pole-to-pole fault forms a closed metallic loop between

the two poles. This causes a symmetric current surge, where the positive and negative pole currents are equal in magnitude but opposite in direction. Conversely, an internal pole-to-ground fault forces the current to return through the earth. This creates a severe asymmetry because the faulted pole current spikes drastically, while the healthy pole current remains negligible. This physical phenomenon allows the use of asymmetry to mathematically isolate the fault geometry from the overall signal amplitude.

It is also critical to consider how fault resistance and propagation distance attenuate the transient energy. Comparing the two pole-to-ground faults reveals that high impedance severely dampens the fault current magnitude. Specifically, increasing the fault resistance from $10\ \Omega$ to $500\ \Omega$ drastically reduces the peak current surge within the first millisecond. The external fault demonstrates a similar effect. Located 245 km from Terminal 1, it exhibits a reduced peak current despite having a near-zero fault resistance of $0.01\ \Omega$. This demonstrates that both high impedance and long propagation distances severely absorb transient energy. Consequently, conventional amplitude-based thresholds are ineffective for detecting high-impedance faults.

This attenuation is further evidenced in the frequency domain. Figure 6 compares the Fast Fourier Transform magnitude spectrum of the positive pole current for the $10\ \Omega$ and $500\ \Omega$ internal pole-to-ground faults. The low-resistance fault generates transients rich in high-frequency energy, with a spectral peak reaching 4500 A. In contrast, the high fault resistance acts as a damping element. It drastically suppresses the high-frequency spectral content and significantly reduces the peak magnitude.

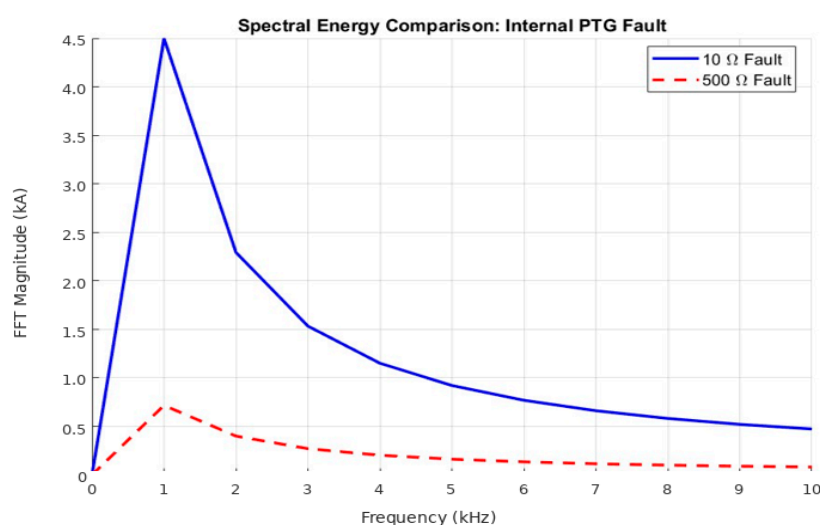


Figure 6. FFT magnitude spectrum.

5.6. Hierarchical Feature Routing and Three-Stage Architecture

In multi-stage classification systems, the specific data features that clearly define one boundary are frequently ineffective for another. To overcome this limitation, a tiered feature extraction strategy is utilized. Distinct sets of data captured within a strict one-millisecond observation window are routed to specific phases of the evaluation pipeline. Although the final decision relies on a step-by-step logic, the three gradient boosting models execute their calculations simultaneously to minimize processing delay. The initial output therefore acts as a rigid filter. If the first stage restrains the system, the results from the second and third stages are completely ignored.

Stage 1: Secure Binary Classifier

This primary stage demands input features that react reliably to any shift away from normal, steady-state conditions. To achieve this, the model processes a concise set of

broad terminal statistics alongside logarithmically scaled energy measurements. Because these indicators are highly sensitive to changes in signal amplitude, they provide a stable foundation for distinguishing genuine fault transients from routine load variations.

This first stage is dedicated solely to separating normal grid behaviour from actual faults. It is trained using a heavily skewed mathematical formula known as an asymmetric loss function. This function punishes the algorithm far more severely for triggering a false alarm on normal data than for missing a fault. This stability is achieved by modifying the standard binary cross-entropy loss with specific penalty multipliers:

$$L_{\text{asymmetric}} = -[w_{\text{normal}} \cdot y \cdot \log(\hat{y}) + w_{\text{fault}} \cdot (1 - y) \cdot \log(1 - \hat{y})] \quad (1)$$

where $y \in \{0, 1\}$ is the true label, $\hat{y}$ is the predicted probability, and $w_{\text{normal}} \gg w_{\text{fault}}$ are the class weights. The class weights were determined using Bayesian hyperparameter optimization (Optuna with a Tree-structured Parzen Estimator sampler) targeting zero false alarms, resulting in $w_{\text{normal}} = 129.78$ and $w_{\text{fault}} = 1.0$. By weighting normal grid samples 129.78 times more heavily during training, the decision boundary is biased to strictly enforce relay security.

In addition to the probabilistic output, a deterministic physics-based pickup threshold is applied. The trip decision logic is formally expressed as:

$$T_{\text{stage1}} = (P_{\text{fault}} \geq \theta_{\text{ML}}) \vee (E_{\text{modal}} > E_{\text{pickup}}) \quad (2)$$

where P_{fault} is the posterior probability output by the CatBoost classifier, $\theta_{\text{ML}} = 0.90$ is the calibrated machine learning confidence threshold (requiring 90% posterior certainty), E_{modal} is the logarithmic common-mode current energy, and E_{pickup} is the deterministic threshold:

$$E_{\text{pickup}} = \max(E_{\text{modal, normal}}) \cdot (1 + \delta)$$

Here, $\delta = 0.01$ applies a 1% safety margin. Because common-mode energy is extracted in the logarithmic domain ($\text{Log_I_Com_Energy} = \log_{10}(E_{\text{modal, linear}} + \epsilon)$), the maximum value observed during normal steady-state operation across the training set is $\max(E_{\text{modal, normal}}) = 6.0961$. Direct multiplication by 1.01 scales this threshold to $E_{\text{pickup}} = 6.1571$. Mathematically, multiplying a log-scaled quantity $\log_{10}(E)$ by 1.01 corresponds to an exponential power transformation in the linear physical energy domain ($\log_{10}(E^{1.01})$). This provides an expanding physical security margin above peak steady-state switching noise, preventing spurious trips during routine load fluctuations.

Stage 2: Fault Topology Classifier

The topology classifier must separate pole-to-pole faults, which produce symmetric differential-mode surges, from pole-to-ground faults, which generate strong common-mode ground currents. To exploit these distinct physical loop geometries, a specialized subset of modal asymmetry indices, cross-pole correlations, and common-mode transient energy is routed to this stage [71,72].

The Modal Energy Ratio measures the physical asymmetry between ground-mode and line-mode transient energies to determine the specific fault topology. To calculate this ratio, let $i_p(t)$ and $i_n(t)$ be the instantaneous positive and negative pole currents measured at Terminal 1 during the one-millisecond observation window, Tw . The common-mode, or ground, current is defined as the algebraic sum of these pole currents. Conversely, the differential-mode, or line, current is defined as the exact difference between them:

$$i_{\text{com}}(t) = i_p(t) + i_n(t) \quad (3)$$

$$i_{diff}(t) = i_p(t) - i_n(t) \quad (4)$$

The transient energy for each of these distinct modes is then integrated across the observation window:

$$E_{com} = \int_0^{T_w} i_{com}^2(t) dt \quad (5)$$

$$E_{diff} = \int_0^{T_w} i_{diff}^2(t) dt \quad (6)$$

Following this integration, the Modal Energy Ratio is computed as:

$$MER = \frac{E_{com}}{E_{diff} + \epsilon} \quad (7)$$

In this mathematical formulation, $\epsilon = 10^{-12}$ is a minimal scalar offset to prevent division by zero during perfectly balanced transient events.

For internal pole-to-ground faults, the earth return path causes the common-mode energy to dominate, resulting in a high Modal Energy Ratio. During pole-to-pole faults, the system remains highly symmetric, meaning the common-mode transient energy approaches zero. This physical symmetry collapses the overall ratio toward zero. This mathematical divergence allows the Modal Energy Ratio to reliably classify fault topology during the second stage of the classification framework.

This independent binary classifier evaluates the modal asymmetry features. If Stage 1 detects a fault and Stage 2 classifies it as pole-to-pole, an immediate internal trip decision is issued, effectively bypassing the need for further zone discrimination.

Stage 3: Zone Discrimination Classifier

The final stage separates internal faults from distant external faults. Because this is the most challenging physical boundary to establish, the system routes its largest subset of data features to this phase. These inputs include higher-order statistical moments, spectral complexity indices, high-frequency attenuation ratios, and physical impedance estimations.

This stage combines dimensionless statistical and spectral ratios with dimensional transient inductance metrics. This specific approach reduces the reliance on overall signal strength while strictly preserving essential topological information. Additionally, to guarantee mathematical stability during periods of near-zero energy, a minimal scalar offset of 10^{-12} is applied before any logarithmic energy transformations occur.

Standard statistical moments, signal complexity indices, and spectral metrics were calculated using established digital signal processing definitions [71,72].

Apparent Transient Inductance

The apparent transient inductance feature provides an estimate of the effective impedance observed during the initial transient. This metric is derived from the ratio of the mean absolute voltage to the maximum rate of change of the current within the observation window:

$$L_{app} = \frac{\overline{|v_p|}}{\max\left(\left|\frac{di_p}{dt}\right|\right) + \epsilon} \quad (8)$$

where $v_p[n]$ and $i_p[n]$ are the discrete positive-pole voltage and current samples, $\Delta t = 20 \mu s$ is the discrete sampling interval used to compute the derivative, and $\epsilon = 10^{-12}$ is a minimal scalar offset included to ensure numerical stability.

For internal faults, the close proximity of the fault results in a steep current rise, yielding a lower L_{app} . Conversely, for external faults, the intervening network impedance limits the rate of current change at the measurement terminal, increasing the observed L_{app} . This

empirical separation supports reliable zone discrimination across varying fault resistances when combined with the complementary statistical and spectral features utilized in Stage 3.

The Stage 3 classifier is trained exclusively on pole-to-ground faults. To counteract the inherent class imbalance between internal and remote external faults within the training set, Stage 3 utilizes balanced class weighting during the optimization process. This adjustment mathematically upweights the minority external fault class. Consequently, it prevents the model from defaulting to internal trip decisions and strictly enforces accurate zone selectivity.

5.7. Training Strategy and Hyperparameter Configuration

The training and testing datasets are constructed from strictly disjoint parameter sweeps. The training set contains fault resistances up to 10 Ω , while the test set introduces unseen resistances up to 500 Ω . This strict separation provides a rigorous out-of-distribution evaluation of the system.

To prevent overfitting and simulate realistic substation electromagnetic interference, a noise-based data augmentation strategy was utilized. Because high-fidelity electromagnetic transient simulations are computationally expensive, the original noiseless training samples were augmented by injecting additive white Gaussian noise (AWGN) directly into the raw time-domain voltage and current signals. This noise was injected at three distinct signal-to-noise ratios: 40 dB, 30 dB, and 20 dB.

This augmentation process effectively quadrupled the size of the training dataset. Consequently, it forced the gradient boosting models to learn reliable, noise-augmented transient features. During the out-of-distribution testing phase, these same four conditions (noiseless, 40 dB, 30 dB, and 20 dB) were applied to the test set to rigorously evaluate the scheme's immunity to measurement uncertainty.

The structural hyperparameters of the three classifiers were fine-tuned using a probabilistic, surrogate-based Bayesian optimization framework, which was configured to minimize the logarithmic loss function. To balance model complexity with inference latency, the search space constrained the models to shallow tree topologies with depths between 4 and 8, alongside learning rates between 0.01 and 0.1. The final optimized configurations are detailed in Table 2.

Table 2. Hyperparameters.

Hyperparameter	Stage 1 (Fault Detection)	Stage 2 (Fault Type)	Stage 3 (Zone)
Tree Depth	4	5	7
Learning Rate	0.062	0.031	0.048
L2 Regularization	1.02	5.88	3.41
Boosting Iterations	600	320	1080

5.8. Stage 3: CatBoost-Based Classification and Interpretability

5.8.1. Theoretical Foundations of the CatBoost Algorithm

CatBoost, short for Categorical Boosting, is a modern gradient boosting framework introduced by [73] to address two major limitations of conventional gradient boosting decision trees: prediction shift and inefficient handling of categorical features. Although this work uses only numerical features, the ordered boosting mechanism contributes to reliable generalization in safety-critical applications.

In standard gradient boosting, an additive model is formed as:

$$F(x) = \sum_{m=1}^M \alpha_m h_m(x) \quad (9)$$

where $h_m(x)$ denotes the m -th tree, α_m is its weight, and M is the total number of trees. Trees are trained sequentially to minimize a loss function L , such as log-loss for classification:

$$h_m(x) = \operatorname{argmin}_h \sum_{i=1}^N L(y_i, F_{m-1}(x_i) + h(x_i)) \quad (10)$$

A key limitation in standard gradient boosting is prediction shift. Because the model used to compute gradients for a sample has already been influenced by that sample's label during prior boosting steps, the resulting estimator becomes statistically biased. This can lead to overfitting and degraded generalization, especially on small or noisy datasets.

CatBoost addresses this issue through ordered boosting. Training samples are randomly permuted to form a sequence. For each sample, the model is updated using only the preceding samples in the permutation. This ensures that the gradient computation for a given sample does not include information from its true label, reducing target leakage and improving generalization.

Additionally, CatBoost uses oblivious trees, where each tree at a given depth splits on the same feature with the same threshold. For a tree of depth d , this structure requires only d split decisions, compared to up to $2^d - 1$ splits in conventional trees. This structurally deterministic design provides a fixed execution time suitable for real-time protection, while its symmetry acts as an implicit regularization to reduce memory usage and improve generalization [71].

The overall architecture of the CatBoost algorithm, illustrating the ordered boosting and oblivious tree structure, is depicted in Figure 7.

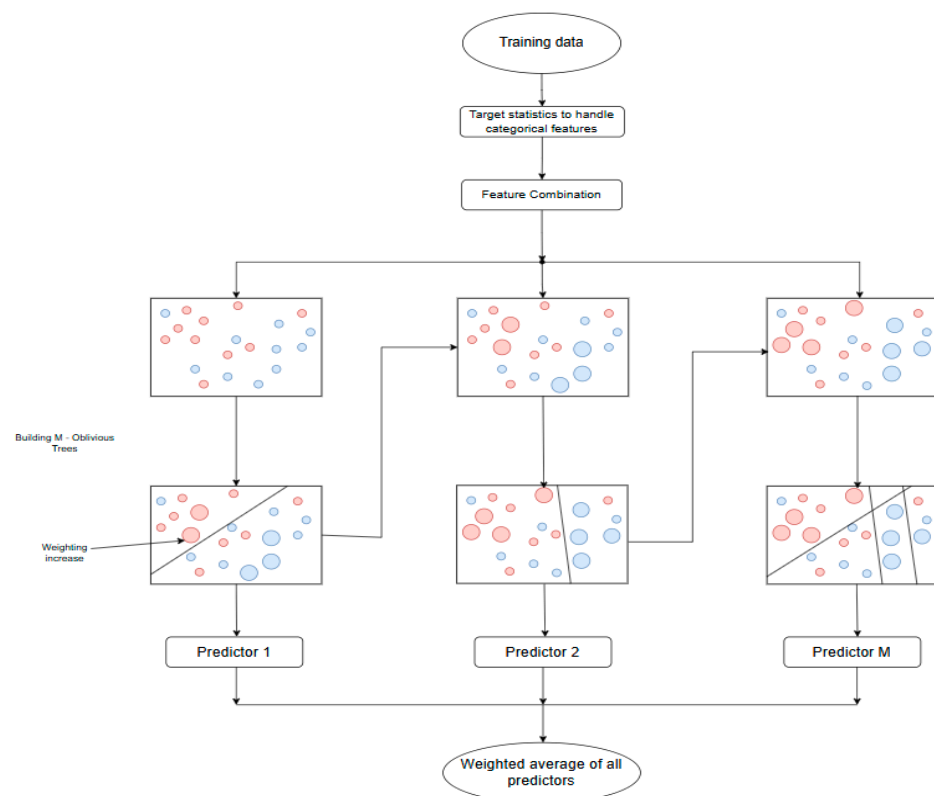


Figure 7. Catboost algorithm flowchart.

5.8.2. Performance Evaluation Metrics

The trained model was evaluated using a combination of standard machine learning metrics and custom protection engineering indicators. This multi-metric approach is necessary because the consequences of different error types in HVDC protection are highly asymmetric.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (11)$$

This represents the overall proportion of correct predictions across all classes. While intuitive, accuracy can be misleading when class distributions are imbalanced, which is common in protection applications where fault conditions are rare compared to normal operation.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (12)$$

This measures the completeness of detection. A high recall indicates that the classifier identifies most instances of a particular fault type. Low recall suggests that the classifier frequently misses that fault type.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (13)$$

This measures the reliability of positive predictions. A high precision indicates that when the classifier predicts a particular fault type, it is likely correct. Low precision suggests frequent false alarms for that fault type.

$$\text{F1-Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (14)$$

This is the harmonic mean of precision and recall, providing a single metric that balances both concerns. It is particularly useful when seeking a balance between avoiding false alarms and avoiding missed detections.

In addition to these standard metrics, three protection-specific indicators are used to evaluate the scheme according to numerical relay standards:

Dependability: The overall recall for internal faults, computed as the total number of correctly detected internal faults (both pole-to-ground and pole-to-pole) divided by the total number of actual internal faults. A dependability failure corresponds to a missed internal trip.

Security: The true negative rate of the binary starting element (Stage 1) with respect to normal grid conditions, expressed as the percentage of normal samples correctly restrained. A security failure corresponds to an unwarranted trip.

Overreach: The percentage of out-of-zone external faults incorrectly classified as internal faults, measuring the scheme's zone discrimination capability.

6. Results

6.1. Overall Classification Performance

The scheme was evaluated on an out-of-distribution test set spanning fault resistances from $0.05 \, \Omega$ to $500 \, \Omega$ across four noise levels (noiseless, 40 dB, 30 dB, and 20 dB SNR). Table 3 summarizes the overall metrics.

The scheme successfully restrains during all normal grid operations and remote pole-to-ground disturbances, ensuring zero false trips under these evaluated conditions. The overall dependability of 92.24% indicates reliable detection of internal faults despite test conditions including fault resistances 50 times higher than the training maximum.

Table 3. Overall Performance Metrics.

Metric	Value
Overall Accuracy	91.73%
Security	100.00%
Dependability	92.24%
Total Test Samples	2480
Normal Samples	400
Fault Samples	2080

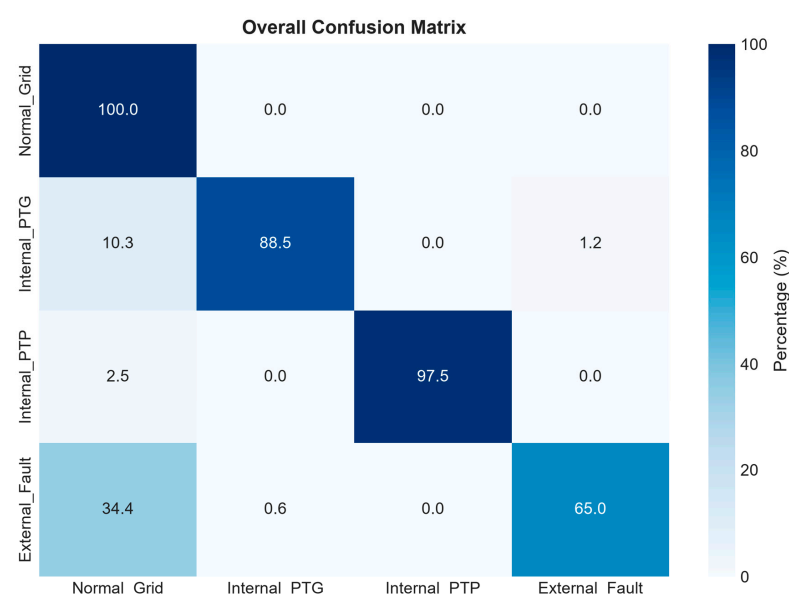
To validate the statistical robustness of the reported metrics, a bootstrap resampling analysis ($N = 1000$ iterations) was performed on the fixed, independently generated test batch. The analysis yielded tight 95% confidence intervals for all critical metrics: Security (100.00–100.00%), Dependability (91.06–93.41%), and Overreach (0.00–1.99%). These narrow confidence intervals show that the model’s performance is statistically stable and reliable, even when accounting for variance in small fault subclasses.

6.2. Per-Class Classification Performance

Table 4 presents the per-class classification metrics and Figure 8 shows the overall confusion matrix.

Table 4. Per-Class Classification Performance.

Class	Precision (%)	Recall (%)	F1-Score (%)
Normal Grid	67.8	100	80.81
Internal PTG	99.9	88.48	93.84
Internal PTP	100	97.5	98.73
External Fault	88.14	65	74.82

**Figure 8.** Overall confusion matrix.

The Normal Grid class achieves 100% recall, confirming that no steady-state conditions are misclassified as faults. The 67.80% precision indicates conservative classification:

190 fault samples (115 internal PTG, 20 internal PTP, 55 external) are misclassified as normal, preventing unwarranted trips.

Internal PTP faults achieve 100% precision and 97.50% recall. Internal PTG faults achieve 99.90% precision and 88.48% recall, with 129 missed detections (115 classified as normal, 14 as external). External faults show 65.00% recall, 55 are classified as normal, and only 1 (0.62%) is misclassified as internal PTG, yielding a minimal overreach rate.

6.3. Multi-Dimensional Performance Analysis

Table 5 presents the cumulative dependability across resistance ranges and SNR levels.

Table 5. Cumulative Dependability (%) Across Resistance Ranges and SNR Levels.

Cumulative Resistance	Noiseless	40 dB	30 dB	20 dB	Overall
0–10 Ω	100	100	100	100	100
0–50 Ω	100	100	100	100	100
0–100 Ω	100	100	100	100	100
0–150 Ω	100	100	99.31	100	99.83
0–500 Ω	92.29	92.71	91.67	92.29	92.24

The false trip rate remains strictly at zero across all evaluated conditions. Cumulative dependability is 100% for resistances up to 100 Ω across all noise levels. At the 0 to 150 Ω range, dependability remains at or above 99.31%. For the 0 to 500 Ω range, dependability varies between 91.67% and 92.71%. Because the classifier was trained exclusively on faults up to 10 Ω , the 92.29% dependability at 500 Ω under noiseless conditions demonstrates out-of-distribution generalization. Furthermore, dependability varies by less than 0.62 percentage points from noiseless conditions to 20 dB SNR across all resistance bands, which confirms the method's immunity to measurement noise.

6.4. Physical Limits and Granular Error Analysis

Figure 9 plots misclassified internal faults against resistance.

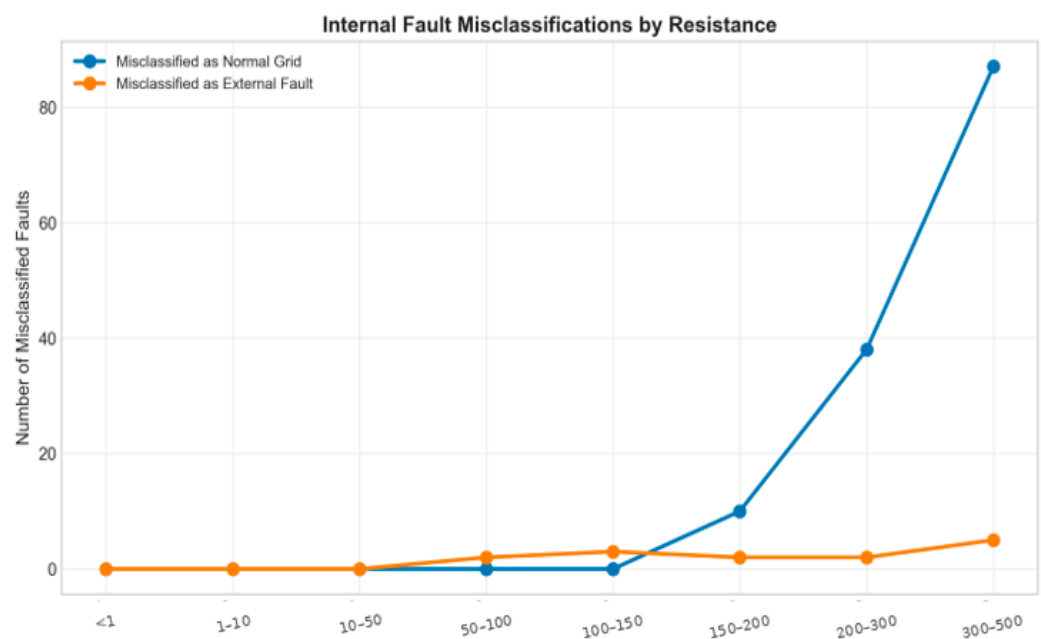


Figure 9. Number of misclassified internal faults plotted against fault resistance range. Misclassifications remain near zero below 100 Ω and increase exponentially above 150 Ω .

6.5. Physical Interpretation of Hierarchical Feature Routing

To verify that the proposed three-stage architecture serves as a data-driven realization of physical protection principles, the feature importance rankings of the gradient boosting models were analysed at each stage. The results confirm that each stage independently prioritizes features that align with specific physical phenomena.

Additionally, out of 149 total misclassified internal faults, 135 are categorized as normal grid conditions, and only 14 are labelled as external faults. This demonstrates that detection failures at extremely high impedances fail safely and prevent unwarranted relay operation. This behaviour reflects the severe transient attenuation caused by high electrical resistance.

Stage 1 (Binary Fault Detection):

The initial detection phase relies primarily on the mean values of the pole currents alongside the logarithmic energies of the common-mode and differential-mode currents. Together, these metrics account for more than 87% of the decision weight. This aligns with fundamental high-voltage direct current physics, where a fault triggers an immediate shift in the steady-state direct current and causes a substantial increase in traveling wave energy across all modes. Incorporating the mean voltage and apparent impedance within the features creates a reliable detection boundary that is largely independent of the specific fault structure.

Stage 2 (Fault Type Classification):

Differentiating between pole-to-ground and pole-to-pole faults is heavily dominated by the ratio of ground-mode to differential-mode transient energy at 40.7% importance, alongside the current asymmetry between poles at 39.2%. This directly mirrors the electromagnetic wave theory governing these faults. A pole-to-ground fault forces current through the earth return path to create severe modal asymmetry, while a pole-to-pole fault remains highly symmetric, as visualized in Section 5.5. Routing these specific modal features to the second stage isolates the physics of fault topology from the broader detection logic utilized in the first stage.

Stage 3 (Zone Discrimination):

Separating internal faults from external faults requires analysis of the transient waveform's shape and direction. The most critical feature is the statistical skewness of the negative pole current, which carries a 20.7% weight and captures the directional characteristics of the initial transient wavefront. This statistical metric measures the asymmetry of the current distribution, allowing the classifier to separate the distinct signal profiles of faults originating inside the protected zone from those originating outside.

Furthermore, the model heavily utilizes apparent transient inductance at 13.7% and high-frequency voltage attenuation at 6.0%. These features capture the effective impedance and spectral energy distribution of the transient event, enabling the model to distinguish local disturbances from those that have propagated across the network. The significant reliance on spectral flatness and fractal dimensions further proves that the third stage effectively analyses the physical distortion and signal roughness of the transient waveforms.

6.6. Comparison with Baseline Methodologies

To evaluate the proposed architecture, it was compared against two standard methods using the same out-of-distribution test set.

The first baseline is a single, flat multi-class CatBoost classifier that predicts all four target classes simultaneously. For a fair comparison, this model used the exact same feature set, training data, and class-weight balancing as the proposed pipeline.

The second baseline is a conventional deterministic threshold scheme. To ensure an independent comparison, this baseline utilized the standard rate of change of current (di/dt) threshold, which is the foundational start element in conventional HVDC traveling wave protection [36,38]. The threshold was dynamically set at the 99.9th percentile of the di/dt observed during normal grid conditions in the training set to prevent false tripping on load transients.

As detailed in Table 6, the proposed 3-stage pipeline achieved 100.00% security and a 0.62% overreach rate. In contrast, the flat classifier yielded a 10.62% overreach rate and a dependability of 71.25%. The conventional di/dt threshold suffered from an 89.75% security rate, a 23.12% overreach rate, and a dependability of only 63.96%. These results indicate that the proposed staged approach provides significantly better zone discrimination and high-impedance fault detection than standard flat classifiers or fixed di/dt thresholds.

Table 6. Comparison of Proposed Method Against Baseline Methods.

Metric	Proposed 3-Stage Pipeline	Baseline 1: Flat Multi-Class ML	Baseline 2: Fixed Threshold
Overall Accuracy	91.73%	75.93%	68.95%
Security	100.00%	99.00%	89.75%
Dependability	92.24%	71.25%	63.96%
Overreach Rate	0.62%	10.62%	23.12%

6.7. Physical Limits and Practical Implications

The system achieves 100% dependability for bolted and low-resistance faults between 0 Ω and 50 Ω . For moderate high-impedance faults between 50 Ω and 150 Ω , the dependability remains highly reliable at approximately 98.7%. When evaluated against extreme high-impedance faults between 150 Ω and 500 Ω , the system maintains an 80.86% dependability rate during out-of-distribution testing.

The scheme recorded zero unwarranted trips across the entire out-of-distribution test set, with a minimal 0.62% overreach rate confirming accurate zone discrimination. However, 34.38% of highly attenuated external faults fall below the Stage 1 pickup threshold and are classified as normal grid conditions. While this preserves core security, it inherently sacrifices situational awareness for distant external disturbances. Furthermore, two explicit evaluation boundaries and architectural limitations define the current scope of the scheme. First, the “External” class is represented exclusively by remote pole-to-ground (PTG) fault transients at a fixed passive load terminal (245 km from Terminal 1). Second, to ensure ultra-fast clearance for severe metallic faults, Stage 2 routes any disturbance classified as pole-to-pole (PTP) directly to an internal trip decision, bypassing the Stage 3 zone discrimination. Under the current logic, this architectural shortcut could plausibly trigger an unwarranted trip if a remote external PTP fault occurs.

Regarding practical deployment, while global parameters were utilized strictly for offline validation, real-time implementation will rely solely on local measurements. Given the hierarchical nature of the proposed decisions, the architecture supports two deployment modes: a parallel execution mode to minimize total inference latency, where it depends on another threshold method for initial detection of disturbance, or a sliding window approach where the Stage 1 decision dictates whether Stages 2 and 3 are executed both having their own tradeoffs.

7. Conclusions

This paper presents a hierarchical transient feature extraction framework for detecting high-impedance faults in VSC-HVDC systems. The proposed three-stage gradient boosting

architecture processes physics-informed features extracted from a strict one-millisecond observation window, relying on sequential hierarchical logic for the final trip decision.

When evaluated on a four-terminal HVDC network, the protection scheme achieved complete security (zero false trips) and 92.24% overall dependability across fault resistances up to 500 Ω and noise levels down to a 20 dB signal-to-noise ratio. For cumulative fault resistances up to 150 Ω , the dependability exceeded 99.3%. Furthermore, feature importance analysis confirmed that the model relies on physically meaningful signatures, such as modal energy ratios and apparent transient inductance, rather than spurious amplitude correlations.

Despite these results, the current scheme is fundamentally limited by extreme high-impedance faults (150–500 Ω) due to severe transient attenuation pushing signals below the noise floor. Additionally, the architectural bypass of Stage 3 for PTP events and the reliance on a single external fault geometry represent critical operational boundaries. To address these limitations and guarantee absolute security, future work will focus on extending Stage 3 zone discrimination to all fault topologies (including PTP) and integrating diverse multi-terminal external fault scenarios. Subsequent research will also explore communication-assisted elements to improve the detection of extreme high-impedance faults, extend the verification of the method in MMC model and validate the exact latency and memory footprint of the proposed deployment modes on a real-time hardware-in-the-loop (HIL) testbed.

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