Sustainable Energy and Artificial Intelligence 2(2) (2026) 107-119 DOI: 10.61882/seai.2601-1040

Hamedan University of Technology
Iranian Association of Electrical and Electronics Engineers

Sustainable Energy and Artificial Intelligence

Online ISSN: 3060-8015

Journal Homepage: www.enai.hut.ac.ir

Optimized Hybrid LSTM-XGBoost Technique for Real Time Disturbance Detection in MT-HVDC Systems

Reza Talebi[1], Mohammad Hassan Moradi[1*], Farhad Namdari[2]

[1] *Department of Electrical Engineering, Faculty of Engineering, Bu-Ali Sina University Hamedan, Iran*

[2] *Department of Engineering, Faculty of Environment, Science, and Economy, University of Exeter, Exeter, UK*

* *Corresponding Author: mhmoradi@basu.ac.ir*

Article Info

Article type:
Original Article

Article history:
Received 2026-01-27;
Revised 2026-02-15;
Accepted 2026-02-23.

How to cite this article:
Talebi, R., Moradi, M. H. and Namdari, F. (2026). Optimized Hybrid LSTM-XGBoost Technique for Real Time Disturbance Detection in MT-HVDC Systems. *Sustainable Energy and Artificial Intelligence*, 2(2), 107-119.
DOI: 10.61882/seai.2601-1040

Abstract

Modern Multi-Terminal HVDC (MT-HVDC) grids are expanding rapidly with large-scale renewable integration, yet disturbance detection still faces challenges in achieving the required speed, adaptability, and selectivity. Recent advances highlight a shift toward data-driven approaches that learn disturbance signatures directly from measurements, reducing reliance on handcrafted features, threshold tuning, and complex signal-processing pipelines. This study proposes a hybrid AI-based disturbance detection method that integrates a lightweight LSTM network with an XGBoost classifier for real-time operation in MT-HVDC systems. The method relies solely on voltage measurements sampled at 1 kHz, significantly reducing data-rate requirements while preserving the temporal resolution necessary for fast decision-making. Voltage waveforms are segmented into 1 ms windows, from which integrated voltage and rate-of-change features are extracted and encoded into compact temporal embeddings by the LSTM. These embeddings are subsequently classified by XGBoost to provide fast, interpretable, and probabilistic disturbance decisions. A detailed MT-HVDC test system was developed in PSCAD to generate a wide range of fault scenarios and operating conditions. Comprehensive benchmarking and multi-objective hyperparameter optimization identified an efficient single-layer LSTM with hidden size 8 and batch size 32 as the optimal balance between accuracy and computational efficiency. Results demonstrate strong generalization capability and robust performance under non-ideal conditions. Overall, the proposed method offers a scalable, data-centric and deployment-ready solution that enhances disturbance detection speed, improves fault-clearance verification, and contributes to reducing Total Fault Clearance Time in next-generation HVDC protection architectures.

Keywords: Disturbance; LSTM; XGBoost; HVDC; Fault, Machine Learning.

1. Introduction

The increasing integration of Direct Current (DC) technologies into modern power networks is reshaping system efficiency, controllability, and reliability. DC grids facilitate seamless interaction between renewable energy resources, DC powered devices, and critical loads, positioning them as a cornerstone of future energy systems. However, the protection of High-Voltage Direct Current (HVDC) networks remains a significant challenge due to the rapid evolution of DC faults, the absence of natural current zero crossings, and the severe stresses imposed on converter controls. These characteristics demand protection schemes capable of delivering extremely fast and highly selective disturbance detection.

Conventional disturbance detection methods, which rely on fixed thresholds [1], often fall short in providing the required speed, robustness, and adaptability under varying operating conditions. Enhancing sensitivity necessitates increasingly complex relay characteristics [2], and to compensate for the limitations of primary values measurements, mathematically derived features such as current derivatives [3] and voltage rate-of-change [4] have been introduced. Yet these approaches remain vulnerable to noise, measurement errors, and high-resistance fault conditions. Signal-processing-based methods including wavelet transforms [5] and other time–frequency techniques, offer improved feature extraction but introduce substantial complexity in selecting optimal settings, configuring decomposition levels, and tuning operational thresholds. Their performance remains heavily dependent on careful feature engineering and expert-driven parameterization.

To overcome these limitations, recent research has increasingly integrated Artificial Intelligence (AI) with advanced signal processing and mathematical feature extraction techniques to generate richer and more discriminative inputs [6]. These transformed representations enable Machine Learning (ML) and Deep Learning (DL) models to capture subtle disturbance signatures and improve classification accuracy across diverse operating conditions.

The evolution of AI integrated HVDC protection spans classical classifiers such as Support Vector Machines (SVM) [7] and k-Nearest Neighbors (KNN) [8] ensemble methods like XGBoost [9], and more advanced deep learning architectures [10]. Hybrid variants, including wavelet-enhanced Convolutional Neural Networks (CNN) [11], - Artificial Neural Network (ANN) based combinations [12], and mathematical feature extraction pipelines coupled with ML algorithms [13], further extend this landscape. Emerging quantum-neural approaches which integrate convolutional features like travelling-waves with Quantum Neural Network Components (QDNNs) [14], highlight the growing computational sophistication of intelligent disturbance-detection. Fig. 1, illustrates the taxonomy of AI techniques integrated into HVDC control and protection systems.

Despite these advancements, the performance of hybrid AI-based protection schemes still depends on effective feature selection and the careful configuration of underlying signal processing stages. Recent end-to-end HVDC protection frameworks demonstrate that DL can replace conventional signal processing stages [15,16] achieving superior accuracy and robustness across diverse operating conditions [17,18]. Complementing these developments, hybrid AI approaches leverage learned representations [19] to overcome the limitations of mathematically engineered features [20], offering more adaptive, scalable, and resilient solutions for next-generation HVDC networks.

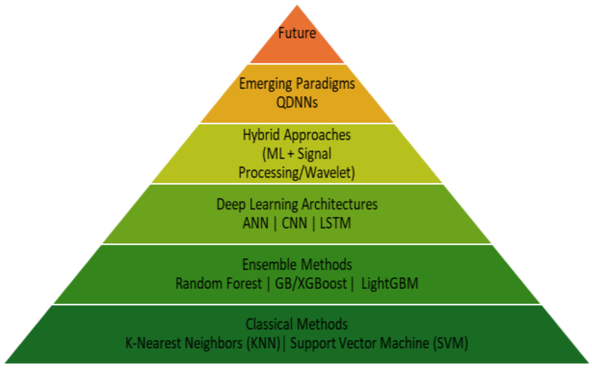

Fig. 1. Taxonomy of AI techniques in HVDC systems.

A central challenge that persists across all protection strategies is the need to minimize the combined duration of fault diagnosis and fault interruption, known as the Total Fault Clearance Time (TFCT). TFCT is a critical determinant of transient stability, as prolonged fault presence drives the system further from its stable operating point. In HVDC networks, TFCT must be exceptionally short due to the rapid propagation of DC faults, the lack of natural current zero crossings, and the risk of converter blocking. These challenges are further intensified in multi-terminal (MT) HVDC systems connected to weak AC grids, where low inertia and heightened sensitivity significantly increase vulnerability to instability during fault events [21].

However, accurate fault diagnosis alone does not guarantee grid stability. Fault interruption and the risk of protection maloperation and breaker failure remains a critical bottleneck in HVDC protection. Addressing this challenge requires a dual-layer protection philosophy in which AI-enhanced local fault detection provides rapid and selective response, while centralized diagnostic intelligence ensures system-wide coordination and resilience across interconnected MT-HVDC networks. Fig. 2. illustrates emerging hybridization framework for future-ready HVDC protection schemes.

Accordingly, the deployment of fast, reliable, and well-coordinated protection for assuring successful fault clearance or breaker or protection system failure condition is essential to protect HVDC grids [22]. Building on these requirements, this study proposes a novel hybrid disturbance detection method that integrates an optimized Long Short-Term Memory (LSTM) network for temporal feature extraction with an XGBoost classifier for real-time disturbance identification and verification of successful fault clearance in MT-HVDC systems. The method is fully data-centric, eliminating the need for manual feature engineering and removing dependence on traditional signal processing stages. By replacing high complexity preprocessing pipelines with an AI-driven architecture, the proposed approach significantly reduces disturbance detection latency and contributes to achieving shorter fault interruption time. Its adaptive design ensures robust performance across diverse network configurations and operating conditions, offering a meaningful advancement toward next-generation HVDC protection schemes.

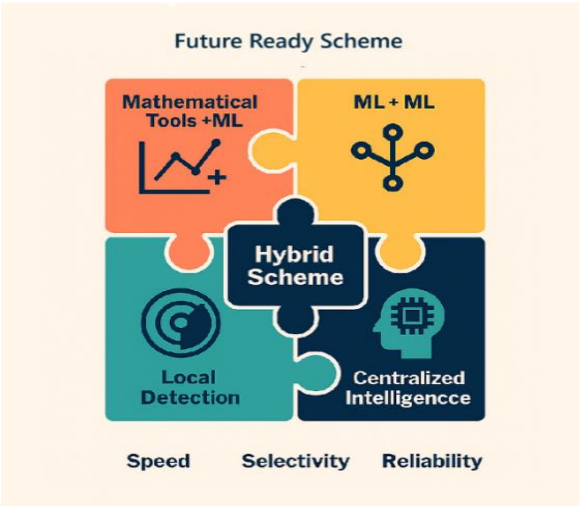

Fig. 2. Hybrid framework for future ready schemes.

2. Literature Review

Reliable and fast protection remains one of the most critical challenges in HVDC and multi-terminal HVDC (MT-HVDC) networks. Early protection strategies relied primarily on local measurements and fixed thresholds, offering simplicity, immunity to communication delays, and fast operation. However, their performance deteriorated under varying operating conditions, high-resistance faults, and partial breaker failures, motivating the development of more adaptive and selective diagnostic techniques.

Initial research focused on exploiting abrupt changes in local electrical quantities to detect breaker malfunctions. Sun et al. (2018) [23] introduced a Quickest Change Detection (QCD) scheme that monitored DC bus voltage variations as the breaker generated counter-voltage during opening. While highly effective for complete breaker failures, its sensitivity declined for single-module failures where partial counter-voltage masked the disturbance.

To improve interoperability and vendor-neutral deployment, Wang et al. (2019) [24] proposed a di/dt-based criterion for distinguishing successful clearing from breaker failure. Although conceptually simple, the method struggled with threshold selection because traveling-wave reflections caused partial failures to resemble normal clearing. Wang et al. (2020) [25] further advanced breaker-failure detection by estimating counter-voltage across the energy-absorption branch and applying an overcurrent criterion. Despite improved dependability, the method remained sensitive to surge-arrester nonlinearities and required careful calibration of voltage-based thresholds.

These studies highlight a persistent limitation of threshold based schemes which cannot simultaneously guarantee speed, selectivity, and robustness, especially as HVDC grids grow in scale and complexity.

To enhance sensitivity under challenging conditions, researchers introduced mathematically derived features such as current derivatives [3] and voltage rate of change [4]. More advanced signal processing techniques including wavelet transforms (WT) and Hilbert Huang Transform (HHT) were employed to extract high frequency fault signatures.

Radwan et al. (2024) [22] developed a setting-less breaker-failure backup protection scheme using WT and HHT applied to a 1 ms moving window of local voltage. Instantaneous frequency and energy features enabled rapid separation of successful trips from failures within ~1 ms. However, the method required high sampling rates, careful window selection, and remained sensitive to operating conditions and fault distance. Overall, signal processing-based approaches improved robustness but introduced significant configuration complexity, limiting their practicality for real-time MT-HVDC protection.

As HVDC systems became more dynamic, researchers increasingly integrated AI with engineered features to improve classification accuracy. Fayazi et al. [27] (2025) presented a hybrid methodology for parallel HVAC/HVDC overhead transmission lines, where Discrete

Wavelet Transform (DWT) was used to derive a fault energy index, subsequently classified using a Decision Tree. While effective in rapid fault type identification, the method carried risks of overfitting if the Decision Tree (DT) was not adequately pruned.

Tsotsopoulou et al. [28] (2023) applied XGBoost to current and voltage derivatives for fault detection in superconducting HVDC cables. Although effective, the method relied heavily on specialized cable behavior and extensive training data, restricting generalization.

Yousaf et al. [12]**Error! Reference source not found.** (2023) proposed a multisegmented intelligent scheme combining Stationary Wavelet Transform (SWT) with a random-search-optimized multilayer ANN. Segmenting the fault window reduced computational load and improved sensitivity to subtle signatures, but the approach depended on careful segmentation and parameter tuning.

These hybrid methods demonstrated the value of AI but remained constrained by feature engineering overhead, sensitivity to preprocessing choices, and limited adaptability across network configurations.

Communication-based protection has also gained attention, particularly for coordinated AC–DC protection. IoT-enabled architectures facilitate data exchange between AC and HVDC grids, but face challenges related to integration complexity, cybersecurity, and communication delays. Zeng et al. (2025) [29] showed that hybrid forecasting models can be centrally deployed, yet their reliance on communication infrastructure limits applicability in fast HVDC protection.

To overcome computational bottlenecks in classical neural networks, recent work has explored quantum enhanced learning. Poursaeed and Namdari (2025) [14] introduced an explainable Quantum Deep Neural Network (QDNN) combining convolutional layers with quantum neural components to process traveling-wave features. While demonstrating strong localization accuracy and robustness, practical deployment remains constrained by the immaturity of quantum hardware and training frameworks.

Across the literature, protection strategies have evolved from threshold-based schemes to signal processing enhanced methods, AI-assisted feature engineering approaches, and emerging quantum-neural models. Each class offers strengths, speed, robustness, and adaptability, but none simultaneously achieve:

- Fast temporal feature extraction
- Low detection latency
- Robustness under noise and varying operating conditions and MT-HVDC configurations
- The ability to verify successful fault clearance

all of which are essential for minimizing Total Fault Clearance Time and ensuring transient stability.

At the same time, AI-based algorithms introduce their own trade-offs between interpretability, computational efficiency, and temporal-modeling capacity. Table 1., summarizes the comparative performance of the most applicable ML and DL techniques used in protection systems, highlighting the diversity of approaches and their respective limitations.

Taking together, these gaps motivate the development of fully data-centric, hybrid AI frameworks capable of delivering fast, reliable, and adaptive disturbance detection without reliance on handcrafted features or complex signal-processing pipelines.

3. Proposed Method

3-1. Overview

The proposed protection framework is a fully data centric, hybrid AI architecture designed to deliver fast, noise resilient, and temporally aware disturbance detection in MT HVDC systems. The method operates exclusively on voltage measurements, selected for its superior robustness under DC fault conditions and integrates three core components:

1. Data and feature extraction from low-resolution voltage windows
2. Temporal representation learning using LSTM networks
3. High-performance classification using XGBoost

Table 1. Comparative criteria of most applicable AI techniques.

Criteria	RF	SVM	GBM	LSTM
Temporal Modelling	Not supported	Not supported	Requires engineering	Native support
Interpretability	High	Moderate	High	Low
Feature Engineering Need	High	High	High	Minimal
Robustness To Noise	High	Moderate	High	Sensitive
Scalability	Excellent	Limited	Excellent	Moderate
Suitability	Limited	Moderate	Good	Excellent

Unlike conventional protection schemes that rely on extensive signal-processing pipelines, the proposed hybrid solution unifies LSTM-based temporal feature extraction with XGBoost-based classification. This combination enables fast and reliable disturbance detection, directly supporting the reduction of TFCT and enhancing overall system stability.

3-2. Data and Feature Extraction

To enhance noise resilience while preserving sensitivity to rapid voltage transitions associated with fault initiation and interruption presented method implements dual-feature representation. Despite existing protection schemes which implement high sampling rate of input signals, in proposed method voltage is signal measured with 1 kHz sampling rate and grouped into sequential 10 ms windows (10 samples per window). Each window is processed at 1 ms resolution to extract two complementary features:

- Voltage integral (area-based feature)
- Rate of change of voltage (derivative-based feature)

3-2-1. Voltage Integral Feature

The cumulative voltage over a window of duration T is calculated as equation 1:

$$A_v = \int_{-T}^{0} V.dT = \sum_{-T}^{0} V_T.\Delta t \quad (1)$$

V is the measured voltage

A_v: is the area of the integrate of voltage signal in t ms window.

Given a constant sampling rate interval Δt, the expression simplifies to:

$$A_v = \sum_{-T}^{0} V_T = V_0 + V_{-1} + V_{-2} + \cdots + V_{-T} \quad (2)$$

The average voltage is then:

$$V_{average} = \frac{A_v}{\Delta t} \quad (3)$$

This integral feature (A_V) provides a compact descriptor of the voltage trajectory, capturing the cumulative effect of disturbances and offering robustness against high-frequency noise.

3-2-2. Rate of Change Feature

To enhance sensitivity to abrupt voltage variations, the rate of change (first derivative) of integrated voltage windows is calculated as:

$$V_d = \frac{d(V)}{dt} = \frac{\Delta V}{\Delta t} = \frac{V(t_0) - V(t_0 - \Delta t)}{\Delta t} \quad (4)$$

V_d:is the first derivative of voltage signal

$\Delta V = V_k - V_{k-1}$

$\Delta t =$ Samppling rate

Since Δt is constant:

$$Thus: \quad V_d = \Delta V = V_k - V_{k-1} \quad (5)$$

In Equation (5), k represents the sampling instant, with V_k and V_{k-1} standing for the present and previous sampled line Voltage. This derivative feature captures fast transients characteristic of fault initiation and interruption.

3-2-3. Real Time Windowing Logic

The input array is continuously refreshed as new voltage samples arrive, ensuring real-time responsiveness, temporal consistency, and computational efficiency. By segmenting the waveform into fixed-duration windows and extracting both the integral and derivative features, the proposed method jointly capture both slow-varying and fast-transient components of the voltage waveform. This balanced representation is inherently noise resilient and well suited for distinguishing successful fault interruption from breaker failure conditions.

3-3. LSTM Based Networks

LSTM networks are employed to learn temporal dependencies within the voltage windows, enabling the protection system to move beyond static thresholds and manually engineered features. Their gated architecture allows the model to:

- Capture dynamic fault signatures
- Internalize temporal patterns without handcrafted feature engineering
- Produce bottleneck embeddings that represent the most discriminative temporal features

The bottleneck embeddings correspond to the final compressed representation learned by the LSTM. A ReLU activated dense layer reduces the encoded temporal features into a lower dimensional space, retaining only the most salient information for classification. The selected LSTM architecture is as follows:

- LSTM encoder with latent dimension of 8.
- Bottleneck dense layer of 64 units
- Batch normalization and dropout layers used to improve generalization and reduce overfitting.
  Training configurations are as follows:
- Optimizer: Adam with learning rate 1e-3.
- Loss: categorical cross-entropy.
- Epochs: 100, batch size: 128.
- Early stopping and checkpointing to retain the best model.

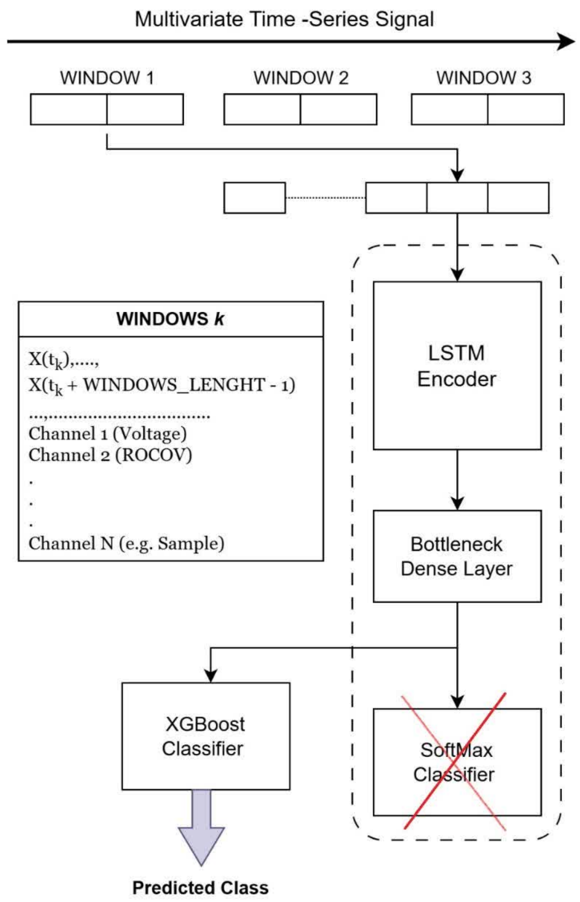

Fig. 3. Framework of proposed hybrid model.

In a conventional classification pipeline, the bottleneck features would be forwarded to a *softmax* layer to generate class probabilities. However, As depicted in Fig 3., with in the proposed hybrid model the *softmax* classifier head is omitted and only is used for model training.

3-4. XGBoost-Based Classification

XGBoost complements the LSTM encoder by providing a fast, robust, and interpretable classifier capable of operating on the learned temporal embeddings.

The classifier is trained on LSTM bottleneck embeddings with continuous validation monitoring and probabilistic outputs to support adaptive thresholding and reduce the likelihood of false trips.

XGBoost is used as the final decision layer due to its:

- High classification accuracy
- Robustness to noise and outliers
- Fast training and inference
- Ability to generate probabilistic outputs

To prevent classifier overfitting, validation monitoring is enabled and balanced accuracy is implemented for evaluation metric. The classifier outputs are:

- Predicted class of disturbance detection (Successful / Failed fault clearance).
- Class probabilities for interpretability and threshold tuning.

Table 2. summarizes the trade-offs between standalone LSTM and XGBoost, and the proposed hybrid method.

Table 2. Hybrid vs. standalone LSTM and XGBoost

Metric	LSTM	XGBoost	Proposed Hybrid
Temporal Awareness	Available	Not Available	Available
Accuracy	High	Moderate	High
Interpretability	Low	High	Moderate
Training Time	Slow	Fast	Moderate
Feature Engineering Need	Low	High	Low
Deployment Complexity	High	Low	High

3-5. Evaluation and Decision Layer

The final stage of the proposed framework focuses on evaluating model performance and generating reliable protection decisions, ensuring that the architecture satisfies the stringent operational requirements of HVDC disturbance detection. This dual emphasis on predictive accuracy and operational assurance directly supports reduced TFCT and enhances overall system stability.

Model performance is assessed using key indicators including accuracy, precision and recall, false-alarm rate, and detection latency. Together, these metrics demonstrate the capability of the proposed architecture to deliver rapid and dependable disturbance detection under real-time operating conditions. Particular emphasis is placed on minimizing false alarms while maintaining low detection latency, ensuring practical feasibility for protection-class applications.

The XGBoost classifier produces probability scores for each decision outcome, providing a measure of confidence that enhances the robustness of the protection logic. These probabilistic outputs enable adaptive thresholding, reduce misclassification risk, and improve resilience under uncertain or noisy operating conditions. They also facilitate coordinated protection actions across interconnected terminals, ensuring that the final decision reflects both local signal behavior and system-level reliability requirements.

By combining discriminative temporal representations with probabilistic decision reasoning, the proposed hybrid framework present a disturbance detection framework for deployment in modern and future ready MT-HVDC protection environments.

4. Simulation and Results

4-1. Model Network Configuration

To evaluate the performance of the proposed hybrid protection framework under realistic operating conditions, a comprehensive electromagnetic transient (EMT) simulation environment was developed. The study employs the well-established MT-HVDC benchmark system introduced by W. Leterme et al. [30], widely recognized for its accurate representation of converter dynamics, fault behavior, and protection interactions. This benchmark has been implemented in PSCAD 5.0.1, making it an appropriate platform for validating advanced disturbance detection schemes.

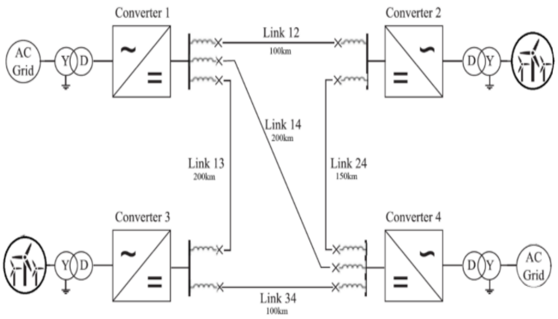

Fig. 4. Topology of proposed MT-HVDC network.

Fig. 4. illustrates the four-terminal meshed MT-HVDC network used in this work. The system integrates two offshore wind farms with a mainland AC grid through a symmetric bipolar ±320 kV DC architecture. Wind farm terminals operate under P–Q control, while the AC-connected terminals employ V-droop and Q-control strategies. Each transmission line is equipped with DC circuit breakers (DCCBs) at both ends, supported by series reactors to limit transient fault currents and facilitate rapid fault isolation.

The principal electrical parameters of the test system are summarized in Table 3. Other parameters are selected within practical ranges to capture a broad spectrum of operating conditions, including variations in MMC characteristics, Line and Bus filter reactors, and DCCBs opening times. All transmission links are modelled as 320 kV XLPE-insulated cables comprising a central conductor, lead sheath, and steel armor separated by multilayer insulation. The sheath and armor are assumed to be perfectly grounded to ensure electromagnetic.

Table 3. Parameters of a 640 kV MT-HVDC grid.

Name	Symbol	Value	Unit
System Voltage	U_s	640	kV
Peak Fault Current	I_{pk}	25	kA
Relay Trip Time	t_{RY}	3	ms
Metal-Oxide Surge Arrester Voltage	U_{MOSA}	480	kV
Fault Current Suppression Time	t_{FS}	12	ms

4-2. Step 0: Data Preparation

Voltage measurements were extracted directly from PSCAD simulations as input into the model framework. For each simulation, the voltage waveform was segmented into 1 ms windows, corresponding to 10 samples at 1 kHz, and processed to compute:

- Voltage integral within 1ms time-window
- Rate-of-Change (ROC) of time -windows

These features jointly capture slow-varying and fast-transient components of the disturbance. The processed data were exported as structured temporal windows, labeled according to disturbance outcome (successful interruption or failure), and normalized before being passed to the AI pipeline implemented in Python.

4-3. Step 1: Temporal Feature Extraction

The LSTM encoder receives sequences of 10 feature segments (1 ms resolution), each containing normalized voltage and ROC values. Building on this preprocessed dataset, the LSTM-based encoder is trained to learn temporal dependencies within each window and compress them into a compact latent representation.

A lightweight encoder architecture is employed, consisting of a single LSTM layer that produces concise bottleneck embedding. This embedding captures the most salient temporal characteristics of the disturbance and is extracted for all training, validation, and test samples. These latent embeddings serve as discriminative, low dimensional representations of MT-HVDC disturbance dynamics and form the input to the downstream classifier.

4-4. Step 2: XGBoost Classification

The extracted LSTM embeddings are passed to an

XGBoost ensemble classifier for final disturbance classification.

Balanced accuracy is used as the primary evaluation metric, and validation-set monitoring is applied to prevent overfitting. The classifier outputs both the predicted disturbance class and the associated probability distribution, enabling confidence aware decision making.

This two-stage inference workflow demonstrates how the hybrid architecture combines deep temporal feature extraction with fast, interpretable, and probabilistic classification suitable for real-time HVDC protection.

4-5. Step 3: Evaluation and Decision Layer

The final stage evaluates the reliability of the proposed scheme and generates protection decisions that meet the stringent requirements of HVDC disturbance detection. Performance is assessed using accuracy, precision, recall, false-alarm rate, and detection latency. These metrics collectively demonstrate the model's ability to deliver rapid and dependable disturbance identification under real-time operating conditions. The probabilistic outputs generated by XGBoost enable adaptive thresholding, reduce misclassification risk, and enhance resilience under uncertainty. This confidence-based decision logic ensures high dependability while minimizing false trips, directly contributing to reduced TFCT and improved system stability.

5. Model Evaluation & Benchmarking

5-1. Model Configuration Tuning

Within hybrid architecture, the LSTM encoder is responsible for learning temporal dependencies from voltage windows. As LSTM is a resource-demanding components [31] and its performance is highly sensitive to hyperparameters such as hidden size, number of layers, batch size, and sequence length [32], a systematic benchmarking study was conducted to identify an optimal configuration suitable for real-time HVDC protection.

The benchmarking study was conducted across three temporal resolutions: 10 samples (1 ms resolution), 20 samples (0.5 ms resolution), and 50 samples (0.2 ms resolution). Each configuration was assessed using a consistent set of classification and calibration metrics. Classification metrics (accuracy, F1-score) evaluated predictive performance, while calibration metrics (MAE, MSE, RMSE, MAPE, R^2) quantified confidence alignment. This multi-metric approach ensures that the selected configuration balances accuracy with computational efficiency which is an essential requirement for real-time deployment.

5-2. Multi-Objective LSTM Optimization

To identify the most effective LSTM architecture, a multi-objective ranking strategy was employed. Candidate models were generated using combinations of:

- Hidden sizes: [8,32,64,128]
- Batch sizes: [32,64,128]

Each configuration was evaluated against two objective groups:

- Minimize: MAE, MSE, RMSE, MAPE, computational load
- Maximize: F1-score, R^2

All metrics were normalized to a [0,1] scale using min–max normalization, with inverted scaling applied to metrics being minimized. This approach aligns with established multi-criteria decision analysis (MCDA) practices [33].

Fig. 5. illustrates the optimization workflow, where normalized metrics are aggregated into a composite performance score and ranked to identify the most promising configurations.

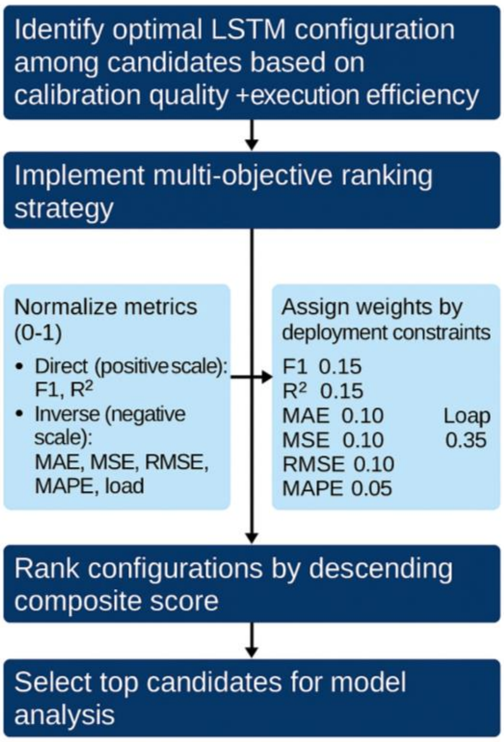

Fig. 5. Multi-objective optimization workflow.

This ranking strategy is inspired by Pareto-efficient model selection and randomized hyperparameter search, which have been shown to outperform grid search in high-dimensional spaces [34]. The objective is to Maximize: F1 score, R^2 and minimize the Computational load and other metrics as described in Fig. 5.

The resulting heatmap, as depicted in Fig. 6, shows that shorter sequence lengths (10 samples) consistently achieve the highest composite scores, particularly with hidden sizes of 8 and 32. Longer sequences (20 samples) exhibit reduced performance due to increased computational cost without corresponding gains in accuracy. These findings indicate that a 10-sample window provides the best balance between temporal resolution and computational efficiency.

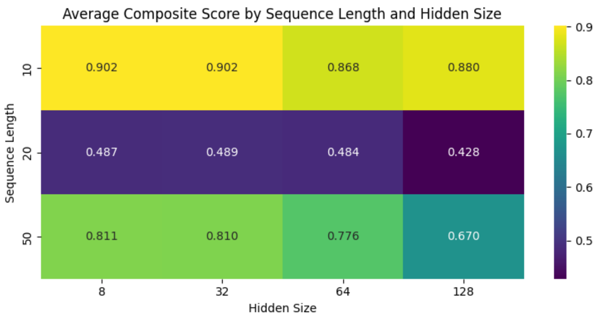

Fig. 6. Heatmap visualization of LSTM parameters.

5-3. XGBoost Performance Evaluation

To benchmark the performance of the XGBoost classifier, Random Forest (RF) was selected as a comparative baseline due to its widespread use in power-system diagnostics and strong performance under noisy conditions. Both models were trained on the same LSTM embeddings to ensure a fair comparison.

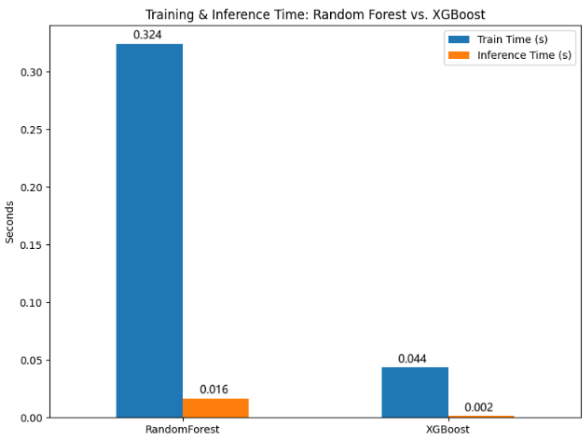

Fig. 7. Training & inference time of RF vs XGBoost.

XGBoost consistently achieved higher precision and F1-score, demonstrating superior capability in capturing non-linear disturbance patterns. It also delivered significantly faster execution. As shown in Fig. 7., XGBoost completed training in 0.037 s and inference in 0.001 s, compared to 0.290 s and 0.013 s for RF. These improvements highlight XGBoost's suitability for real-time protection environments.

5-4. End-to-End Evaluation of Hybrid Model

The final evaluation considers the complete LSTM + XGBoost pipeline. Balanced accuracy is used as the primary metric to ensure equal weighting of disturbance classes and robustness to class imbalance. Since the strongest standalone LSTM performance was consistently achieved using a 10-sample window, this configuration was adopted as the baseline for hybrid evaluation. Operational efficiency was assessed using the total inference time per 10 ms window:

$$T_{inference} = T_{LSTM\ Forward} + T_{XGBoost\ infer}$$

This metric reflects the true deployment latency of the hybrid model and enables direct comparison of computational cost across different sampling resolutions.

Table 4. Highest ranking of final benchmarking results.

Window Length (ms)	Hidden Size	Batch Size	Performance Score (0~1)	Balanced Accuracy	Inference Time
10	8	32	0.9894	1.0	0.084
10	64	32	0.9839	1.0	0.092
10	32	32	0.9637	1.0	0.130
10	8	128	0.96219	1.0	0.089

Table 4. summarizes the best-performing configurations. The model with hidden size 8, one LSTM layer, and batch size 32 achieved the most favorable balance between accuracy and latency, making it the most practical choice for real-time HVDC protection. Larger hidden.

6. Conclusion and Discussions

6-1. Summary of Contributions

This study presented a fully voltage-based hybrid machine-learning framework for disturbance detection and fault-clearance verification in MT-HVDC systems. By relying exclusively on voltage measurements, the method eliminates the need for wide-band sensors, complex signal-processing pipelines, or simulation-derived thresholds. Voltage waveforms are processed into 1 ms windows and encoded using an optimized LSTM network, producing compact temporal embeddings that are classified by XGBoost to deliver fast and reliable disturbance decisions.

The proposed architecture achieves high classification accuracy while maintaining inference latencies suitable for real-time protection. Its low data-rate requirements and modular structure support deployment across both edge-level IEDs and centralized protection platforms. A systematic benchmarking and multi-objective optimization process identified the most practical configuration which implement single layer LSTM with hidden size 8 and batch size 32, offering the best balance between accuracy, computational efficiency, and operational feasibility.

Compared with existing schemes, the proposed method achieves a minimum detection time of 1 ms using only 1 kHz voltage measurements sampling rate, representing a substantial reduction in sensing and communication requirements while maintaining strong generalization across diverse operating conditions.

A comparative analysis with existing schemes which are indicated in Table 5, highlights the distinct advantages of the proposed approach. Prior methods typically require high-frequency sampling (10–100 kHz), which imposes significantly heavier computational loads, rely on multi-signal inputs or threshold-based logic, and often lack generalization capability across varying operating conditions. In contrast, the proposed framework achieves comparable or superior detection speed while operating at lower sampling frequency, using a single measurement type. This combination of low data-rate requirements, high detection speed, and generalized applicability distinguishes the proposed method from existing solutions.

6-2. Discussion and Limitations

Despite its strong performance, several limitations must be acknowledged. The method depends on single-point voltage measurements; sensor malfunction, calibration drift, or communication loss would directly affect detection capability. Redundancy strategies or multi-point sensing architectures may therefore be required for high-availability deployments.

The two-stage training pipeline introduces heterogeneous hardware demands: LSTM training benefits from GPU acceleration, whereas XGBoost is CPU-optimized. This may challenge deployment on conventional substation hardware unless lightweight inference-only models are used.

Finally, although XGBoost provides probabilistic outputs, the hybrid pipeline offers less transparency than threshold-based schemes. Explainability tools such as SHAP or attention-based attribution may be required to satisfy regulatory and operator expectations. However, because the LSTM bottleneck produces latent features, direct mapping of classifier importance scores back to raw voltage samples remains non-trivial.

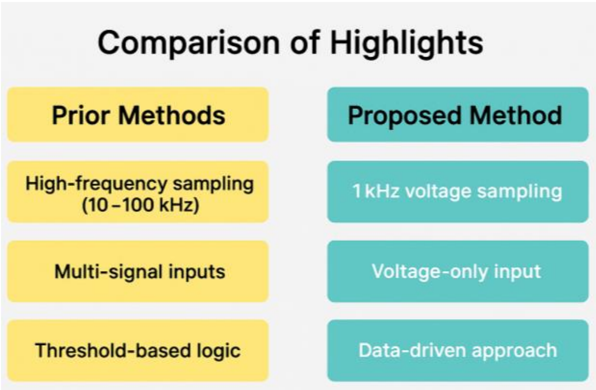

Fig. 8. Comparative highlights of proposed method.

Fig. 8. depicts comparative highlights of the proposed voltage-based hybrid ML method versus prior HVDC protection schemes.

6-3. Future Directions

Several avenues exist to extend the proposed framework. Enhancing measurement robustness through multi-point sensing, sensor-health monitoring, and fault-tolerant communication protocols would improve resilience under degraded conditions.

Beyond fault clearance verification, the pipeline could evolve into a unified HVDC diagnostic and supervisory tool, integrating both protection and control functions. Such an extension would enable proactive system monitoring, coordinated control actions, and improved situational awareness.

Alternative sequence-modeling architectures also warrant investigation. GRUs and 1D-CNNs offer faster inference for latency-critical applications, while Transformer encoders and Temporal Convolutional Networks (TCNs) may provide improved accuracy by capturing long-range dependencies. TCNs represent a promising balance between accuracy and computational efficiency for power system time-series analysis. Although laboratory benchmarking and simulation results have demonstrated feasibility, full validation requires live HVDC substation trials. Embedding the algorithm into real-time protection systems will allow assessment of latency, interoperability and resilience under operational stress.

Table 5. Comparative results of proposed scheme.

Reference	Criterion	Threshold Base	Operating Time	Sampling Freq.	Generalized Scheme
Leterme et al. Error! Reference source not found., Error! Reference source not found.	voltage-current plane (UI-plane)	Yes	5ms	50kHz	No
Sun et al. Error! Reference source not found.	voltage	Yes	4ms	50kHz	No
Wang et al. Error! Reference source not found.	voltage and current data	Yes	8ms	100kHz	No
Wang et al. Error! Reference source not found.	Counter Voltage across surge arrester	Yes	5ms	100kHz	Yes
Pérez-Molina et al. Error! Reference source not found.	voltage derivative	Yes	2ms	10kHz	Yes
Radwan et al. Error! Reference source not found.	voltage waveform	No	1ms	100kHz	No
Proposed Scheme	voltage waveform	No	1ms	1kHz	Yes

Declaration of Generative AI and AI-Assisted Technologies in the Manuscript Preparation Process

During the preparation of this work the author(s) used Copilot in order to generate illustrations and translating texts from Persian to English language. After using this tool/service, the authors reviewed and edited the content as needed and took full responsibility for the content of the published article.

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Biography

Reza Talebi is a researcher and electrical engineer specializing in power system protection, secondary systems, and digital substations. He is currently pursuing a PhD in Power Electrical Engineering at Bu-Ali Sina University, where his research focuses on advanced protection schemes, digital substation architectures, and intelligent protection system performance. With more than 20 years of technical and professional experience, Reza's work centers on improving the reliability, automation, and intelligence of modern power networks. His research interests include digital substations, protection system engineering, and the integration of renewable energy into resilient grid architectures. Through his combined academic research and industry practice, he contributes to advancing modern power system protection.

Professor M.H. Moradi is a lecturer in the department of electrical engineering, University of Bu–Ali Sina in IRAN. He obtained his B.Sc., M.Sc. and PhD from Sharif University of Technology, Tarbiat Modares University and Strathclyde University in Glasgow, Scotland in 1991, 1993 and 2002 respectively. His research interests include New and Green Energy, Micro Grid Modeling and Control, DG Location and Sizing in Power System, photovoltaic systems and power electronics, Combined Heat and Power Plant, Power Quality, Supervisory Control, Fuzzy Control.

Professor Farhad Namdari is a leading expert in *electrical energy systems*, specializing in *smart grids*, *renewable energy*, and *Wide Area Monitoring, Protection, and Control (WAMPAC)*. With over 25 years of experience in both academia and industry, he has made significant contributions to *power system protection*, *AI applications in smart grids*, and the *integration of renewable energy sources into modern grids*. His recent focus also includes applying electrical power solutions in healthcare and exploring the use of electromagnetic fields and energy systems in medical applications.