A Review of Conventional and Intelligent Protection Techniques for HVAC Transmission Line Fault Analysis

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Abstract - **Reliable fault detection, classification, protection, and location are essential for secure operation of modern HVAC and HVDC transmission networks. This task has become more complex due to long EHV corridors, DFIG-based wind farms, converter-interfaced renewable sources, LCC and MMC-HVDC links, series-compensated lines, and hybrid AC–DC systems. These networks may produce limited fault current, non-stationary transients, converter-controlled responses, frequency-dependent travelling-wave propagation, and reflection effects at converter or cable–overhead interfaces. Consequently, conventional overcurrent, impedance, distance, and differential protection schemes may lose sensitivity and accuracy under high-resistance faults, weak infeed, load encroachment, CT saturation, close-in faults, and converter-dominated conditions. This review analyses classical protection, travelling-wave methods, DWT, CWT, WTMM, WPT, S-transform, HHT, decaying DC methods, and intelligent classifiers including ANN, BPNN, SVM, decision tree, random forest, LSTM, RNN, and GCN. The study shows that travelling-wave and wavelet-based methods offer high-speed detection and accurate location, while intelligent methods improve classification when trained with diverse fault data. The review concludes that hybrid protection combining transient features, travelling-wave location, and machine-learning-assisted classification is a promising direction for practical transmission-line protection.**

Keywords—: HVAC transmission line, HVDC transmission line, fault detection, fault classification, fault location, travelling wave, distance protection, differential protection, signal processing, machine learning,

I. INTRODUCTION

Electric power transmission lines are among the most critical components of modern power systems because they provide the main path for bulk power transfer between generating stations, renewable energy plants, converter stations and load centres. Any fault on a high voltage transmission corridor can produce severe current surges, voltage depression, insulation stress, equipment damage and system instability. Therefore, transmission line protection must not only identify the occurrence of a fault, but must also classify the fault type, determine the faulty phase or pole, distinguish internal and external faults, and estimate the fault location with acceptable accuracy. Conventional protection philosophy has mainly relied on voltage and current measurements, but the extraction and interpretation of these signals have changed considerably with the development of digital relays, signal processing methods and intelligent diagnosis techniques [1], [2].

To address these issues, recent studies have proposed adaptive distance characteristics, active phase control and modified relay logic for renewable integrated transmission systems [3], [4]. Differential protection has also been improved by using signed correlation, current direction indicators and communication assisted decision logic, especially for lines connected to large scale wind farms [5], [6].

HVDC and hybrid AC DC transmission systems introduce another level of difficulty because converter stations, control actions and dc line characteristics alter the transient fault response. In LCC HVDC connected AC systems, commutation failure and fast converter dynamics can distort the steady state quantities used by classical phase selectors. High speed transient energy based phase selection has therefore been investigated for AC lines connected to LCC HVDC inverter stations [7]. For MMC HVDC and hybrid HVDC systems, travelling wave polarity, converter boundary reflection, frequency distortion and voltage or current travelling wave energy become important for fault location and directional pilot protection [8], [9]. These studies show that HVAC and HVDC fault diagnosis should not be treated using a single protection assumption.

Travelling wave methods have become an important research direction for high speed detection and accurate fault location in long transmission lines. A fault produces steep voltage and current wavefronts that travel from the fault point toward the line terminals. By measuring the arrival time, polarity and reflection of these wavefronts, the fault position can be estimated with high accuracy. Early travelling wave research developed maximum likelihood based location and GPS assisted travelling wave fault locator systems [10], [11]

Signal processing methods provide a strong foundation for detecting fault generated non stationary components. Wavelet transform, continuous wavelet transform, discrete wavelet transform, wavelet packet transform, S transform and Hilbert Huang transform have been used to identify transient singularities, decompose frequency bands, estimate wavefront arrival instants and generate fault features [12], [13]. DWT based methods can support detection, classification and location by extracting detail coefficients and energy features from voltage or current signals [14], [15]. Wavelet packet and multiwavelet entropy based features further improve the representation of transient information for fault recognition and classification [37], [38]. However, the performance of these approaches depends on sampling frequency, mother wavelet, decomposition level, threshold selection, noise level and feature selection strategy.

Intelligent techniques have also been applied to transmission line fault diagnosis because fault patterns are nonlinear and vary with fault type, resistance, location, inception angle and network condition. ANN, BPNN, SVM, decision tree, hidden Markov model, Kalman filter, LSTM and graph convolutional neural network based methods have been reported for fault detection, classification, zone identification and location support [16], [17], [18].ANN and BPNN methods can classify faults using voltage, current and sequence component features, while LSTM methods are suitable for time series fault data [19], [20]. GCN methods are useful when system topology and bus or line relationships are included in the learning process [21].

From the reviewed literature, it is clear that no single method is sufficient for all HVAC and HVDC transmission line fault scenarios. Classical impedance and distance methods are practical and widely accepted, but they may lose accuracy under converter dominated and high resistance conditions. Differential and pilot methods provide strong selectivity, but require reliable communication and synchronization. Travelling wave methods offer high speed and accurate location, but depend on high bandwidth measurements and correct wavefront identification. Signal processing methods improve transient feature extraction, but depend on transform settings and noise immunity.

II. Literature Review

Transmission-line fault protection has gradually shifted from conventional impedance, distance, and differential relay schemes toward fast transient-based, travelling-wave, wavelet-transform, and intelligent data-driven methods. Early and conventional protection studies mainly used voltage and current phasors, impedance calculation, directional comparison, and differential-current principles for fault detection and tripping decisions [22], [23]. These methods are useful for practical relay coordination, but their performance can be affected by renewable-energy integration, CT saturation, fault resistance, synchronization error, and changing grid operating conditions.

Recent studies have focused on transient components because fault-generated high-frequency signals appear immediately after fault inception. Transient-energy-based relaying, synchronous squeezed S-transform, incremental active-power signum logic, decaying DC information, and high-speed transient-information methods have been used for fast fault detection, phase selection, and protection decision making [24],[25].

Travelling-wave and wavelet-based methods are highly suitable for fault-location studies because they use the first arrival time, reflected wavefronts, wavelet modulus maxima, and time-frequency characteristics of fault transients [16], [27], [28], These approaches can provide high-speed and accurate location results, especially for long HVAC transmission lines. However, their accuracy depends on proper wave-speed selection, high sampling rate, noise immunity, sensor bandwidth, and correct identification of the first or second travelling-wave front. Therefore, travelling-wave methods are powerful but require careful signal processing and validation under different fault types, fault resistance values, and line conditions.

Artificial-intelligence and machine-learning-based methods have also been widely applied for transmission-line fault detection, classification, and location. ANN, BPNN, LSTM, GCN, SVM, decision tree, hidden Markov model, and other learning-based techniques use voltage, current, sequence components, waveform patterns, and sometimes grid-topology information to identify different fault types [28]–[30], [42]–[45]. These methods can learn complex nonlinear fault patterns, but their reliability depends strongly on the quality, size, and diversity of the training dataset. Many studies are still limited to simulation-based datasets and require further testing under real-time, noisy, renewable-integrated, and unseen operating conditions.[43],[44].

Overall, the reviewed literature shows that no single method is fully sufficient for all fault scenarios. Conventional relays are reliable but slower or less adaptive under modern grid conditions; transient and travelling-wave methods are fast but require accurate signal capture; and AI-based methods are flexible but dataset-dependent. This direction is strongly supported by the reviewed works, which highlight the need for fast operation, high location accuracy, reduced communication dependency, and improved performance under high fault resistance, renewable penetration, noise, and variable operating conditions[31],[32]

TABLE I COMPARATIVE SUMMARY OF TRANSMISSION-LINE FAULT PROTECTION TECHNIQUES

Category	Main Technique	Main Signal / Feature	Refs.	Main Gap
Conventional and adaptive relay protection	Distance, differential, quadrilateral, directional and backup protection.	Voltage-current phasors, impedance and current comparison.	[3], [7], [8], [14], [19], [20]	Sensitive to grid-condition variation, CT saturation, synchronization error and renewable integration.
Transient-based protection	Transient energy, SST, incremental power, decaying-DC and high-speed transient logic.	Initial fault transients, active-power sign and decaying-DC current.	[1], [2], [4], [15], [18], [20]	Requires accurate transient extraction; sensitivity can reduce for high-resistance or weak-inception faults.
Travelling-wave protection and location	Wave front arrival time, reflected waves, equivalent TW and adaptive waveform similarity.	Voltage/current travelling waves, WTMM and arrival-time difference.	[16], [22]-[24], [27], [28], [46]	Needs high sampling rate, correct wave-speed estimation and noise-resistant wavefront detection.
Wavelet and time-frequency methods	DWT, CWT, WPT, S-transform, HHT and multi wavelet processing.	Wavelet coefficients, modulus maxima and time-frequency features.	[31]-[41]	Threshold selection, signal noise and practical sensor bandwidth affect accuracy.
AI and deep-learning methods	ANN, BPNN, LSTM, GCN, SVM, decision tree and HMM.	Voltage/current data, sequence components, fault-pattern and topology features.	[9]-[13], [42]-[45]	Dataset-dependent; limited validation for unseen and real-time operating conditions.
Review and taxonomy studies	Comparative review of classical, signal-processing, TW, AI and hybrid methods.	Multiple electrical and intelligent fault features.	[11], [21]	Useful for research justification but does not provide one complete practical relay algorithm.

III. Fault Types and Protection Requirements in HVAC/HVDC Transmission Lines

This section should define the fault environment before comparing algorithms. For HVAC lines, include LG/SLG, LL, LLG and LLL/LLLG faults.

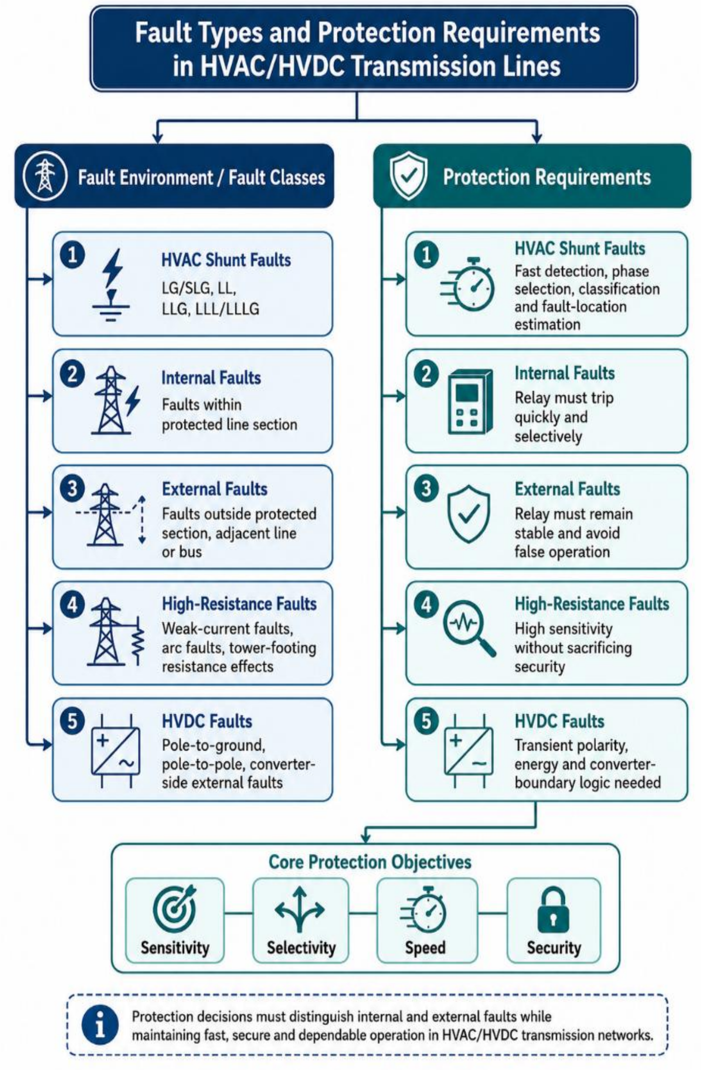

Fig. 1. Fault types and protection requirements in HVAC/HVDC transmission lines.

For HVDC lines, include pole-to-ground and pole-to-pole faults. Internal and external faults must be separated because the primary relay decision is either secure tripping or stable blocking.[41],[42]

The protection theory should emphasize four attributes: sensitivity, selectivity, speed and security. Sensitivity is required for high-resistance and weak-infeed faults; selectivity avoids tripping healthy lines; speed is needed for stability and equipment safety; and security avoids maloperation under noise, CT saturation, communication delay and converter transients.

III. TAXONOMY OF FAULT DETECTION AND LOCATION TECHNIQUES

After fault types are introduced, the next section should classify available methods according to

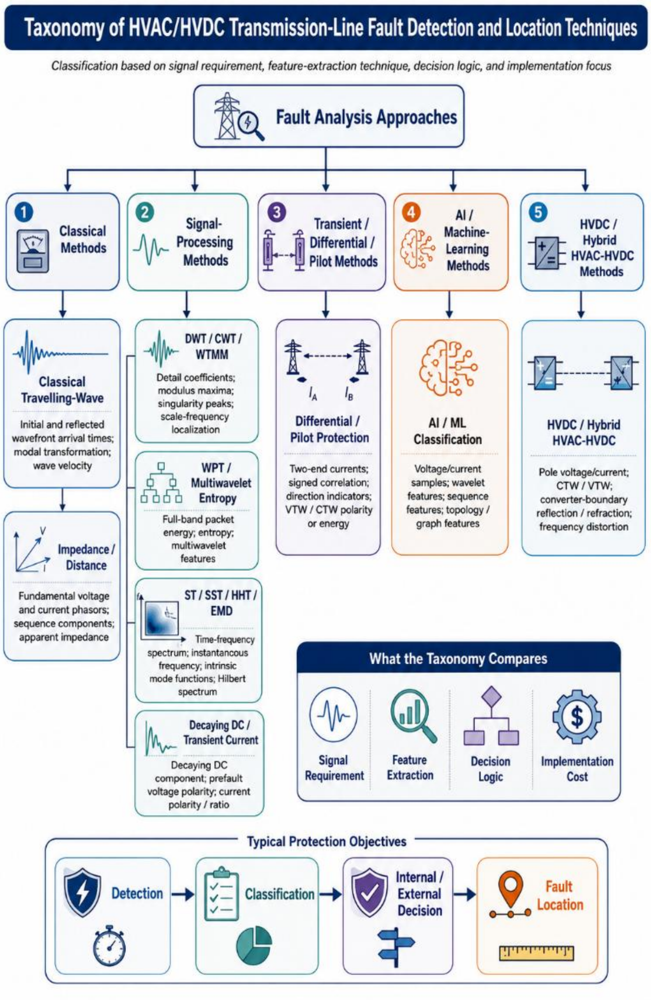

Fig. 2. Taxonomy of HVAC/HVDC transmission-line fault detection and location techniques

signal requirement, feature-extraction technique, decision logic and implementation cost. This avoids a purely descriptive review and makes the paper decision-oriented.[33],[34

III A. CLASSICAL PROTECTION AND LOCATION METHODS

Classical methods are main because they represent the industrial standard. Overcurrent relays are simple but may drop sensitivity in converter fed systems because fault current is limited and controlled. Distance relays use apparent impedance and are easy to coordinate in zones, but their reach may be affected by fault resistance, load flow, infeed, mutual coupling, series compensation and converter phase control [35], [29].

Differential and pilot protections improve selectivity by comparing two end currents or directional quantities. However, their practical performance depends on communication channel availability, synchronization accuracy, CT saturation tolerance and line charging-current compensation [35], [36]. Therefore, classical methods should be presented as baseline and backup solutions rather than complete answers for every modern HVAC/HVDC condition.

Table I. Classical Protection and Location Methods

Fault Analysis Approach	Main principle
Overcurrent / directional OCR	Current magnitude and direction thresholds
Impedance / distance	Apparent impedance from voltage/current phasors
Differential protection	Two-end current comparison
Pilot protection	Communication-assisted directional or differential decision

III B. SIGNAL-PROCESSING AND TRAVELLING-WAVE-BASED METHODS

Fault inception creates non-stationary high-frequency components that cannot be fully represented by fundamental phasors. Wavelet transform, DWT, CWT, WPT, S-transform, SST, HHT/EMD, mathematical morphology and decaying DC extraction are used to reveal transient singularities, energy concentration, frequency shifts and travelling-wave arrival instants [31], [34].

DWT/CWT and WTMM are particularly suitable for identifying first and reflected wavefronts, while WPT and entropy-based features improve classification. S-transform and HHT are useful when frequency varies strongly with time, especially in HVDC or converter-dominated systems [39], [41].

Travelling-wave methods are among the strongest candidates for long HVAC line fault location because they use the first high-frequency transients generated at the fault point. A two-terminal method estimates fault distance from arrival-time difference at both terminals, whereas a single-ended method uses initial and reflected waves recorded at one terminal [37], [46].

The review should highlight that constant wave velocity is a simplification. Recent studies show that propagation velocity can depend on frequency, line geometry, cable/overhead sections and converter boundaries. Hence, the comparison should state whether a method assumes fixed velocity, corrects velocity using time-frequency information, or models frequency-dependent electrical parameters [23], [25].

Table II. Fault Analysis Parameters and Assessment Criteria

Fault Analysis Parameter	Assessment Parameter
Fault cases	LG/SLG, LL, LLG, LLL/LLLG, pole-to-ground, pole-to-pole, internal and external faults.
Fault location	Near-end, mid-line, remote-end; multiple distances such as 50, 100, 150, 200, 250, 350 km for a 400 km line.
Fault resistance	Low to high resistance; e.g., 0.01 ohm to hundreds or 1000 ohm depending on system.
Fault inception angle	0 deg, 30 deg, 60 deg, 90 deg or random inception angle.
Measurement and sampling	Sampling rate, synchronized/unsynchronized data, GPS, sensor bandwidth, CVT/CT limitations.
Signal feature	Voltage/current, phasor, sequence, DWT/CWT coefficients, WTMM, energy, entropy, CTW/VTW.
Performance metric	Detection time, classification accuracy, location error km/%, reliability/security, false trip rate.
Robustness factors	Noise, load variation, renewable penetration, CT saturation, communication delay, topology change.

III C. AI AND MACHINE-LEARNING-BASED FAULT DIAGNOSIS

AI and machine-learning methods are useful because fault patterns are nonlinear and vary with system condition. ANN, BPNN, SVM, decision tree, random forest, LSTM and GCN can classify fault type or fault zone using voltage/current samples, sequence components, wavelet coefficients or topology-aware graph features [9], [10].

However, AI performance depends strongly on training-data quality, fault diversity, unseen operating conditions, noise, high-resistance faults and topology changes. Therefore, in this review, AI should be presented as a strong classification layer after physically meaningful feature extraction rather than as a complete replacement for power-system protection logic [13], [45].

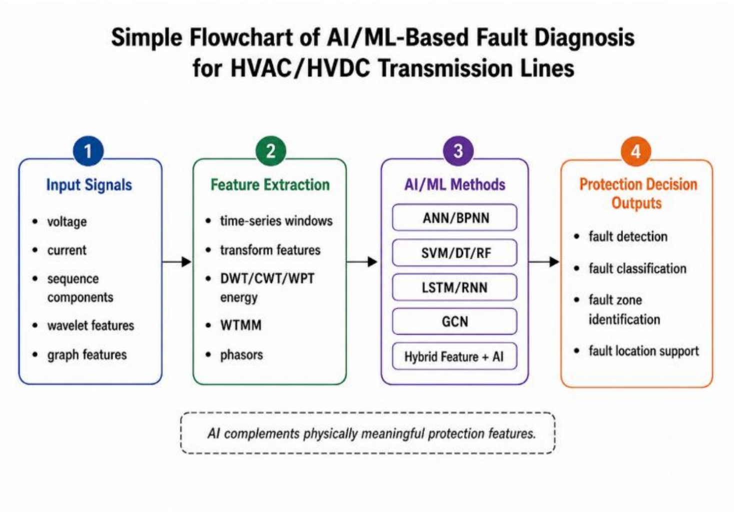

Fig. 3. Simple flowchart of AI/ML-based fault diagnosis for HVAC/HVDC transmission lines.

IV. CONCLUSION

This review establishes that transmission-line fault diagnosis has evolved from conventional overcurrent, impedance and differential principles toward high-speed transient analysis, travelling-wave location, advanced signal processing and intelligent data-driven decision making. The evolution is driven by the changing behavior of modern HVAC/HVDC networks, where renewable integration, DFIG wind farms, converter-interfaced resources, series compensation and hybrid AC-DC corridors alter fault-current magnitude, phase, frequency content and wave-propagation characteristics. Therefore, the protection objective is no longer limited to detecting overcurrent or calculating apparent impedance; it must also ensure fast fault detection, correct phase or pole classification, secure internal/external discrimination and accurate fault-location estimation under diverse operating and disturbance conditions.[38],[39]

Travelling-wave-based protection and location methods provide one of the strongest technical directions for long HVAC and HVDC lines because the first high-frequency transients generated at the fault point can support very fast operation and accurate distance estimation. Their main strength is reduced dependence on load flow and source impedance. Their practical limitations are the need for high sampling rate, high-bandwidth measurement, modal transformation, wavefront identification, synchronization or communication, and accurate propagation velocity. Recent frequency-dependent, time-frequency and adaptive waveform-similarity approaches show that fixed wave velocity is not sufficient for hybrid cable-overhead lines, long EHV corridors or converter-boundary-dominated HVDC systems.[40],[41]

Signal-processing methods such as DWT, CWT, WTMM, WPT, S-transform, SST, HHT/EMD, mathematical morphology and decaying-dc extraction are central to modern fault diagnosis

because they convert non-stationary voltage and current transients into measurable features. DWT/CWT and WTMM are particularly suitable for first-arrival and singularity detection, WPT and entropy features improve classification information, ST/SST/HHT are useful fo strongly time-varying converter transients, and decaying-dc or transient-current polarity methods provide fast protection indicators. Nevertheless, their performance depends on the selected mother wavelet or transform, decomposition level, threshold, sampling frequency, noise level and feature-selection strategy.

AI and machine-learning techniques improve the classification and decision-making stage by learning nonlinear relations between fault features and fault type, phase, zone or location class. ANN/BPNN, SVM, decision tree, random forest, LSTM/RNN and GCN methods can process voltage/current samples, sequence components, wavelet coefficients, time-series windows and topology-aware graph features. However, AI-only protection is not sufficient unless the training data represent multiple fault types, locations, fault resistances, inception angles, loading levels, renewable penetration, noise levels and topology changes. Therefore, AI should complement physically meaningful protection features instead of replacing power-system protection logic.

For the reviewed HVAC/HVDC transmission-line protection problem, the most suitable research direction is a hybrid protection and location framework. For a long HVAC line, DWT/CWT or WTMM-based transient extraction can be used for fast fault inception detection; phase-wise energy, sequence or sign-based features can support LG, LL, LLG and LLL/LLLG classification; and double-ended travelling-wave timing, frequency-corrected velocity or adaptive waveform similarity can provide accurate fault-location estimation. For HVDC and hybrid AC-DC networks, CTW/VTW polarity, transient energy, converter-boundary reflection/refraction and frequency-modified travelling-wave logic should be consider separately because HVDC fault behavior is system-specific.

The key research gaps identified from the review are fixed velocity assumptions in travelling-wave location, weak detection of high-resistance and low-inception-angle faults, ambiguity in single-ended reflected-wave identification, limited field or real-time validation, insufficient standardized benchmark datasets, limited AI interpretability, and inadequate consideration of converter-dominated transient behavior. Future research should focus on standardized simulation and experimental datasets, OPAL-RT/RTDS or field validation, explainable AI models, frequency-dependent line modelling, and protection schemes that remain secure under communication delay, CT/CVT limitations, noise and topology variation.

V. Future Work

Future research in HVAC and HVDC transmission line protection should move toward intelligent, fast and adaptive fault diagnosis schemes that can operate reliably under modern grid conditions. Conventional overcurrent, distance and differential relays remain important as industrial baseline methods, but their performance can be affected by high fault resistance, weak infeed, converter controlled current, series compensation and renewable integration [3], [5], [7], [19]. Therefore, future protection schemes should combine physical protection principles with high speed transient analysis, travelling wave theory, wavelet based feature extraction and intelligent decision logic.

Travelling wave based fault location is a strong future direction because it can provide very fast and accurate estimation of fault position in long transmission lines. The arrival time of initial and reflected wavefronts can be used to locate the fault with less dependence on load flow and source impedance. However, future work should address practical issues such as wavefront detection, synchronization, sensor bandwidth, noise and wave velocity correction [22], [24], [46]. Frequency dependent travelling wave methods should also be studied for hybrid cable overhead lines and HVDC systems, where propagation velocity, reflection and refraction vary with line structure and converter boundary conditions [23], [25], [26].

Discrete wavelet transform, continuous wavelet transform and wavelet transform modulus maxima can be further used to extract high frequency fault transients from voltage and current signals. These methods are useful because fault inception produces non stationary components that are not clearly visible in fundamental frequency phasors. Future studies should compare different mother wavelets, decomposition levels, threshold values, sampling rates and feature energy indices to improve detection accuracy under LG, LL, LLG and LLL faults [31], [34], [35], [36]. Wavelet packet transform and entropy based features may also be explored for improved fault classification under noisy signals and high resistance faults [37], [38].

A major future direction is the use of LSTM based neural networks for transmission line fault detection and classification. In this approach, normal voltage and current waveforms can be used to train the model, and abnormal fault conditions can be detected when the reconstruction error or sequence prediction error increases sharply. This is useful because it reduces the need to manually define every possible fault pattern. Future work should test LSTM models for different fault types, fault resistances, inception angles, loading conditions and fault locations along the transmission line [13]. Other intelligent models such as ANN, BPNN, SVM, decision tree and GCN can also be compared using the same dataset to identify the most reliable classifier for practical protection applications [9], [10], [12], [44], [45].

A hybrid travelling wave, DWT and LSTM based protection framework can be considered as a promising direction for future research. In such a scheme, travelling wave arrival time can be used for fast fault location, DWT or CWT can be used for transient feature extraction, and LSTM or other machine learning models can be used for fault type classification and decision support. This combination can improve protection speed, selectivity, sensitivity and accuracy under high resistance faults, noisy measurements, renewable penetration and changing operating conditions [21], [22], [35], [36]. The hybrid scheme should be evaluated using clear performance indices such as detection time, classification accuracy, absolute location error, percentage location error, false trip rate and robustness under different system conditions.

Another important research direction is the protection of converter dominated and hybrid AC DC networks. LCC HVDC, MMC HVDC and renewable integrated systems can change the magnitude, phase and frequency content of fault currents. Therefore, future protection logic should include converter boundary effects, pole to ground faults, pole to pole faults, CTW and VTW polarity, transient energy and frequency modified travelling wave features [2], [25], [26]. This will make the protection scheme more suitable for future smart grids where HVAC lines, HVDC links and renewable sources operate together.

Overall, future work should aim to develop a physics guided intelligent protection scheme for long HVAC transmission lines, with possible extension to HVDC and hybrid AC DC networks. The most suitable direction is to combine travelling wave based location, DWT or CWT based transient extraction and machine learning based classification. Such a method should be validated under different fault types, fault resistances, inception angles, line lengths, noisy conditions and renewable penetration levels to ensure reliable operation in practical transmission systems.

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