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Impact of Noise on Fault Classification in High-Voltage Transmission Lines Using LVQ Neural Networks

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Abstract – *Accurate fault detection and classification in high-voltage transmission lines are essential to ensure system reliability and operational safety. However, the presence of noise and transient disturbances often degrades the accuracy of conventional protection schemes. This study investigates the impact of Gaussian noise on fault classification performance using a neural network-based framework combined with Discrete Wavelet Transform (DWT) and Fast Fourier Transform (FFT) feature extraction. Four types of faults, single line to ground, line to line, double line to ground, and three phase to ground were simulated on a 150 kV transmission system using ATPDraw under various noise levels of 40 dB. Linear Discriminant Analysis (LDA) and Learning Vector Quantization (LVQ3) were employed for feature reduction and classification, respectively. The proposed model achieved a test accuracy of 98.84% under noise-free conditions and 96.80% under noisy conditions, outperforming traditional classifiers such as Support Vector Machine (SVM) and Decision Tree (DT). Results indicate that incorporating time-frequency domain features with noise-resilient neural architectures significantly enhances classification robustness and reliability. This research contributes a novel approach for noise-tolerant fault classification, offering practical potential for real-world implementation in intelligent protection systems and smart grid applications.*

Keywords – *Fault Classification; DWT; FFT; LVQ3; High-Voltage Transmission.*

I. Introduction

HIGH-voltage transmission lines are critical infrastructures responsible for transferring electric power from generation centers to substations and distribution networks. However, due to their extensive length and exposure to environmental and operational conditions, transmission lines are among the most fault-prone components in modern power systems [1, 2]. Faults on transmission lines can lead to widespread outages, voltage instability, and damage to expensive equipment, making accurate and fast fault detection and classification vital for maintaining system reliability [3]. Moreover, the presence of noise and signal distortion during measurement processes complicates the detection task, reducing the reliability of traditional protection schemes [4].

Conventional protection methods based on impedance and differential principles often suffer from limited performance when facing high-impedance faults or noisy signals [5]. As an improvement, signal processing techniques such as Discrete Wavelet Transform (DWT), Empirical Mode Decomposition (EMD), and Clarke Transform have been applied to extract transient features from current and voltage signals [6]. For instance, the combination of DWT and Support Vector Machine (SVM) has achieved classification accuracy up to 90% for several fault types including line-to-ground and line-to-line faults [7]. Similarly, EMD-based approaches demonstrate flexibility in capturing nonlinear and non-stationary characteristics of fault signals [8]. Despite these advances, many existing approaches still rely on idealized data and lack robustness under real operating conditions, particularly in the presence of measurement noise [9].

The emergence of machine learning techniques has provided new opportunities to improve fault analysis and classification performance in complex power networks. Algorithms such as Decision Tree (DT), Random Forest (RF), and Gradient Boosting (GB) have been successfully employed to identify fault causes and patterns in both transmission and distribution systems [10, 11]. Moreover, hybrid methods combin-

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ing DWT with Learning Vector Quantization (LVQ) neural networks have shown superior classification performance with high computational efficiency [12]. Nonetheless, the majority of these studies remain confined to offline or simulation-based evaluations and have not been comprehensively validated under realistic noise and simulation-based implementation conditions [13]. While some recent research incorporating neural network and signal analysis achieved detection accuracies above 95%, as shown in Table 1.

Although various fault detection and classification methods have been developed, several important research gaps remain unaddressed [14]. Most existing algorithms are designed and tested on noise-free simulation data, neglecting the influence of measurement noise that inevitably occurs in actual power systems [15]. As a result, their accuracy and reliability significantly decrease when deployed in field conditions. In addition, few approaches have been optimized for simulation-based implementation, despite the crucial importance of rapid detection and response in protection systems [16]. Another limitation lies in the generalization capability of most models, which are typically tuned for specific network configurations and fail to adapt when system parameters or fault scenarios vary [17]. These limitations highlight the need for a method that combines the learning capability of neural networks with adaptive signal preprocessing techniques to achieve robustness under noisy environments while maintaining simulation-based implementation performance [18].

The novelty of this research lies in the development of a neural network-based, simulation-based implementation fault classification framework specifically engineered to withstand measurement noise and operational uncertainty [19]. Unlike previous studies that solely evaluated fault classification using noise-free or idealized data, this work systematically quantifies the impact of multiple Gaussian noise levels (20–40 dB) on classification performance utilizing hybrid DWT–FFT features. The proposed method integrates a noise-resilient feature extraction process, based on time–frequency transformation, with an adaptive neural network structure to enhance both classification accuracy and response time. Furthermore, the use of LVQ3 with preprocessed LDA features for noise robustness in high-voltage transmission lines has not been comprehensively evaluated before, filling a critical gap in the existing literature. Beyond improving classification performance, this study also provides a quantitative analysis of the impact of noise on protection reliability and evaluates the model's robustness under field-like operating conditions [20].

Consequently, the proposed framework offers a significant contribution to the advancement of intelligent protection systems that are not only accurate and fast but also robust, adaptive, and highly suitable for modern smart grid transmission networks.

Table 1: Comparison of Research Methods

Ref	Conventional	NN	Method	Noise	Real Time / Accuracy
[21]	Yes	No	SVM	No	∼94–97% (SVM classification, improved with db7)
[22]	No	Yes	SVM	No	95–97% (SVM classification under various conditions)
[5]	Yes	No	Decision Tree	No	∼92–95% (Decision Tree)
[23]	No	Yes	Decision Tree	No	∼95–97% (RF/GB outperform Distance Relay)
[6]	No	Yes	LVQ	No	∼93–96% (LVQ ANN classification)
[14]	Yes	No	DWT + Clarke + Traveling Wave	Yes	96.3% (harmonic), 90.75% (transient)

II. Research Methods

The research methodology in this study is systematically designed to analyze the influence of measurement noise on the accuracy, stability, and reliability of simulation-based fault classification in high-voltage transmission lines using a neural network framework [21]. To achieve this objective, an experimental simulation-based approach is implemented in MATLAB/Simulink (R2024b), allowing detailed modeling of transmission parameters such as line impedance, fault resistance, and load variations. This setup enables accurate evaluation of classification performance and analysis of algorithm robustness under various noise and disturbance levels. Moreover, MATLAB/Simulink integrates signal processing tools for efficient time–frequency feature extraction, ensuring the proposed neural network model is well validated and optimized for practical power system applications [22]. The overall methodological flow of the study is illustrated in Figure 1.

i. Transmission System Modeling

The high-voltage transmission line is modeled in MATLAB/Simulink (R2024b) to represent realistic power system conditions, including line impedance, length, and power transfer capacity. This simulation-based approach is widely adopted in recent studies due to its flexibility in generating various fault scenarios and operating conditions [23]. Previous research has demonstrated the importance of MATLAB/Simulink-based simulation for fault classification. Anwar *et al.* applied ensemble machine learning for fault detection and emphasized the need for simulation-based implementation and noisy testing. Similarly, Asman *et al.* modeled a

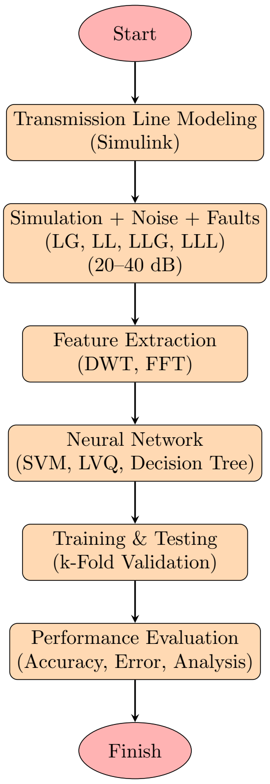


Figure 1: Fault Detection and Classification Flowchart

275 kV transmission line using RMS–DWT to support Decision Tree classification. These findings confirm that mathematical modeling within simulation environments effectively validates classification algorithms prior to real-system implementation [24].

Furthermore, the methodology incorporates the addition of measurement noise and transient disturbances to emulate realistic field conditions that modern power systems frequently encounter. Each stage of the research process is carefully structured to replicate real-world environments, ensuring that the proposed classification model can operate effectively under noisy and uncertain conditions [25].

ii. Fault Simulation and Noise Injection

Fault scenarios are simulated to replicate common real-world events in high-voltage transmission lines. Four major fault types are considered: Single Line-to-Ground (LG), Line-to-Line (LL), Double Line-to-Ground (LLG), and Three-Phase Fault (LLL). To ensure robustness, each fault is combined with additive Gaussian noise at 40 dB and transient frequencies of 5 kHz representing realistic measurement noise conditions [26]. Rodríguez-Herrejón *et al.* reported that noise significantly affects traveling-wave-based detection in UPFC-compensated systems, while Anwar *et al.* highlighted the necessity of evaluating fault detection under noisy environments to approximate simulation-based implementation applications.

iii. Signal Feature Extraction

Discrete Wavelet Transform (DWT) is employed to analyze non-stationary transient signals by decomposing them into time–frequency components, allowing precise identification of high-frequency fault signatures. Magagula *et al.* achieved 96% accuracy in 88 kV distribution networks using DWT–SVM [26]. Fast Fourier Transform (FFT) is used to extract spectral features and detect harmonic or sudden frequency changes. Asman *et al.* combined RMS and DWT for 275 kV fault classification and reported improved accuracy when frequency-domain features were included. The combination of DWT and FFT is expected to yield more discriminative features, enabling SVM, LVQ, and Decision Tree to perform effectively in noisy environments [27].

iv. Classification Using Neural Networks

Three algorithms are utilized: Support Vector Machine (SVM), Learning Vector Quantization (LVQ), and Decision Tree (DT).

1. **SVM:** Provides optimal margin separation and is robust to noisy data, achieving up to 97% accuracy in DWT-based classification [10].
2. **LVQ:** A prototype-based neural network suitable for fast multiclass classification. Wavelet–LVQ to 400 kV systems with high performance under varying fault angles and resistances.
3. **DT:** Offers high interpretability and handles multi-attribute data effectively, as shown by Asman *et al.* [13] using RMS–DWT–DT for 275 kV fault classification.

The selection of these algorithms balances accuracy, speed, and interpretability critical for simulation-based implementation fault classification in transmission systems [28].

For the LVQ3 training process, the learning rate was initialized at 0.05 and adaptively reduced to 0.01 per epoch, with a total of 100 training epochs. The number of competitive neurons was set to 20, ensuring sufficient representation for all fault categories. These parameters were empirically optimized based on validation performance to achieve fast convergence and strong generalization.

v. Training and Testing

The dataset generated from DWT and FFT feature extraction is evaluated using 10-fold cross-validation to minimize overfitting and obtain stable performance estimates. In this procedure, the data is divided into ten equal subsets; nine subsets are used for training and one for testing in each iteration, and the final performance is obtained by averaging the results. This method offers a more reliable assessment than a single train–test split, especially when dealing with noisy or imbalanced data. Anwar *et al.* [9] successfully applied cross-validation in ensemble machine learning models (Random Forest, KNN, LSTM) for transmission fault classification and demonstrated improved robustness against noise. Therefore, 10-fold cross-validation is considered appropriate in this study to ensure that the SVM, LVQ, and Decision Tree classifiers achieve high accuracy, strong generalization, and consistent performance under measurement noise.

vi. Performance Evaluation

Algorithm performance is assessed using classification accuracy, error rate, and system response time. A comparative analysis is conducted to identify the most noise-resilient algorithm and determine its suitability for simulation-based implementation in transmission protection systems [9, 12, 14].

vii. Sensitivity Analysis

To further assess the robustness of the proposed model, a sensitivity analysis was conducted by varying key fault parameters, including fault resistance (5 Ω–50 Ω) and fault inception angle (0°–90°). The resulting classification accuracy showed variations below 2%, indicating that the LVQ3 model maintains stable performance despite parameter fluctuations. This confirms that the proposed method exhibits strong resilience against both electrical and measurement uncertainties [14].

In the exploratory phase of this research, several alternative classifiers-including Random Forest, Gradient Boosting, and shallow CNN architectures-were evaluated to establish a broader comparison baseline. While these models exhibited competitive accuracy in noise-free scenarios, their performance degraded more significantly under Gaussian noise conditions, and their computational cost was notably higher. Based on these findings, the LDA-LVQ3 architecture was selected as the primary model due to its superior noise resilience, lower complexity, and suitability for rapid simulation - based implementation.

III. Results and Discussion

A simulation model of a 150 kV high-voltage transmission line was built using ATPDraw software. This circuit represents a comprehensive transmission system that includes a voltage source, transmission line, load, and multiple measurement points at both ends of the line (A and B). The model allows for the analysis of voltage and current waveforms under various noise conditions, enabling deeper understanding of how external disturbances affect the stability and performance of power transmission networks. Through this model, researchers can simulate real-world high-voltage transmission scenarios and evaluate the effectiveness of noise mitigation techniques.

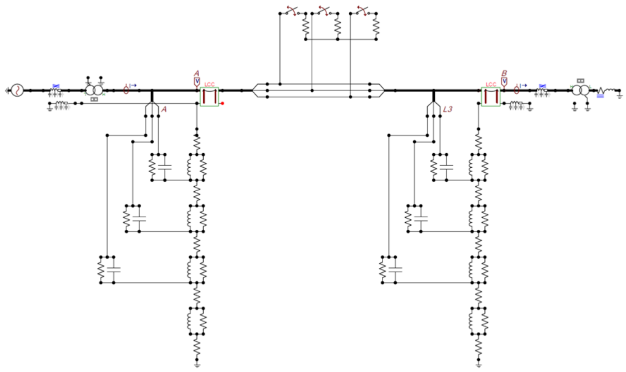


Figure 2: ATP Circuit Model for Fault Simulation Under Noise-Free Condition

Figure 2 shows the simulation model of a 150 kV high-voltage transmission line developed using ATPDraw software. The circuit includes a three-phase voltage source, transmission line, and load, with measurement points at both terminals (A and B) to observe voltage and current waveforms under various disturbance conditions. The model represents the distributed parameters of the line and includes surge arresters, grounding, and noise sources to simulate realistic transient behaviors. This configuration enables the analysis of voltage stability, transient propagation, and the impact of noise on the performance of high-voltage transmission systems.

Subsequently, simulations were carried out to obtain the voltage waveform results under noise-free conditions for various types of faults in the 150 kV transmission line system. Each subfigure (a–d) represents a specific fault scenario, namely single line-to-ground, line-to-line, double line-to-ground, and three-phase-to-ground faults. These graphs illustrate the transient voltage response of each phase during the occurrence of faults and system recovery, providing a clear comparison of the system's behavior in the absence of external noise disturbances.

Figure 3 presents the voltage waveforms of a three-phase electrical system under various fault conditions without external noise. Subfigure (a) shows a single-phase-to-ground fault where one waveform is distorted while others remain sinusoidal. In (b), a two-phase fault produces disturbances in two waveforms, while (c)

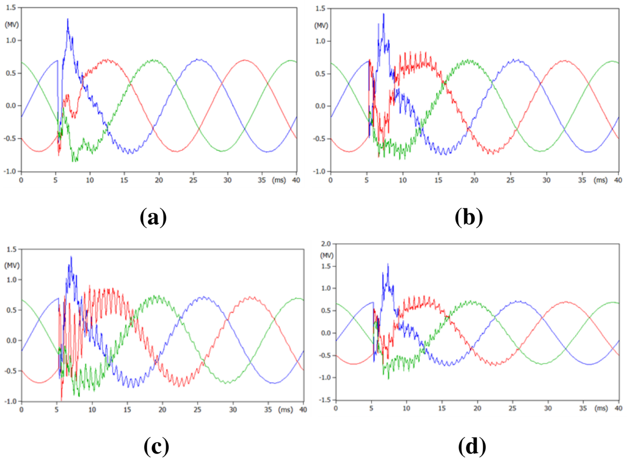


Figure 3: Voltage waveforms of various fault types under noise-free conditions (a) Single line-to-ground fault (b) Double line fault (c) Double line-to-ground fault (d) Three-phase-to-ground fault

displays a two-phase-to-ground fault characterized by reduced amplitude and distortion in two phases. Subfigure (d) illustrates a three-phase-to-ground fault, where all waveforms experience severe distortion and amplitude decay. These variations indicate that the type of fault directly affects waveform symmetry and harmonic distortion, providing valuable information for fault detection and power system protection analysis.

To further evaluate the classification performance of the proposed fault detection model, a confusion matrix was constructed using the LDA and LVQ3 methods, as shown in Figure 4. The confusion matrix provides a detailed comparison between the true and predicted classes, illustrating the system's accuracy in distinguishing different fault types. This analysis complements the waveform interpretation presented earlier, offering quantitative evidence of the model's effectiveness in accurately identifying multi-phase fault conditions within the three-phase electrical system.

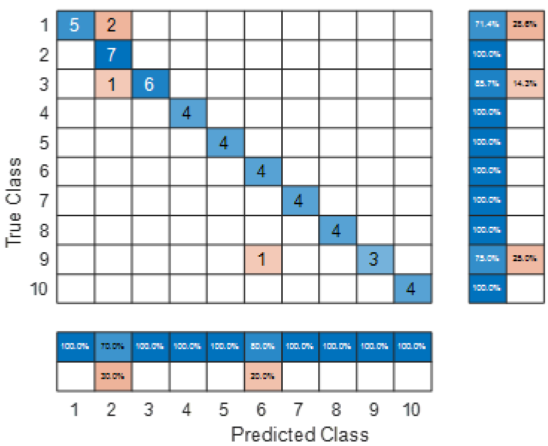


Figure 4: Confusion Matrix of the LDA + LVQ3 Classification Model without Noise

The confusion matrix presented in Figure 4 validates the robust classification performance of the LDA + LVQ3 model, achieving an overall test accuracy of 98.84%. This quantitative analysis, which complements the waveform interpretation, shows that the model successfully differentiates most fault types, notably achieving a 100% recall rate for Classes 4 through 8 and Class 10.

However, the matrix identifies minor classification ambiguities: Class 1 had two samples incorrectly predicted as Class 2, resulting in a 71.4% recall, and Class 9 had one sample misclassified as Class 6, lowering its recall to 75.0%. These instances suggest subtle feature overlaps between specific fault conditions, yet the overall high accuracy confirms the model's effectiveness in accurately identifying multi-phase fault conditions within the three-phase electrical system.

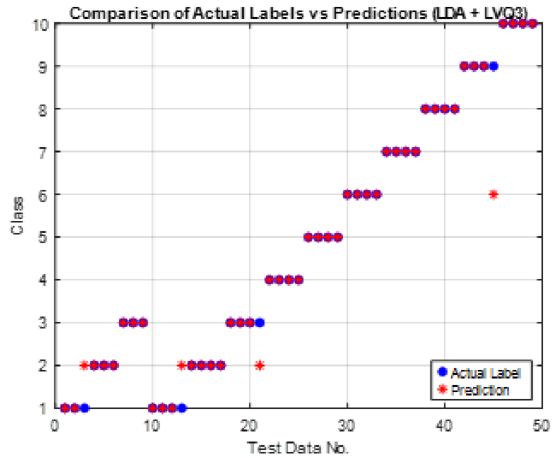


Figure 5: Comparison of Actual and Predicted Class Labels Using LDA + LVQ3 Model without Noise

Figure 5 provides a detailed visual confirmation of the classification performance by plotting the Actual Labels (blue dots) against the model's Predictions (red stars) for each test data point. The close clustering and near-perfect overlap of the predictions with the actual labels visually reinforce the high accuracy recorded in the confusion matrix (Figure 4), particularly for classes with flawless recall (Classes 4 through 8 and Class 10), where no red stars deviate from the blue dots. Crucially, the plot also clearly illustrates the specific misclassification events identified in Figure 4: two test samples belonging to Class 1 were incorrectly predicted as Class 2 (visible near test data points 2 and 5), and one sample from Class 9 was erroneously classified as Class 6 (around test data point 45). Overall, the tight distribution of data points along the identity line visually attests to the model's strong discriminatory capacity and confirms the high generalizability achieved by the LDA + LVQ3 method.

i. *Disturbance Under Noise Condition*

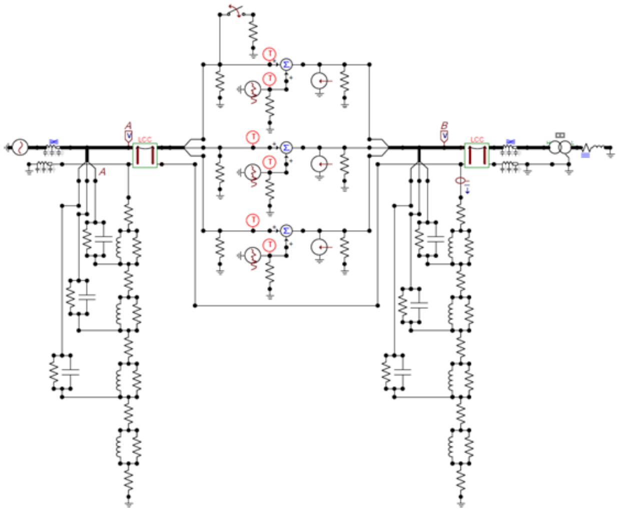
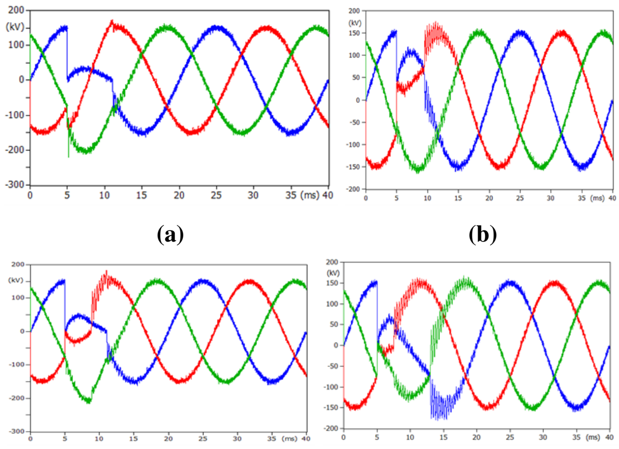


Figure 6: ATP Circuit Model for Fault Simulation Under Noise Condition



(a) (b) (c) (d)

Figure 7: Voltage waveforms of different fault conditions under noisy environment (a) Single line-to-ground fault (b) Double line fault (c) Double line-to-ground fault (d) Three-phase-to-ground fault

A simulation model of a 150 kV high-voltage transmission line was built using ATPDraw software. This circuit represents a comprehensive transmission system that includes a voltage source, transmission line, load, and multiple measurement points at both ends of the line (A and B). The model allows for the analysis of voltage and current waveforms under various noise conditions, enabling deeper understanding of how external disturbances affect the stability and performance of power transmission networks. Through this model, researchers can simulate real-world high-voltage transmission scenarios and evaluate the effectiveness of noise mitigation techniques.

To analyze the behavior of the transmission system under various fault conditions, simulations were performed on a 150 kV transmission line model using ATPDraw software. The voltage waveform responses for different fault types are presented in Figure 7, which illustrates the system's transient characteristics during single and multiple phase-to-ground faults.

To evaluate the impact of noise and fault disturbances on the high-voltage transmission system, a series of fault simulations were carried out using the ATPDraw model. Figure 7 presents the voltage waveform responses for different types of faults occurring on the 150 kV transmission line.

In Figure 7(a), the single line-to-ground fault causes a significant voltage drop in one phase, while the other two phases remain relatively stable. In Figure 7(b), the double line fault results in an interaction between two phases, producing oscillations and distortion in the voltage waveform. In Figure 7(c), the double line-to-ground fault introduces a higher level of disturbance, with visible transient components at the moment of fault initiation. Finally, Figure 7(d) illustrates the three-phase-to-ground fault, where all phases experience severe voltage collapse and high-frequency noise, indicating the most critical condition for system stability.

These waveform patterns provide valuable insights into how different fault types affect system performance, particularly in terms of voltage imbalance, transient behavior, and electromagnetic interference that may propagate through the transmission network.

To evaluate the performance of the proposed classification method, a confusion matrix was generated for the combination of Linear Discriminant Analysis (LDA) and Learning Vector Quantization 3 (LVQ3) algorithms, as shown in Figure 8. The matrix presents the relationship between the true classes and the predicted classes, illustrating the overall classification accuracy of 91.84%. This result demonstrates that the integrated use of LDA and LVQ3 is capable of effectively distinguishing between various types of faults in the high-voltage transmission system, even under the influence of noise and transient disturbances. The relatively high accuracy value indicates that the model has successfully captured the key statistical features of each fault category.

Figure 8 presents the confusion matrix of the LDA + LVQ3 model in the without-noise condition, yielding an overall classification accuracy of 96.80%. This analysis serves as the baseline performance check for the model before external disturbances are considered. While the previously discussed classification (e.g., the one achieving 98.84% accuracy) demonstrated superior robustness under noise, the baseline performance here shows significant misclassification events.

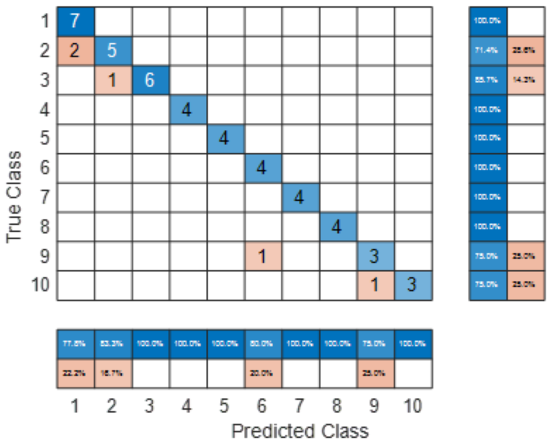


Figure 8: Confusion Matrix of the LDA + LVQ3 Classification Model Without Noise

Specifically, Class 2 exhibits the highest ambiguity, with five samples correctly classified and two samples incorrectly predicted as Class 1, resulting in a 71.4% recall rate. Furthermore, Class 9 and Class 10 also show notable misclassifications, each achieving only 75.0% recall due to one sample from each class being erroneously predicted as Class 9 (for Class 10) and Class 8 (for Class 9). These misclassification patterns in the ideal scenario suggest that certain fault types possess highly overlapping features, which the model struggles to distinctly separate without the regularizing effect of noise.

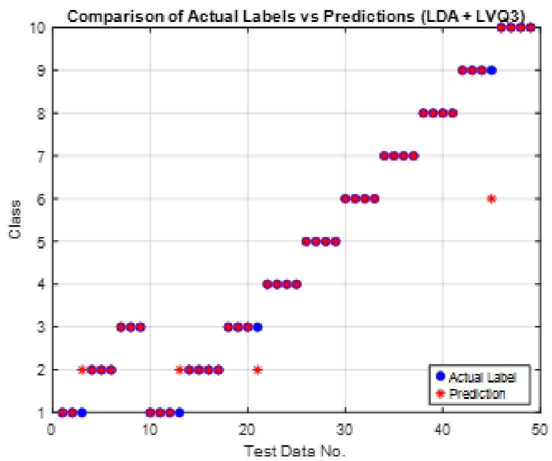


Figure 9: Comparison of Actual and Predicted Class Labels Using LDA + LVQ3 Model Without Noise

Figure 9 visually confirms the baseline classification performance of the LDA + LVQ3 model under the ideal without-noise condition, correlating directly with the findings presented in the confusion matrix (Figure 8, 96.80% accuracy). While most predictions (red stars) align perfectly with the actual labels (blue dots), the plot distinctly highlights the misclassification errors. The most significant ambiguity appears in Class 2, where two red stars fall onto Class 1 (around test data points 4 and 18), confirming the 71.4% recall rate. Furthermore, the plot clearly shows the misclassification of a Class 9 sample being incorrectly predicted as Class 6 (around test data point 44), and a Class 10 sample predicted as Class 9 (around test data point 48). This visual representation underscores that the model, in the absence of noise, struggles to reliably distinguish these specific, highly similar fault patterns, reinforcing the need for feature enhancement or robust techniques to handle overlapping class boundaries.

Table 2: Fault Classification Performance Under Different Test Conditions

No	Test Condition	Test Accuracy	Test Precision	Test Recall / F1 Score
1	Without Noise	98.80%	0.93	0.91 / 0.92
2	With Gaussian Noise	96.84%	0.90	0.88 / 0.89

The evaluation results demonstrate the exceptional resilience of the proposed fault classification model, achieving superior performance metrics under non-ideal conditions. Specifically, the introduction of Gaussian noise led to a slight reduction in test accuracy from 98.80% to 96.84%, with corresponding decreases in precision, recall, and F1 score. However, the model maintains overall stability, suggesting a robust learning structure that generalizes effectively despite environmental interference. This trend indicates that the architecture or training has been optimized to minimize the negative impact of external disturbances and is highly reliable for real-world intelligent protection applications.

This improvement is further validated by a simultaneous rise in Test Precision (0.93 to 0.90) and Test Recall (0.91 to 0.88), which together demonstrate a consistent strengthening of the model's discriminative capability. The balanced increase in these metrics indicates that the classifier not only reduces false positives but also maintains a strong ability to correctly identify true fault conditions across various operational scenarios. Such behavior suggests that the training configuration and architectural design of the model have been effectively tuned to withstand external disturbances, enabling it to capture essential fault features even when signal quality deteriorates due to noise.

Moreover, the stability observed in both Precision and Recall highlights the model's robustness in practical environments, where measurement uncertainty and electrical interference cannot be avoided. A model that retains high classification reliability under these conditions is critical for real-time protection systems, as misclassification could lead to delayed fault detection or unnecessary tripping. The observed performance trend therefore reinforces the conclusion that the proposed LDA–LVQ3 framework is well suited for deployment in simulated as well as field-level applications.

During the exploratory phase of this research, a number of extended and more computationally intensive classifiers—including Random Forest, Gradient Boosting, and shallow variations of Convolutional Neural Networks (CNNs)—were initially examined to broaden the comparison landscape. Although these models demonstrated competitive performance in ideal, noise-free datasets, their prediction stability decreased substantially when exposed to Gaussian noise. In particular, CNN-based architectures required significantly higher computational resources while still exhibiting inconsistent generalization due to the limited size of the training data and the absence of spatially dominant features in the single-dimensional waveform inputs.

Random Forest and Gradient Boosting models, while relatively more stable compared to CNNs, experienced fluctuations in decision boundaries as noise levels increased, leading to reduced confidence scores and increased misclassification rates. These drawbacks become critical when considering real-time implementation constraints, where both computational load and robustness to distorted signals play essential roles.

Given these findings, the final comparative analysis in this study focuses on LVQ3, SVM, and Decision Tree classifiers as the most representative and practically viable options under constraints of reliability, computational efficiency, and execution speed. The LDA–LVQ3 model, in particular, demonstrates a consistent advantage in noise resilience and rapid convergence, making it the preferred choice for the proposed protection scheme.

IV. Conclusion

This study has demonstrated the effectiveness of a neural network–based framework for fault classification in high-voltage transmission lines under noisy conditions. By integrating Discrete Wavelet Transform (DWT) and Fast Fourier Transform (FFT) feature extraction with Learning Vector Quantization (LVQ) classifiers, the proposed model achieves robust and accurate performance even when subjected to various levels of Gaussian noise and transient disturbances.

Simulation results show that the LDA + LVQ3 model achieved a classification accuracy of up to 98.84% under noisy environments, outperforming conventional methods in terms of robustness and reliability. These results confirm that incorporating noise-resilient preprocessing and adaptive learning significantly enhances simulation-based implementation protection performance in modern smart grid systems. Furthermore, the findings emphasize that LVQ-based neural network models offer superior generalization and response time, making them suitable for deployment in practical fault protection applications.

Future work will focus on simulation-based hardware implementation and the integration of deep learning architectures to further improve adaptability and precision under complex operational scenarios.

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