SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V13I7P118

Volume 13 Issue 7, 257-274, July 2026

Original Article

Robust Ensemble Framework for Fault Detection in Transmission Lines Using Hybrid Classifiers and Deep Q-Networks

Sandeep Godhade[1], Jayendra Kumar[2]

[1,2]School of Electronics Engineering, VIT-AP University, Andhra Pradesh, India.

[2]Corresponding Author : kumar.jayendra@vitap.ac.in

Received: 16 May 2026 Revised: 11 June 2026 Accepted: 30 June 2026 Published: 29 July 2026

Abstract - *The continuous complexities and the requirement of reliable power transmission have led to the necessity for advanced fault detection systems in order to ensure stability and safety in electrical grids. In this study, an ensemble learning-based technique has been proposed for fault detection in power transmission lines by using Deep Q-Networks (DQN) in conjunction with standard classifiers such as Naive Bayes, Multilayer Perceptron (MLP), Logistic Regression, and Deep Forest. The proposed algorithm uses reinforcement learning for optimizing classifier weights. Voltage and current waveforms are used as input data for extracting features and performing classification. The performance of the proposed technique is highly improved, providing 99.10% accuracy, 99.40% precision, 99.70% sensitivity, and 99.50% F1-score, which is far better than the existing techniques. Moreover, the proposed framework provides reduced processing time (12-13 milliseconds) and low memory consumption (150-152 megabytes).*

Keywords - *Deep Q-Networks, Ensemble Learning, Fault Detection, Reinforcement Learning, Transmission Lines.*

1. Introduction

Advanced fault detection mechanisms are increasingly necessary with the rapid expansion and growing complexity of modern electrical grids. Such faults in transmission lines, which include line-to-line and line-to-ground faults, have great significance in terms of posing risks to the stability and safety of electrical grids, power outages, damage to equipment, and substantial economic losses. Traditional methods of fault detection usually depend on single classifiers or basic machine learning techniques, hence proving not to be adequate because of their limited accuracy and an inability to generalize over diverse fault conditions and operational scenarios. Different fault detection techniques usually focus on the implementation of conventional machine learning algorithms. While they are effective to a certain extent, there exist several limitations associated with them. Such methods are oftentimes limited by the fact that they rely on predefined features; they are sensitive to noise and are incapable of handling complex and high-dimensional data samples. Consequently, they may exhibit suboptimal performance, especially under dynamic load conditions and multiple fault types. Moreover, single-classifier systems may not be able to maximize the rich information buried inside the voltage and current waveforms of the transmission lines, thus leading to reduced precision and recall rates.

This paper addresses these challenges with a novel ensemble learning framework that fuses the newly emerged Deep Q-Networks (DQN) with Naive Bayes, Multilayer Perceptron, Logistic Regression, and Deep Forest Classifiers. The intention of this paper is to improve the accuracy, precision, and robustness of fault detection in transmission line circuits. By combining the strength of several different base classifiers, an ensemble approach is in a unique position to make full use of different feature representations and decision processes with the intention of enhancing the overall detection quality. In our method, a DQN model has been designed to process output voltage and current waveforms from transmission lines. A DQN model is composed of multiple dense layers that include batch normalization and dropout layers to avoid overfitting and ensure robust feature extraction. The DQN-optimized features are fed to an ensemble learning framework, where Naive Bayes provides probabilistic classification, MLP offers deep feature extraction, Logistic Regression comes up with linear decision boundary optimization, and Deep Forest provides hierarchical feature representation.

The experimental results show the effectiveness of the proposed method with a superior accuracy of 99.10% in detecting a variety of fault types. The high performance of the ensemble model marks its potential to be a reliable tool for accurate fault detection in the power transmission systems, able to sustain operational integrity and safety under diverse fault conditions. This work offers a very significant advancement in the area of fault detection in transmission lines, providing a scalable and reliable solution that addresses the weaknesses of conventional methods. The integration of DQN with an ensemble of classifiers provides a comprehensive approach that enhances the reliability and robustness of fault detection mechanisms; hence, contributing to the stability and efficiency of modern electrical grids.

1.1. Motivation

The motivation of this research arises from the critical need to enhance the reliability and safety of power transmission systems in the face of increasing demand and complexity. Electrical grids are essential infrastructures that support various facets of modern society, from residential electricity supply to industrial operations and technological advancements. As such, any disruption in the power transmission network can have far-reaching consequences. Faults in transmission lines, particularly line-to-line and line-to-ground faults, are among the most common and damaging disruptions. Traditional fault detection techniques, which rely heavily on single classifier models or basic machine learning techniques, are proving inadequate due to their limited adaptability and precision under diverse operating conditions. These traditional systems often fall short in environments characterized by fluctuating loads, multiple fault types, and high noise levels, leading to delays in fault detection and mitigation. This inadequacy underscores the need for more sophisticated and robust fault detection mechanisms that can ensure the seamless operation of electrical grids. In response to these challenges, this research introduces a novel ensemble learning framework that leverages the strengths of Deep Q-Networks (DQN) combined with Naive Bayes, Multilayer Perceptron (MLP), Logistic Regression, and Deep Forest Classifiers to improve fault detection in transmission lines.

1.2. Contribution and Novelty

The key contributions of the current work are outlined below:

- A novel ensemble model based on deep Q-networks and naive bayes, multilayer perceptron, logistic regression, and deep forest classifiers is proposed for improving the accuracy and reliability of fault detection techniques for transmission lines.
- A reinforcement learning layer based on DQN is created, which consists of dense neural networks, batch normalization, and dropout for gaining stability in the process of feature extraction and faster convergence.
- Demonstrated superior empirical performance with 99.10% accuracy, 99.40% precision, 99.70% sensitivity, and 99.50% F1-score across varied transmission line fault conditions.
- Validated the scalability and real-time feasibility of the proposed system with reduced processing time (12-13 ms) and memory usage (150-152 MB), outperforming existing methods.

The proposed framework introduces a novel reinforcement learning-based ensemble architecture in which a deep Q-network dynamically optimizes the weights of multiple classifiers according to their fault classification performance. This adaptive weighting strategy distinguishes the proposed method from traditional static ensemble and standalone machine learning models. The weight optimization enhances the framework's adaptability to varying fault conditions, resulting in improved classification accuracy, increased robustness, reduced detection latency, and superior overall fault detection performance.

2. Related Works

This research is driven by the urgent need to enhance the reliability and safety of power transmission systems, as traditional fault detection methods often lack precision and adaptability under diverse conditions. By addressing the limitations of existing techniques, this study aims to develop robust mechanisms for timely fault detection and mitigation, ensuring the seamless operation of critical electrical grids. A review of recent literature [1-31] highlights diverse methodologies aimed at enhancing the accuracy, speed, and reliability of fault detection in Transmission Lines (TLs).

The current-based fault detection scheme for DC microgrids using Variational Mode Decomposition (VMD) achieves fast and accurate detection but faces implementation challenges [1]. Similarly, article [2] introduces a fault identification and localization method for bipolar DC microgrids using Teager energy, offering precise localization but relying on reliable communication channels. A distributed fault detection approach based on Linear Matrix Inequality (LMI) is proposed in [3], providing improved speed and reliability at the cost of computational overhead due to multi-objective optimization. The Dual-Extended Kalman Filter (Dual-EKF) fault-tolerant predictive control for nonlinear DC microgrids, presented in [4], effectively handles actuator and sensor faults but suffers from implementation complexity. Reference [5] employs complex power metrics for fault protection in DC microgrids, demonstrating reliability in on-grid and off-grid modes but encountering high computational demands due to the Fast Fourier Transform (FFT). A multi-agent system and state observers for microgrid protection, proposed by [6], enhance fault detection and system stability while facing synchronization and implementation challenges. For High-Impedance Faults (HIF), it utilizes distributed techniques that effectively localize and protect DC microgrids but underperform with low-impedance faults [7]. Deep learning integrated with Long Short-Term Memory (LSTM) networks is applied for fault detection and classification, achieving high accuracy but with significant computational requirements [8]. A filter capacitor dynamics-based scheme for short-circuit faults in ring-type DC microgrids is proposed in [9], performing well but being heavily reliant on capacitor characteristics. Fast fault diagnosis using minimal sensors for ring bus DC microgrids is introduced by [10], achieving accuracy, but is limited by sensor placement constraints. Reference [11] addresses sensor fault-resilient control for islanded microgrids using sliding mode observers, with complexity in observer design being a limitation. A current-limiting fault ride-through control scheme for DC microgrid converters, proposed in [12], efficiently handles pole-to-pole faults but is limited to specific fault types and converter configurations.

Hierarchical sensor fault-tolerant control for hybrid microgrids is studied in [13], resulting in better fault tolerance but at the expense of a more complicated architecture. Fault detection and classification in DC microgrids using differential reactor voltage is presented in [14], where the accuracy depends on the voltage measurements. Other significant contributions in this domain include line fault detection using the delta V-delta I plane technique [15] and reduced-order unknown input observers for fault isolation [16].

The unit protection strategy for DC microgrids suggested by [17] is dependent on efficient communication. Mathematical morphology-based fault detection strategy [18] and differential power-based selective phase tripping for DC microgrids [19] are quite successful in dealing with certain scenarios but face problems like sensitivity to noise and dependency on correct measurement of power. In addition, author [20] suggests a low-voltage DC microgrid fault detection strategy that uses signatures of the current through the filter capacitor for detecting short-circuit faults. This technique proves to be very efficient in characterizing both high impedance and low impedance faults, but is dependent on current signature analysis.

Author [21] evaluates the effectiveness of using synthetic data for fault isolation in DC microgrids, pointing out pros and cons related to the use of realistic synthetic samples. The series DC arc fault detection technique [22] that uses an unknown input observer produces accurate results, but is quite challenging when it comes to designing the observer. Distributed fault-tolerant control technique [23] for VSC-based islanded microgrids provides high fault tolerance and efficient distributed control, but has a complicated implementation. However, [24] offers a comprehensive review of protection strategies for networked microgrids, pointing out the key challenges and possible solutions, but does not include any experimental evaluation. Reference [25] surveys machine learning techniques for fault diagnosis in AC microgrids and lists some successful techniques, but it consists mainly of literature reviews.

While traditional signal processing and machine learning solutions have proven themselves in ideal conditions, their generalization ability remains rather poor when it comes to operating in uncertain and noisy environments. For solving this problem, the authors of [26] developed an unsupervised Deep Belief Network (DBN) for extracting reliable features of voltage and current transients. The solution proved to be highly resilient in complex conditions on the IEEE-39 bus. In turn, [27] suggested a hybrid approach based on the integration of classical machine learning classifiers (SVM, XGBoost) with deep models (CNN, LSTM, CNN-LSTM). As a result, the authors obtained more than 99.8% of accuracy and successfully localized faults with the Mean Absolute Percentage Error (MAPE) less than 1%. The proposed solution utilizes an extensive database consisting of more than 300,000 simulations of faults. Continuing the development of spatiotemporal learning methods, [28] proposed a 2D Convolutional Neural Network trained on scalograms – images constructed with wavelet transformation. This method allowed to achieve classification accuracies higher than 99.9% and even in the presence of noise and high resistance of faults. Another recent work [29] confirmed the applicability of transformer-based models for power quality disturbances detection in real-time mode. With the help of segmentation of voltage signals and an attention mechanism, the authors achieved classification within 1.67 ms and significantly outperformed CNNs in terms of speed and accuracy. Finally, the author [30] proposed an ensemble learning approach based on PMU data and using several classifiers for transmission-line fault classification. The use of an ensemble approach and XAI techniques improves the reliability of classification and increases its interpretability. The reference [31] suggests a fast and accurate approach for early fault prediction in transistors based on Principal Component Analysis (PCA), Fast Fourier Transform (FFT), and Convolutional Neural Network (CNN).

2.1. Research Gap

Line-to-Line (LL) and line-to-Ground (LG) faults are considered the most common and impactful disturbances to the electrical grid. Existing fault detection approaches, which are mostly based on single classifiers or machine learning algorithms, have shown insufficient adaptability and accuracy in different operational environments. Moreover, these existing solutions tend to fail when there are variable loads, various types of faults, and high levels of noise present, which leads to delays in detecting and solving faults. Thus, an efficient and reliable approach to fault detection in the power transmission system is needed. The current work suggests the best solution using a dynamic ensemble with DQN for the purpose of fault detection.

A review summary of related works is provided in Table 1. The proposed approach with the usage of Deep Q-Networks (DQN) solves the identified problems.

Table 1. Review the summary of related work on fault detection in transmission lines

Reference	Method Used	Findings	Results	Limitations
[1]	VMD Enabled Current-Based Fast Fault Detection	Current-based scheme for fast fault detection in DC microgrids using Variational Mode Decomposition (VMD)	High detection accuracy with minimal delay	Complexity in implementing VMD
[2]	Novel Fault Identification and Localization	Fault identification and localization in bipolar DC microgrids using Teager energy	Accurate fault location even in high resistance faults	Dependence on the communication channel reliability
[3]	Distributed Fast Fault Detection	Linear Matrix Inequality (LMI) based fault detection in DC microgrids	Improved detection speed and reliability	Requires multi-objective optimization, which can be computationally intensive
[4]	Dual EKF-Based Fault-Tolerant Predictive Control	Dual extended Kalman filter for actuator and sensor fault-tolerant control in nonlinear DC microgrids	Effective fault tolerance and predictive control	Complexity in modeling dual-EKF
[5]	Protection Based on Complex Power	Protection of DC microgrids during faults using complex power metrics	Reliable protection in on/off-grid scenarios	High computational requirements for FFT
[6]	Multi-Agent and State Observer-Based Protection	Fault detection using a Multi-Agent System (MAS) and state observers in microgrids	Enhanced fault detection and system stability	Implementation complexity and need for synchronization
[7]	Distributed High-Impedance Fault Detection	High-impedance fault detection and protection using distributed techniques	Effective localization and protection of high-impedance faults	May not perform well with low-impedance faults
[8]	Deep Learning enabled Relay	Online fault detection, classification, and localization using LSTM	High accuracy and real-time fault detection	High computational load due to deep learning models
[9]	Filter Capacitor Dynamics-Based Detection	Short-circuit fault detection using filter capacitor dynamics	Accurate detection of short-circuit faults in ring-type DC microgrids	Dependence on capacitor characteristics
[10]	Fast and Accurate Fault Diagnosis Scheme	Fault diagnosis in ring bus DC microgrids with fewer sensors	Quick and accurate fault diagnosis	Limited by the number and placement of sensors
[11]	Sensor Fault-Resilient Control	Control of distributed energy resources with sensor fault resilience	Maintains control even with sensor faults	Complexity in implementing sliding-mode observers
[12]	Current Limiting Type Fault Ride Through	Fault ride-through control scheme for converters in DC microgrids	Effective in handling pole-to-pole faults	Limited to specific fault types and converter configurations
[13]	Sensor Fault-Tolerant Control	Hierarchical control for hybrid microgrids with sensor fault tolerance	Improved resilience and reliability of microgrids	Complexity in hierarchical control architecture
[14]	Differential Reactor Voltage-Based Detection	Fault detection and classification using differential reactor voltage in smart DC microgrids	Accurate fault detection and classification	Dependence on precise voltage measurement
[15]	Delta V - Delta I Plane-Based Detection	Fault detection using the Delta V - Delta I plane in DC microgrids	High accuracy in real-time simulation	Complexity in implementing the Delta V - Delta I plane method

[16]	Reduced Order Unknown Input Observers	Comprehensive fault detection and isolation using reduced-order unknown input observers	Effective in fault detection and isolation	Complexity in designing reduced-order observers
[17]	Unit Protection of Tapped Line	Unit protection scheme for tapped line DC microgrids	Reliable fault detection and resistance estimation	Dependence on communication for unit protection
[18]	Mathematical Morphology-Based Fault Detection	Fault detection using mathematical morphology in radial DC microgrids	Effective denoising and fault detection	Sensitivity to noise and signal variations
[19]	Differential Power-Based Tripping	Selective phase tripping using differential power metrics	Enhanced fault resilience and selective tripping	Dependence on accurate power measurements
[20]	Filter Capacitor Current Signature	Short-circuit fault detection using filter capacitor current signature	Effective detection of high and low impedance faults	Requires accurate current signature analysis
[21]	Synthetic Data for Fault Isolation	Fault isolation in DC microgrids using synthetic data for ensemble learning	Improved fault isolation accuracy	Challenges in generating realistic synthetic data
[22]	Unknown Input Observer-Based Detection	Series DC arc fault detection using unknown input observers	Accurate fault detection in series DC circuits	Requires a precise observer design
[23]	Fault-Tolerant Distributed Control	Distributed control with simultaneous passive fault detection in VSC-based islanded microgrids	High fault tolerance and distributed control efficiency	Complexity in implementing mixed $H\infty/H_-$ optimization
[24]	Review of Networked Microgrid Protection	Comprehensive review of protection schemes in networked microgrids	Identifies key challenges and solutions	Primarily a review, it lacks experimental validation
[25]	Machine Learning Methods for Fault Diagnosis	Review of machine learning techniques for fault diagnosis in AC microgrids	Identifies effective machine learning techniques for fault diagnosis	Review-based, lacks implementation details

3. Methodology

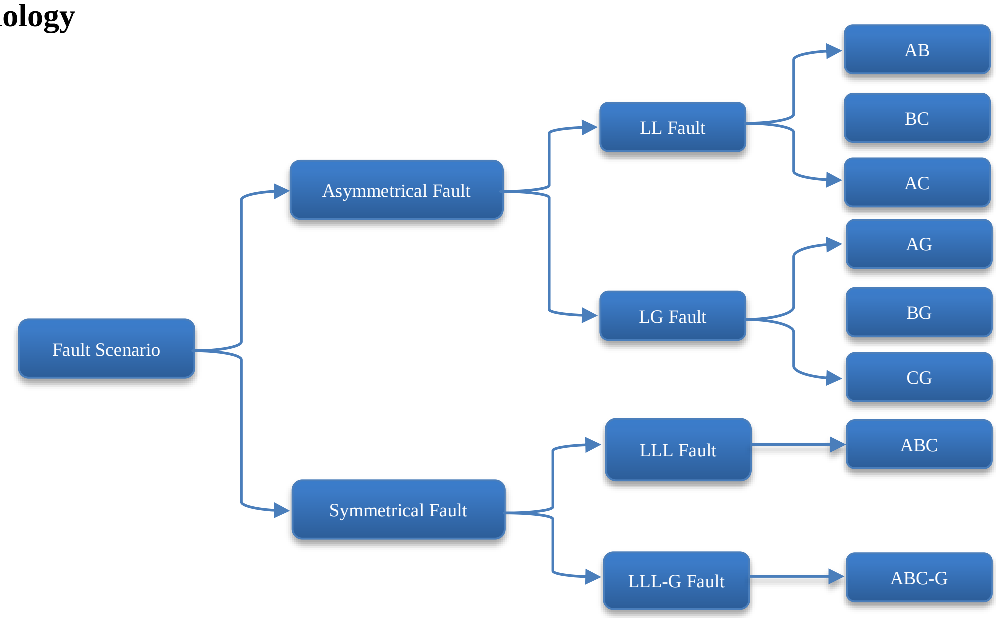


Fig. 1 Classification of faults in transmission lines

The proposed work focuses on short-circuit faults on transmission lines. The different faults are simulated in the MATLAB/Simulink system (i.e., AB, AC, BC, AG, BG, CG, ABC, and ABC-G). They are classified as Line-to-Line (LL), Line-to-Ground (LG), Line-to-Line-to-Line (LLL), and Three-Line-to-Ground (LLL-G) faults. Only LLL faults and LLL-G faults are symmetrical, and the remaining are asymmetrical faults, as shown in Figure 1. Here, A, B, C, and G stand for Phase A, Phase B, Phase C, and Ground, respectively.

3.1. Design of the Proposed Model

The Naive Bayes classifier is chosen because it is probabilistic and thus suitable for noisy and uncertain data samples. The fundamental equation for the Naive Bayes classifier is based on Bayes' theorem, represented via Equation (1),

$$P(Fk \mid X) = \frac{P(X \mid Fk) \cdot P(Fk)}{P(X)} \quad (1)$$

Where, $P(Fk \mid X)$ is the posterior probability of fault Fk given the feature set X, $P(X \mid Fk)$ is the likelihood of observing X given Fk, $P(Fk)$ is the prior probability of fault Fk, and $P(X)$ is the marginal likelihood of observing X samples. This probabilistic approach is particularly useful in dealing with the varying operational conditions of transmission lines.

Further, the Multilayer Perceptron (MLP) model is employed owing to its ability to extract features from deeper layers, which is crucial in distinguishing complex patterns in the waveform of the voltages and currents in the case of different fault scenarios. The MLP network consists of several layers of neurons, where each neuron computes an activation function on the summation of its inputs after multiplying them by some weights. This process of propagating forward in the MLP network can be mathematically expressed using Equation (2),

$$a(l) = \sigma\big(W(l)a(l-1) + b(l)\big) \quad (2)$$

Where (l) refers to the activation of layer l, (l) represents the weight matrix, $b(l)$ stands for the bias vector, while σ denotes the sigmoid activation function. In the process of backpropagation, the gradient of the loss function is calculated with respect to the above parameters using the chain rule.

The logistic regression model is then used because of its efficiency and clarity in defining the linear decision boundaries. The decision function in the logistic regression model is given by Equation (3),

$$P(Fk \mid X) = \frac{1}{1 + e^{-(w \cdot X + b)}} \quad (3)$$

Where w stands for the weight vector, X is the feature vector, and b stands for the bias term.

The model determines the best parameters by optimizing the log-likelihood function as shown in Equation (4),

$$\ell(w,b) = \sum_{i=1}^{N} \big[yi * logP(Fk \mid Xi) + (1 - yi)log\big(1 - P(Fk \mid Xi)\big)\big] \quad (4)$$

Where yi stands for the label of the i-th example, and N stands for the number of fault-type examples.

The last part of the model is the use of the deep forest classifier, which introduces a hierarchical representation of features by building an ensemble of decision trees. The decision trees in the deep forest make independent predictions on subsets of features. Recursive partitioning in the decision tree is given by Equation (5),

$$Gi(t) = \sum_{j=1}^{nt} \left[y(i,j) - \frac{1}{nt}\sum_{k=1}^{nt} y(i,k)\right]^2 \quad (5)$$

Where $G(t)$ stands for the impurity of node t for tree i, $y(i,j)$ stands for the result of the j-th sample in node t, and nt is the number of samples in node t.

The outputs from these models are then combined using a weighted vote strategy, with weights obtained by optimizing the performance of each model on validation sets. The decision rule is given by Equation (6).

$$Fensemble(X) = \sum_{m=1}^{M} \alpha m * Fm(X) \quad (6)$$

Where, F ensemble(X) is the ensemble prediction, αm is the weight assigned to the m-th classifier, and $Fm(X)$ is the output of the m-th classification process.

In order to dynamically tune the weights, the proposed framework incorporates a Reinforcement Learning (RL) approach using Deep Q-Network (DQN). DQN acts as a meta-learner that dynamically tunes the weights of classifiers based on continuous feedback, making the framework more adaptable and robust to different kinds of faults.

The input to DQN is either directly taken from voltage/current waveforms or generated based on the outputs from the ensemble of classifiers. The learning process in DQN is based on Q-learning, where it learns an optimal action-value function to assign the best possible weights.

As part of baseline comparison, the probability distribution-based approach of naive Bayes classifier, the linear decision boundary of logistic regression, and the deep feature extraction capability of MLP are used. The hierarchical feature representation of the deep forest adds to the robustness of the framework. The combination of all these methods increases the performance of the ensemble model and makes the framework more robust to different faults, thus providing a robust tool for fault detection in power transmission networks.

3.2. Deep Reinforcement Learning

As shown in Figure 2, there are five key components within reinforcement learning: the agent, the environment, the State (s_t), the Action (a_t), and the Reward (r_t). The agent is defined by Deep Q-Network (DQN), which handles the optimization process of finding the best weight configuration for better fault detection through ensemble classifiers. The State (s_t) refers to the system information that the agent has at the time, consisting of feature value extraction and the performance feedback obtained from the ensemble classifiers. The Action (a_t) refers to the weight changes on the individual classifiers within the ensemble, thus affecting the final classification result. Finally, the Reward (r_t) refers to the performance feedback provided to the agent based on classification performance metrics such as accuracy, precision, and sensitivity. The environment represents the fault detection framework and simulation model, which evaluates the actions executed by the agent and provides updated system state and performance feedback.

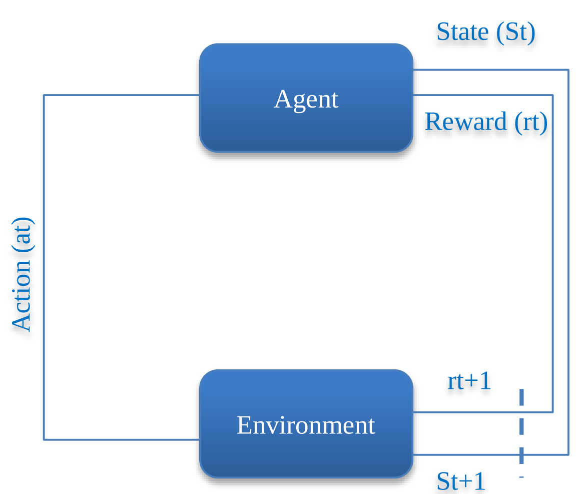


Fig. 2 Structure of reinforcement learning layer

The key objective of RL is to achieve an optimal experience by interacting with the environment and the agent. The operation of the RL algorithm is based on knowledge of the sustainable environment, and it includes a feedback loop to ensure quality and appropriate decisions. It is essential to understand that RL is a well-known learning algorithm based on the agent. The agent is intended to perform work and achieve results in the environment. By attempting various actions, the agent progressively supports those who have received the most rewards [32, 33].

The DQN operates on the principle of Q-learning, a model-free reinforcement learning algorithm that seeks to learn the optimal action-value function, $Q\ (s\ ,\ a\ )$, which represents the expected cumulative reward for taking Action a in state s. The action value function is updated iteratively using the Bellman Process via Equation (7),

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left[r + \gamma \max^{a'} Q(s',a') - Q(s,a)\right] \quad (7)$$

Where α is the learning rate, r is the immediate reward, γ is the discount factor, and $s\,'$ is the next state.

Forward propagation in the DQN is expressed as in Equation (8),

$$h(l) = f\big(W(l)h(l-1) + b(l)\big) \quad (8)$$

Where $h(l)$ is the activation of layer l, $W(l)$ is the weight matrix, $b(l)$ is the bias vector, and f is the Rectified Linear Unit (ReLU) activation function. With such an architecture, the DQN is able to represent input features in a highly complex manner.

For stabilizing learning, the DQN uses a target network Q' that is periodically updated with the weights of the main network. The loss function is computed with Equation (9),

$$L(\theta) = E\left[\left(r + \gamma \max^{a'} Q'(s',a';\theta -) - Q(s,a;\theta)\right)^2\right] \quad (9)$$

Where θ is the parameter of the Q-network and $\theta-$ is the parameter of the target network. As a result, the problem of oscillation and divergence inherent to Q-learning is solved.

The gradient of the loss function with respect to the network parameters θ is computed with backpropagation, as shown via Equation (10),

$$\nabla\theta L(\theta) = E\left[\left(r + \gamma \max^{a'} Q'(s',a';\theta -) - Q(s,a;\theta)\right)\nabla\theta Q(s,a;\theta)\right] \quad (10)$$

This gradient is further used to adjust the network parameters using stochastic gradient descent, leading to convergence of the network to the optimal policy.

In turn, the reward function, *r*, is designed in such a way that it evaluates the performance of the ensemble classifier; in other words, the classifier receives high rewards for correctly classifying faults and low rewards for misclassifications.

The expected cumulative reward for a certain policy π is calculated using the following Equation (11),

$$R\pi = E\pi\left[\sum_{t=0}^{\infty} \gamma t * rt\right] \tag{11}$$

Where $r\,t$ is the reward at timestamp t, instance sets, and this cumulative reward guides the DQN to optimize the ensemble classification process.

The $Q\ (s\,,\ a)$ value function is used to determine the best combination of classifiers along with their weights in an ensemble. Choosing the right combination of classifiers is critical for achieving a balance between various classifiers, such as Naive Bayes, MLP, Logistic Regression, and Deep Forest, in order to obtain the most accurate results. The chosen technique aims to exploit the strengths of different classifiers while avoiding their weaknesses at the same time. The reason behind choosing the Deep Q-Network algorithm is based on its ability to make the ensemble flexible enough to adapt to changes. This makes it possible for the DQN to learn from its previous classification decisions and adjust the classifier weights accordingly.

3.3. Ensemble Learning Framework

Figure 3 depicts the use of the suggested Deep Q-Network (DQN) algorithm as part of the ensemble learning process to identify faults in the transmission line circuit.

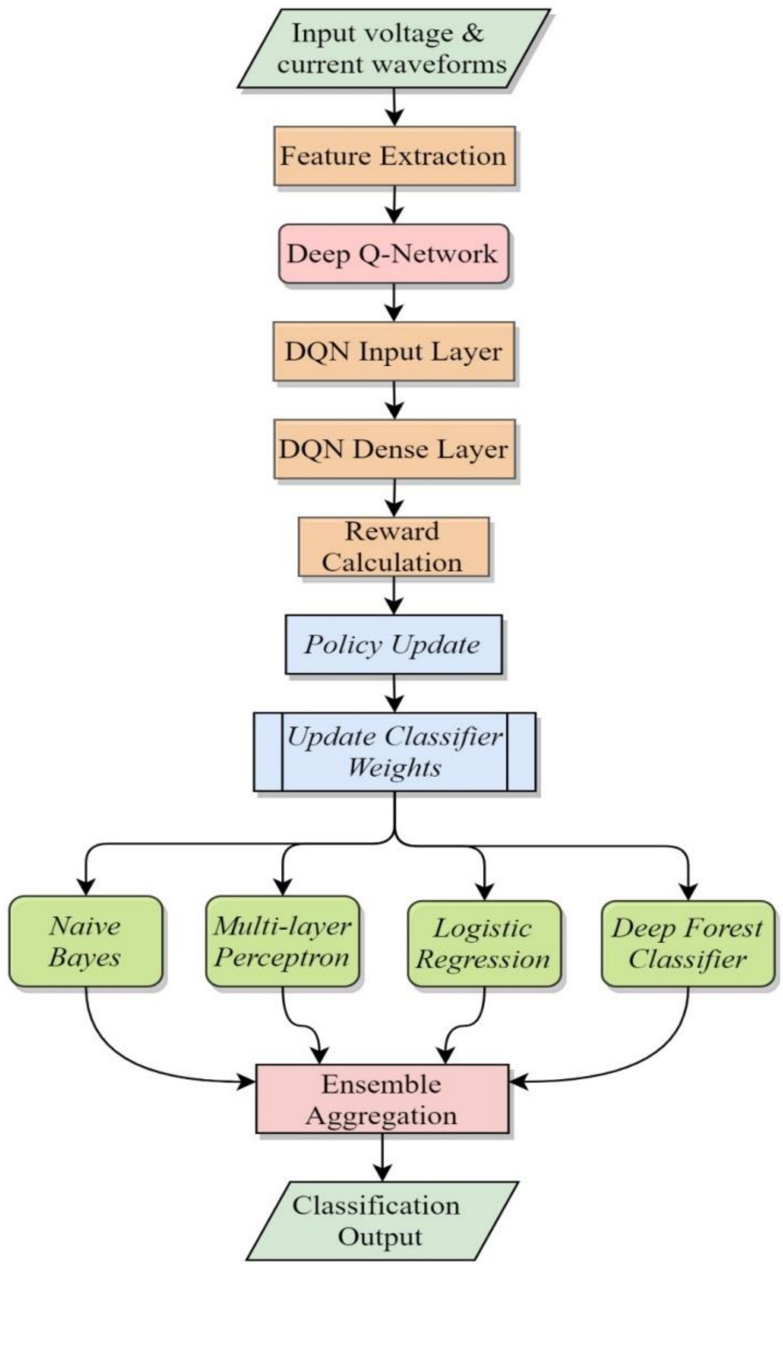


Fig. 3 Architecture of the DQN model combined with an ensemble framework

The DQN algorithm takes input data in the form of voltage and current waveforms in order to identify any fault characteristics and direct the ensemble learning process accordingly. The individual classifiers, including Naive Bayes, MLP, logistic regression, and deep forest classifiers, analyze the input data independently and come up with the results concerning the occurrence of faults. The DQN algorithm gets data either directly from the voltage and current waveforms or indirectly through the outputs generated by the ensemble learning classifiers. The main component of this model is the relationship between the DQN algorithm and the ensemble learning algorithms. The DQN algorithm acts as the intelligent agent that tracks the performance of the ensemble learning process using a set reward function. This process entails optimizing the weights assigned to each classifier in the ensemble according to a certain criterion. The resultant product of this optimization process is a better fault detection system. In other words, this model operates using a closed-loop optimization approach whereby the DQN algorithm optimizes the performance of the ensemble learning process.

Figure 4 illustrates the overall model flow of the proposed fault detection framework that involves the inclusion of the DQN algorithm in the ensemble classification algorithm to enhance the performance of the fault detection process.

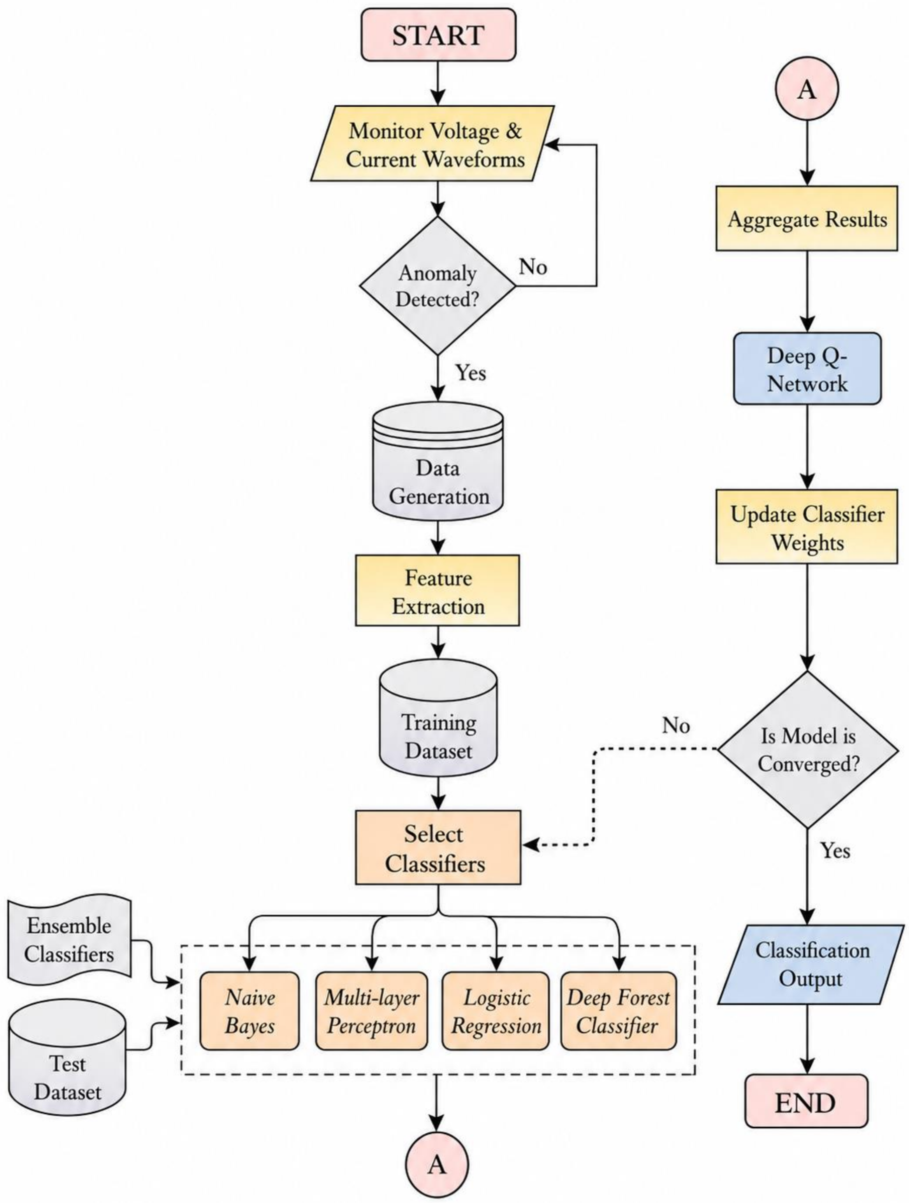


Fig. 4 Model flow of the proposed method for the fault detection process

The model flow begins with the input of voltage and current waveforms obtained from the transmission line circuit under monitoring. Subsequently, these raw waveforms undergo feature extraction, a process that derives relevant characteristics essential for fault discrimination, such as statistical measures, peak values, and RMS values. Following feature extraction, ensemble classification is performed, where the extracted features are input into the ensemble of four individual classifiers, i.e., naive bayes, MLP, logistic regression, and deep forest, each generating independent predictions regarding the type of fault. The DQN receives the outputs from each classifier and, based on its learned policy, dynamically assigns weights to these outputs. This weighting prioritizes the predictions of more reliable classifiers for the prevailing conditions. Fault detection decisions are made based on the aggregated output of the weighted ensemble, determining the accurate type of faults, i.e., Line-to-Line (LL) and Line-to-Ground (LG) faults.

4. Simulation Model

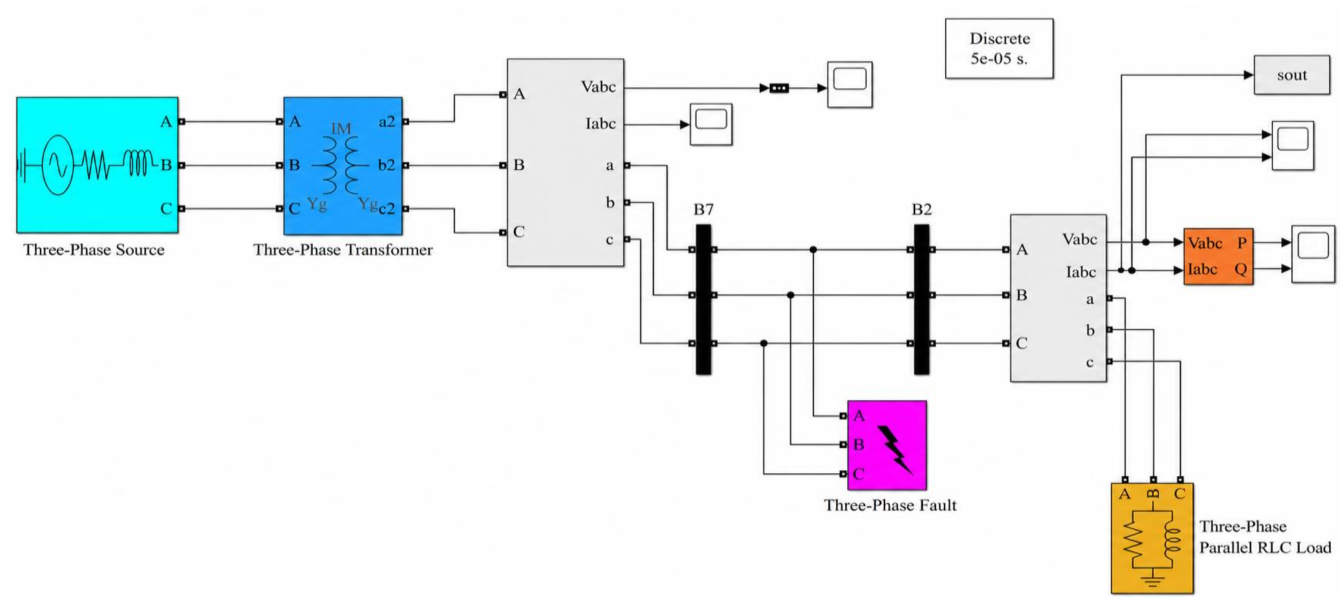


Fig. 5 MATLAB/Simulink model for fault detection in transmission lines

This study proposes an ensemble learning framework using the DQN algorithm for fault detection in the Transmission Lines (TLs). For benchmarking, the TLs model is simulated and investigated in the MATLAB/Simulink 2023 framework, as shown in Figure 5. Most of the existing methods use simulation, as in this study. The model was trained and tested on a Windows PC with an Intel(R) Core(TM) i7-6600U CPU @ 2.60GHz, and 64-bit operating system, an x64 based processor, and 16 GB RAM. The experimental testbed for the proposed ensemble learning framework integrated with a deep Q-network for fault detection in transmission lines will be carefully designed so that it underpins testing in different fault conditions.

Table 2. Sample input parameters and specifications in the simulation model

Parameter	Value
Voltage Source	440 V, 50 Hz
Transmission Line Length	50 km, 75 km, 100 km, 120 km
Fault Resistance	0.01 Ω, 0.02 Ω
Fault Inception Angle	30°,60°,90°,120°
Fault Scenarios	Line-to-Line Fault (LL), Line-to-Ground Fault (LG)
Sampling Rate	10 kHz
Three-phase Transformer	100 kVA, 50 Hz
	Primary Voltage (line-to-line, RMS) = 440 Volts
	Secondary Voltage (line-to-line, RMS) = 350 Volts
	Winding Resistance (R_1, R_2) = 0.01 pu each

The transmission line circuit involves three-phase voltage sources, a three-phase transformer, and transmission lines with embedded monitoring nodes. The faults are systematically introduced along the transmission line to generate a varied dataset that incorporates the distinguishing features of each fault type. The voltage and current waveforms are captured before, during, and after fault occurrences in the data acquisition process. The sample input parameter values are shown in Table 2.

The dataset is divided into the train, test, and validation sets in such a manner that a representative distribution of all fault types and conditions is present in each set. For example, the training set contains 70% of the total data, while 15% goes toward the validation set and 15% goes toward the testing set. Feature extraction involves the process of transforming raw waveforms into meaningful characteristics that can be employed by classifiers. Important features include peak values, RMS values, and statistical parameters of the voltage and current signals, such as the mean value and variance value. These features are computed over sliding windows to capture the dynamic changes in the signals caused by faults. A sliding window of 20 ms, corresponding to 200 samples at a 10 kHz sampling rate, was used for feature extraction. This window size ensures sufficient capture of fault transients while maintaining real-time processing capability.

The ensemble learning framework combines naive bayes, Multilayer Perception (MLP), logistic regression, and deep forest classifiers. The naive bayes classifier is set to use a Gaussian likelihood for continuous features. For the MLP, three hidden layers with 16, 32, and 64 neurons were used. Also, the Rectified Linear Unit (ReLU) with a dropout rate of 0.1 has been utilized as an activation function. Overfitting is prevented in logistic regression using ridge regularization (L2 regularization). The Deep Forest classifier is made up of 100 decision trees, which are each trained on a random subset of features. Deep Q-Network dynamically adjusts the weights of the individual base classifiers in the ensemble, thereby optimizing the ensemble's performance and selecting the most appropriate classifier. The DQN architecture includes an input layer corresponding to the features extracted, followed by three fully connected layers with 64, 128, and 256 neurons, respectively. Batch normalization and dropout layers are applied to improve generalization. Thereafter, the output layer in a DQN produces Q-values, which represent the expected future rewards for different actions; then it updates the model's weights and optimizes the selection of classifiers. Training of the deep Q-network was performed using the Adam optimizer with a learning rate of 0.001 and a discount factor of 0.99.

The reward function for the DQN reflects classification accuracy, precision, and recall. Higher rewards are awarded for correct classification and penalties for misclassification. The DQN iteratively updates its policy based on the observed rewards so that it will converge to an optimal strategy for the selection of the best-suited classifier. In the following section of this paper, an elaborate study has been conducted on the performance of the suggested model. The proposed model is compared comprehensively with existing models for different fault conditions.

5. Results and Discussions

The simulation model has been tested under different fault resistances and inception angles to validate its generalization ability. The experiments were conducted using fault resistances of 0.01 Ω and 0.02 Ω and fault inception angles of 30°, 60°, 90°, and 120°.

A sampling rate of 10 kHz was used for data acquisition in the MATLAB/Simulink environment. The sample dataset used in the experiments comprises the following contextual information, as mentioned below:

Fault Scenario-I

In this scenario, Line-to-Line faults (LL) are generated at 50 km with a resistance of 0.01 Ω and an inception angle of 60°, and the corresponding voltage and current waveforms are shown in Figure 6.

Voltage Waveform:	V_a, V_b, V_c
Current Waveform:	I_a, I_b, I_c
Extracted Features:	Peak Voltage (V_{peak}), RMS Current (I_{rms}), Mean Voltage (V_{mean}), Variance of Current (I_{var}).

Fault Scenario-II

In this scenario, a Line-to-Ground Faults (LG) are generated at 75 km with a resistance of 0.02 Ω and an inception angle of 120°, and the corresponding voltage and current waveforms are shown in Figure 7.

Voltage Waveform:	V_a, V_b, V_c
Current Waveform:	I_a, I_b, I_c
Extracted Features:	Peak Voltage (V_{peak}), RMS Current (I_{rms}), Mean Voltage (V_{mean}), Variance of Current (I_{var}).

5.1. Performance Metrics

The efficacy of the proposed method is measured by using various performance metrics, such as accuracy, precision, sensitivity, and F1-score, as defined in Equations (12) to (15).

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} = \frac{TP + TN}{TP + TN + FP + FN} \tag{12}$$

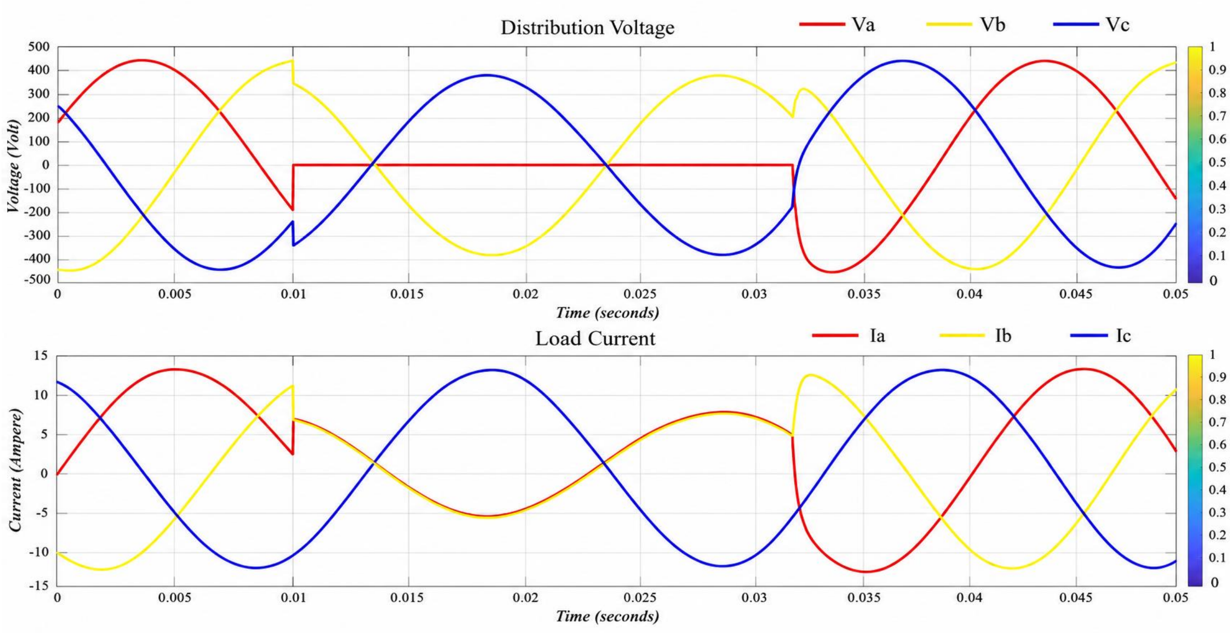
$$\text{Precision} = \frac{\text{True positive (TP)}}{\text{True positive(TP)} + \text{False positive(FP)}} \quad (13)$$

$$\text{Sensitivity} = \frac{\text{True positive (TP)}}{\text{True positive (TP)} + \text{False negative (FN)}} \quad (14)$$

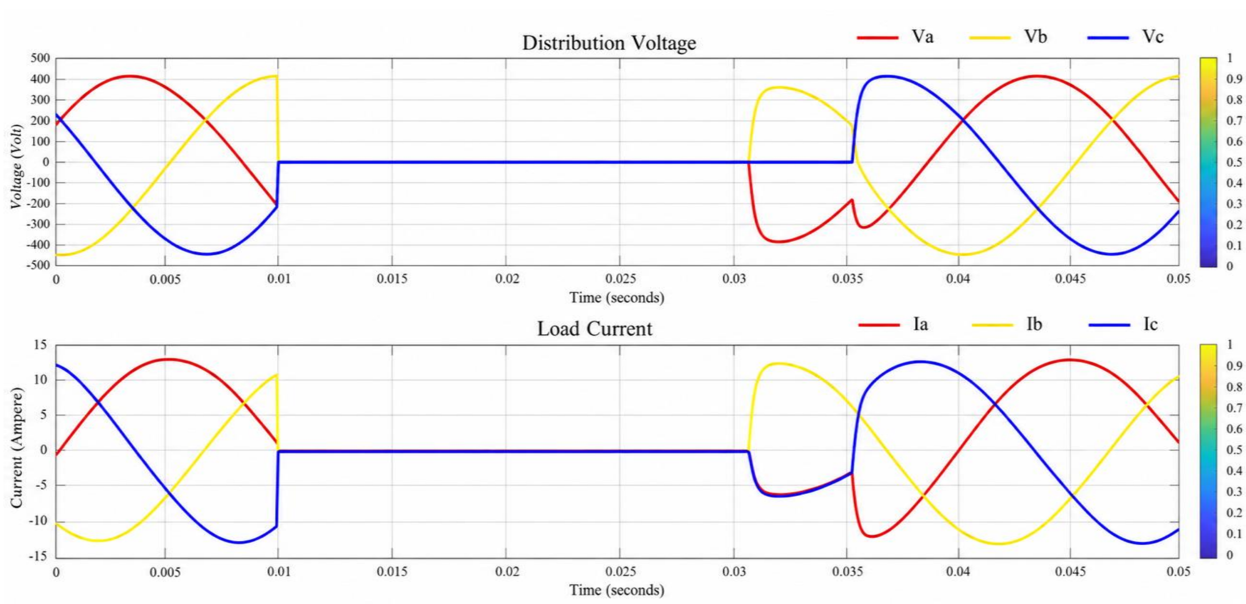
$$\text{F1} - \text{score} = \frac{\text{Precision} \times \text{Sensitivity}}{\text{True positive(TP)} + \text{False positive(FP)}} \quad (15)$$

Here, TP, TN, FP, and FN indicate actually faulty, actually no faulty, no faulty but predicted as faulty, and faulty but predicted as no faulty, respectively. The F1-score should be calculated using the harmonic mean of precision and recall, as illustrated in the above equations. The other parameters, such as training and testing processing times (milliseconds) and memory usage (megabytes), were determined for comparative analysis between the proposed model and the traditional existing methods under various fault scenarios.

5.2. Experimental Result Analysis



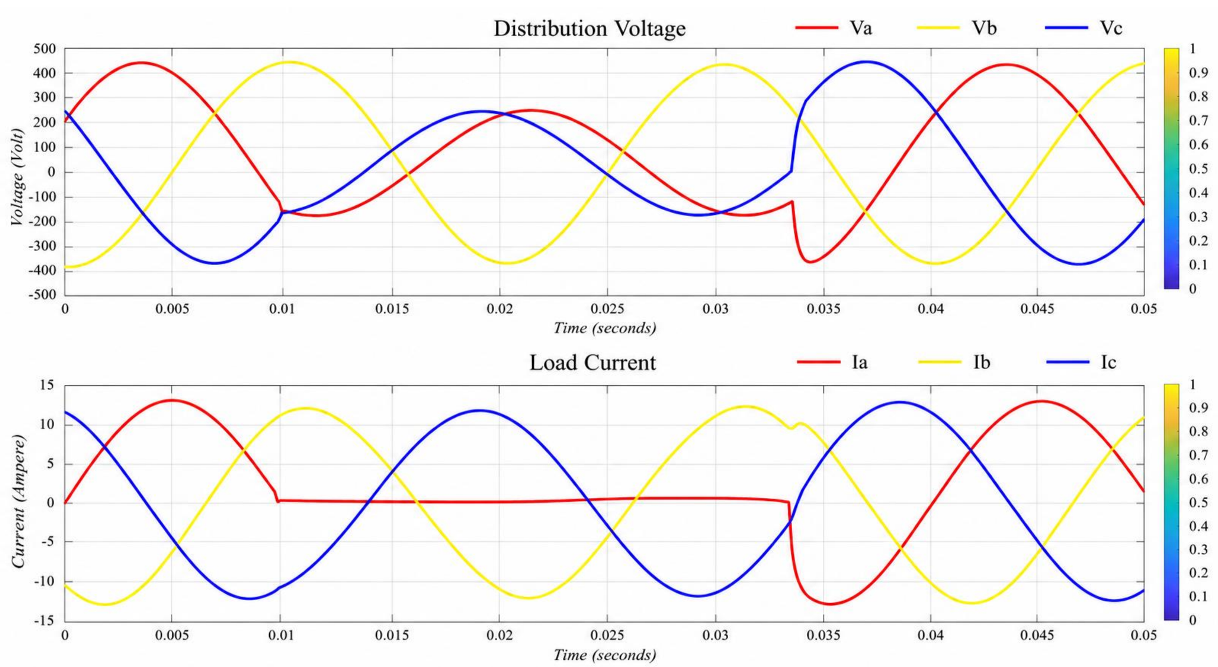
(a) Line-to-Line Fault (Phase A to Phase B Fault)



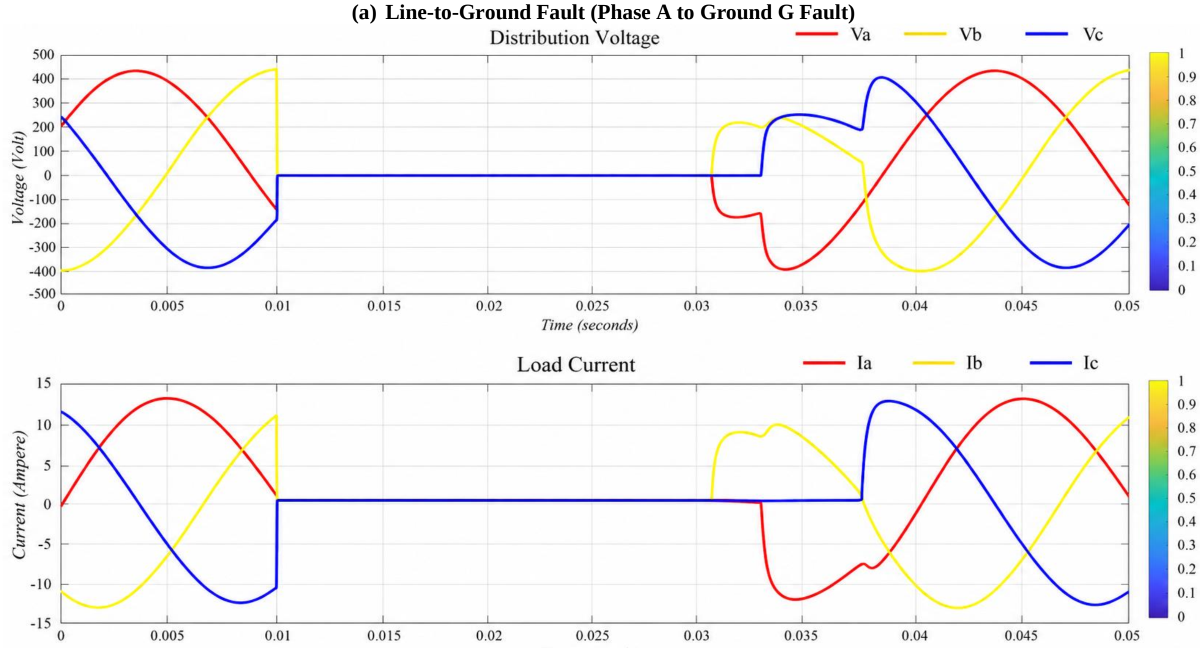
(b) Line-to-Line-to-Line Fault (Phase A to Phase B to Phase C Fault)
Fig. 6 Output voltage and current waveforms for fault scenario-I .

This section analyzes the results of a proposed ensemble learning framework integrated with DQN for fault detection in transmission lines. The data used for training the models consists of simulation-generated voltage and current waveforms obtained from the MATLAB/Simulink transmission line model under various fault scenarios, including Line-to-Line (LL) and Line-to-Ground (LG) faults.

The features extracted from these waveforms contain peak values, RMS values, mean, and variance. The classifiers in the ensemble layer and the DQN are trained and evaluated using these features. Fault conditions were simulated, including line-to-line faults at a distance of 50 km with a fault resistance of 0.01 Ω and a fault inception angle of 60° (Fault Scenario-I), as well as line-to-ground faults at 75 km with a fault resistance of 0.02 Ω and a fault inception angle of 120° (Fault Scenario-II). The resulting voltage and current waveforms for these fault scenarios are visualized in Figure 6 and Figure 7, respectively.



(a) Line-to-Ground Fault (Phase A to Ground G Fault)



(b) Three Line-to-Ground Fault (Phase A to Phase B to Phase C to Ground G Fault)

Fig. 7 Output voltage and current waveforms for fault scenario-II.

In the DQN-optimized ensemble framework, detection of simulated Line-to-Line (LL) faults and Line-to-Ground (LG) faults is achieved by first extracting statistical features from the obtained voltage and current signals using the MATLAB/Simulink model. The extracted features include peak voltage, RMS current, mean voltage, and variance of the current, which are then passed to the ensemble classification layer. The extracted features are then processed by an ensemble classification layer, including naive bayes, MLP, logistic regression, and deep forest classifiers.

The outcomes of these classifiers are then weighted dynamically by a deep Q-network algorithm. Based on the aggregated decision of the ensemble, the model classifies the fault type.

Table 3. Precision values of the ensemble classification layer

Fault Scenario	Naive Bayes	MLP	Logistic Regression	Deep Forest
Line-to-Line (LL), 50 km	96.5%	97.1%	95.8%	97.5%
Line-to-Ground (LG), 75 km	96.8%	97.4%	96.0%	97.7%
Line-to-Line (LL), 100 km	96.3%	96.9%	95.6%	97.3%
Line-to-Ground (LG), 120 km	97.0%	97.5%	96.2%	97.8%

Table 3 presents the precision values achieved by each individual classifier in the ensemble, i.e., Naive Bayes, Multilayer Perceptron (MLP), Logistic Regression, and Deep Forest, for various fault scenarios and transmission line lengths. The table shows the baseline performance of each classifier before the DQN-based optimization of its weights. For instance, for a line-to-line fault at 50 km, Naive Bayes achieved a precision of 96.5%, MLP 97.1%, Logistic Regression 95.8%, and Deep Forest 97.5%.

Table 4. Cumulative reward in the Deep Q-Network (DQN) learning layer

Itera-tion	Naive Bayes Weight	MLP Weight	Logistic Regression Weight	Deep Forest Weight	Cumulative Reward
1	0.20	0.40	0.20	0.20	8.5
2	0.30	0.35	0.20	0.15	9.1
3	0.25	0.40	0.15	0.20	9.5
4	0.30	0.40	0.20	0.10	9.7
5	0.35	0.35	0.15	0.15	10

Table 4 demonstrates the iterative adjustments made by the DQN to the weights assigned to each classifier based on the cumulative reward obtained in each iteration (Iterations 1 to 5). As shown, in the initial iteration, each classifier was assigned an equal weight (0.20 - 0.40).

The DQN managed to fine-tune the weights through the reinforcement learning process in such a way that would ensure maximum efficiency of the whole ensemble. The increase in the cumulative reward from 8.5 to 10 suggests the efficiency of the DQN in discovering a better approach to assigning weights. It allows the system to be flexible in adapting to different fault scenarios.

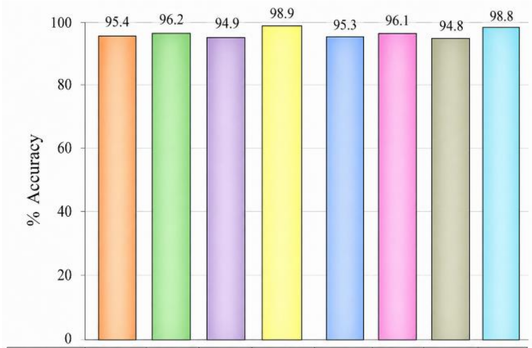
5.3. Comparative Result Analysis

The performance of the proposed framework was compared with the three existing methods previously used, which include Method [3], Method [8], and Method [20], as illustrated in Table 5, Figure 8, and Figure 9.

The conventional features for fault diagnosis in transmission lines include peak voltage, RMS current, mean voltage, and current variance; in the current investigation, these features are adaptively optimized using an ensemble of DQN, making up the novelty of the proposed technique.

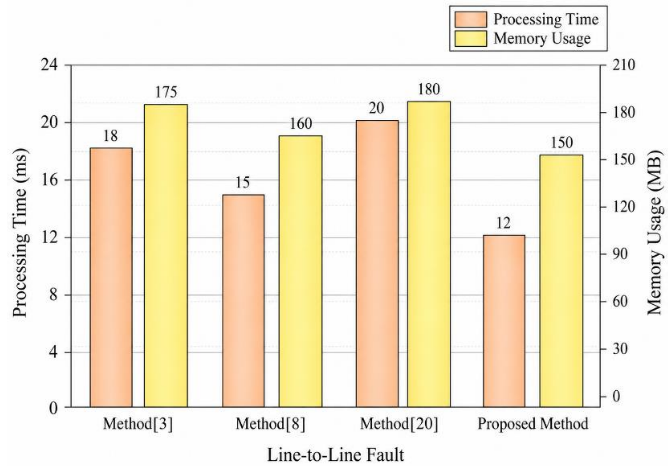
The benefits of these features are listed below: (i) Peak voltage (V_{peak}) is critical in the identification of the first voltage variation at fault initiation, with the amplitude of the peak variation depending on the fault type and intensity; (ii) RMS current (I_{rms}) is used as an important parameter for fault diagnosis, since it acts as a good measure of the overcurrent condition usually generated when there is a fault in the system, with each fault generating different variations in current;

(iii) Mean voltage (V_{mean}) gives information about the continuous voltage reduction when there is a fault in the transmission line, thus helping distinguish between permanent and transient fault cases; (iv) Variance of current (I_{var}) identifies the deviation of current variations in a fault situation, where faults cause changes in the dynamics of the current waveform, and thus variance helps in detecting the faults.



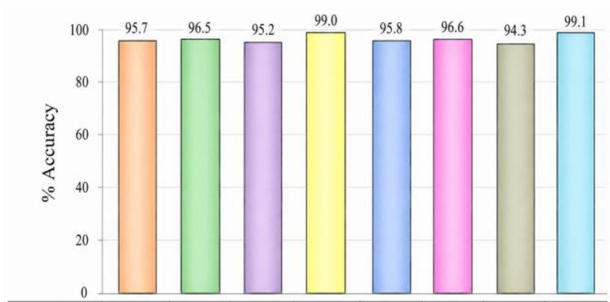
Precision	0.965	0.971	0.958	0.992	0.963	0.969	0.956	0.991
Sensitivity	0.967	0.973	0.961	0.995	0.966	0.972	0.960	0.994
F1-Score	0.966	0.972	0.959	0.993	0.964	0.970	0.958	0.992
Methods	Method [3]	Method [8]	Method [20]	Proposed Method	Method [3]	Method [8]	Method [20]	Proposed Method
Line-to-Line Fault	50 km				100 km			

(a) Performance metrics analysis for LL faults at 50 km and 100 km transmission lines



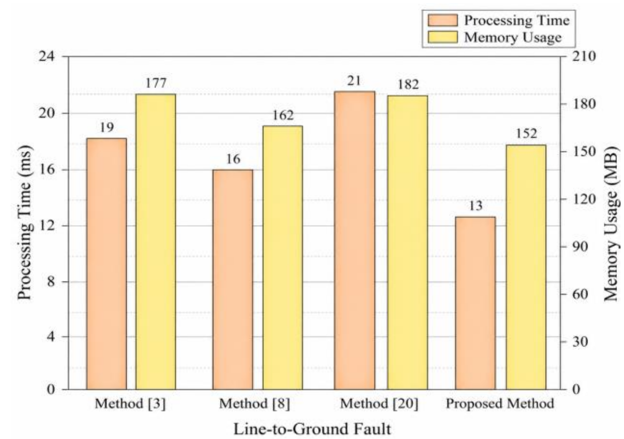
(b) Comparisons of processing time (ms) and memory usage (MB) for LL faults

Fig. 8 Comprehensive comparative analysis for line-to-line fault.



Precision	0.968	0.974	0.960	0.993	0.970	0.975	0.962	0.994
Sensitivity	0.969	0.976	0.963	0.996	0.971	0.977	0.965	0.997
F1-Score	0.969	0.975	0.961	0.994	0.970	0.976	0.963	0.995
Methods	Method [3]	Method [8]	Method [20]	Proposed Method	Method [3]	Method [8]	Method [20]	Proposed Method
Line-to-Ground Fault	75 km				120 km			

(a) Performance metrics analysis for LG faults at 75 km and 120 km transmission line



(b) Comparisons of processing time (ms) and memory usage (MB) for LG faults

Fig. 9 Comprehensive comparative analysis for line-to-ground fault.

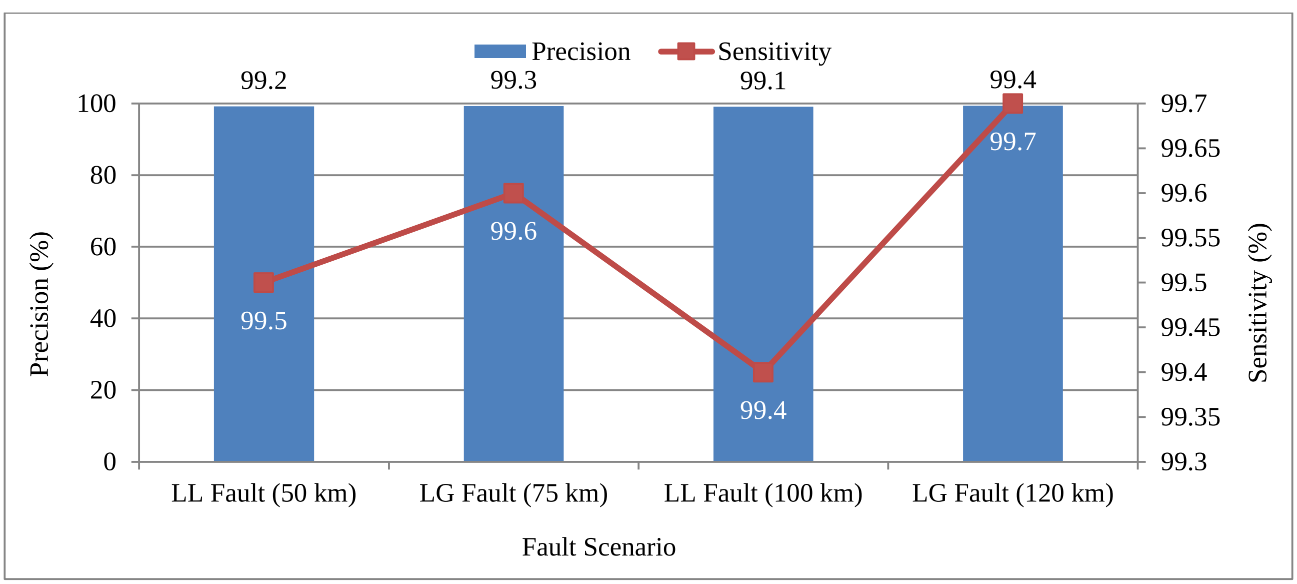


Fig. 10 Precision and sensitivity values under LL and LG fault scenarios

As demonstrated in Figure 8a and Figure 9a, the proposed method consistently achieved the highest values for accuracy, precision, sensitivity, and F1-score across all tested fault scenarios. For example, for a line-to-ground fault at 120 km, the proposed method achieved an accuracy of 99.10%, significantly outperforming Method [3] (95.80%), Method [8] (96.60%), and Method [20] (94.30%). These metrics (defined in Equations (12) to (15)) collectively indicate the superior ability of the DQN-optimized ensemble framework to correctly identify faults while minimizing both false positives and false negatives. Furthermore, Figure 8b and Figure 9b illustrate that the proposed method exhibits a lower processing time (12-13 ms) and reasonable memory usage (150-152 MB) compared to the other existing methods.

Figure 10 shows how effective the proposed model is in terms of accuracy and sensitivity under different fault conditions, which highlights the reliability of the model in terms of accurate fault detection. Overall, it can be concluded that the experimental results prove the superiority of the proposed framework in comparison with existing techniques and emphasize the validity of the proposed framework for detecting faults in transmission lines.

Table 5 presents a comprehensive comparison of accuracy, precision, sensitivity, F1-score, processing time, and memory usage between the proposed method and the existing methods under different fault conditions, such as Line-to-Line faults (LL) at 50 km and 100 km, and Line-to-Ground faults (LG) at 75 km and 120 km. As shown by the performance metrics, the proposed model proves to have high efficiency.

5.4. Limitations

The limitations of the present study are outlined below:

- The DQN-based ensemble system shows great performance in simulations, but its generalization capability could be different for other voltage levels, fault types, noise, and even network sizes.
- At present, the scope of research is limited to short circuit faults in particular line lengths and resistances. Future research needs to make the model more adaptive to high impedance faults.
- Furthermore, the scalability of the approach in terms of computational requirements for real-time deployment requires further examination.

Table 5. Performance evaluation of the proposed method against existing approaches

Fault Scenario	Method	Accuracy (%)	Precision (%)	Sensitivity (%)	F1-Score (%)	Processing Time (ms)	Memory Usage (MB)
Line-to-Line fault (LL), 50 km	Method [3]	95.40	96.50	96.70	96.60	18	175
	Method [8]	96.20	97.10	97.30	97.20	15	160
	Method [20]	94.90	95.80	96.10	95.90	20	180
	Proposed Method	98.90	99.20	99.50	99.30	12	150
Line-to-Ground fault (LG), 75 km	Method [3]	95.70	96.80	96.90	96.90	19	177
	Method [8]	96.50	97.40	97.60	97.50	16	162
	Method [20]	95.20	96.00	96.30	96.10	21	182
	Proposed Method	99.00	99.30	99.60	99.40	13	152
Line-to-Line fault (LL), 100 km	Method [3]	95.30	96.30	96.60	96.40	18	175
	Method [8]	96.10	96.90	97.20	97.00	15	160
	Method [20]	94.80	95.60	96.00	95.80	20	180
	Proposed Method	98.80	99.10	99.40	99.20	12	150
Line-to-Ground fault (LG), 20 km	Method [3]	95.80	97.00	97.10	97.00	19	177
	Method [8]	96.60	97.50	97.70	97.60	16	165
	Method [20]	94.30	96.20	96.50	96.30	21	182
	Proposed Method	99.10	99.40	99.70	99.50	13	152

6. Conclusion

The proposed framework integrates Naive Bayes, Multilayer Perceptron, Logistic Regression, and Deep Forest classifiers, dynamically optimized by DQN. It achieves superior performance with an accuracy of 99.10%, precision of 99.40%, sensitivity of 99.70%, and F1-score of 99.50% across varied fault scenarios, significantly outperforming traditional methods. The system maintains robustness under dynamic conditions with reduced processing time (12-13 ms) and memory usage (150-152 MB), making it highly suitable for real-time applications. DQN continuously refines classifier weights, ensuring adaptive learning and improved detection accuracy. Future work will focus on evaluating the proposed DQN-ensemble framework against advanced deep learning architectures, such as CNN–LSTM hybrids, transformer-based models, and graph neural networks, as well as testing with real-time smart grid data from diverse locations to enhance model generalization under dynamic operating conditions. Additionally, enhancement of the reward function by incorporating monetary and operational constraints is planned to further strengthen fault management. The model will also be validated on larger systems (such as IEEE 30-bus, 33-bus, and 39-bus networks) and higher voltages to further demonstrate its practical applicability and robustness.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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