Hindawi
International Transactions on Electrical Energy Systems
Volume 2024, Article ID 6677830, 15 pages
https://doi.org/10.1155/2024/6677830

Research Article

Enhancing Fault Detection and Classification in MMC-HVDC Systems: Integrating Harris Hawks Optimization Algorithm with Machine Learning Methods

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Received 5 June 2023; Revised 8 December 2023; Accepted 11 January 2024; Published 13 February 2024

Academic Editor: Hamed Badihi

Accurate fault detection in high-voltage direct current (HVDC) transmission lines plays a pivotal role in enhancing operational efficiency, reducing costs, and ensuring grid reliability. This research aims to develop a cost-effective and high-performance fault detection solution for HVDC systems. The primary objective is to accurately identify and localize faults within the power system. In pursuit of this goal, the paper presents a comparative analysis of current and voltage characteristics between the rectifier and inverter sides of the HVDC transmission system and their associated alternating current (AC) counterparts under various fault conditions. Voltage and current features are extracted and optimized using a metaheuristic approach, specifically Harris Hawk's optimization method. Leveraging machine learning (ML) and artificial neural networks (ANN), this technique demonstrates its effectiveness in generating a fault locator with exceptional accuracy. With a substantial volume of data employed for learning and training, the Harris Hawks optimization method exhibits faster convergence compared to other metaheuristic methods examined in this study. The research findings are applied to simulate diverse fault types and unknown fault locations at multiple system points. Evaluating the fault detection system's effectiveness, quantified through metrics such as specificity, accuracy, *F*1 score, and sensitivity, yields remarkable results, with percentages of 99.01%, 98.69%, 98.64%, and 98.67%, respectively. This research underscores the critical role of accurate fault detection in HVDC systems, offering valuable insights into optimizing grid performance and reliability.

1. Introduction

Electric power is generated in the power plant as alternating current (AC), and most loads are designed to operate with AC power. Hence, it leads to the transmission of power through HVAC transmission lines within a transmission system. However, this transmission method comes with several disadvantages, and because of the emergence of power electronic technologies, a high-voltage direct current (HVDC) transmission line has been introduced. These lines effectively transmit significant amounts of electricity power using direct current (DC) over long distances by overhead transmission lines, underground cables, or submarine cables. Within a power system, electricity is generated, transmitted, and distributed [1–3]. Transmission lines are used to supply electricity to distant users. Since the 1970s, the number of lines in use has increased dramatically, as has their cumulative length.

Various factors, including lightning, short circuits, equipment failure, human error, overload, and aging, can all cause issues. Preventing electrical failures by repairing mechanical damage is a typical practice. Faster repair is possible with an early diagnosis of the defect. Consumers may experience brief or extended power outages because of faults, which can result in severe financial losses, particularly for businesses. These defects must be immediately located to maintain a stable power system. Finding a flaw is a challenge that engineers and researchers focus on. The majority of study to date has been on identifying transmission line flaws. Transmission line flaws significantly impact power systems more than distribution systems and subtransmission flaws, mainly because physically inspecting transmission lines requires more time [4, 5]. Achieving precise fault location is crucial to identifying issues accurately. Engineers use fault location algorithms to locate faults. Temporary or permanent problems are common occurrences in transmission lines, often identified as self-clearing transient faults in overhead lines. As a result, there is no long-term disruption to the power supply and circuit breakers play a role in detecting and de-energizing permanent failures; in addition, it is possible to turn back the power supply. The entire line must be inspected until the issue is precisely identified. A defect must be known, or at least partly known, for an effective investigation. Improved service and lower inspection and maintenance cost effectively eliminate power outages. This means no power outages. Temporary defects are significant since they self-correct and do not impact supply in the long term. By identifying vulnerabilities in cables through fault location techniques, preventive maintenance plans can be formulated [6–8].

AC and DC can be carried on transmission lines, each with benefits. Using AC TL reduces the cost of inverters and rectifiers because both the electricity utilized by customers and the distribution networks are AC. DC TL becomes necessary whenever the power demand or transmission distances grow because it links two AC systems with different resonant frequencies. For long-distance network communication and power transmission, MMC-HVDC technology is a potential alternative to AC, and besides, it moves electricity between nonsynchronized AC networks. Because of the skin effect of DC transmission lines, the MMC-HVDC systems' inductive and capacitive characteristics remain unaffected. In connected AC power grids, the control system of an MMC-HVDC project can reduce power oscillations by quickly modulating DC power. System transient stability is enhanced as a result [9, 10]. Naturally, flaws can be found through foot patrols or patrols using other mobility techniques and binoculars. It takes a while to look into a faulty line [10–14].

The HVDC system is preferable to the AC system at high voltages for the following reasons:

(1) For long transmission lines with high transmission power.

HVDC requires additional converter station equipment for transmitting high power over long distances; the DC system's total loss is less than the AC system. In this context, decisions are made based on affordability or economic feasibility. HVDC lines do not need intermediate stations for balancing, but extra high voltage (EHV)-AC lines need these stations, and under the same conditions, station losses in HVDC lines are less than EHV-AC lines.

(2) To connect two AC systems (networks) that have a load-frequency control system.

HVDC system has several advantages over AC system. HVDC systems synchronize two AC systems, which do not need other systems for synchronization. With HVDC, the transmission power is controlled, there are no disturbances in the frequency, and the transients in the AC network on both sides can be improved to the desired extent.

(3) For back-to-back synchronization stations.

An HVDC converter station can be used when someone wants to link several of AC systems with varying frequencies. It also controls power transfer and exchange between them.

(4) Connection of several high-pressure alternating current networks.

The new HVDC system can implement this possibility, and three or more AC networks can be connected synchronously by using it. The current power in each connected AC system can be controlled, and many influences can be transferred.

(5) For underground and submarine transmission cables

These cables are used for medium distances, high voltages, and power transmission in the ocean.

Modular multilevel converter-based HVDC (MMC-HVDC) systems' reliability is crucial to maintain the power systems' security and dependability. Using extra switches (semiconductor devices) in redundant SMs in the arm submodule or a submodule is an effective way to increase reliability in fault-tolerant systems [15–17]. In order to assure continuous converter service, a fault-tolerant operation must be a prerequisite for defect detection, which must be as quick and precise as possible. Because many power electronic SMs exist in the MMC circuit, and each of them has the potential to fail, it is difficult to detect a fault and classify it [15, 17–20].

Three fundamental approaches—AI-based, mechanism-based, and signal processing-based—can detect and classify faults in MMC-HVDC systems [21].

This research suggests a new hybrid method based on current and voltage features obtained from the fault and nonfault signals and the Harris Hawks optimization technique to differentiate the fault types in the MMC-HVDC systems. The ANN is a powerful classifying method for identifying the error type by calculating the similarity probability between training and experimental data. Based on the current and voltage signal characteristics retrieved from a DC line, the ANN algorithm predicts the behavior of the components. In this study, we choose the best features from the current and voltage data using the Harris Hawks optimization technique. The Harris Hawks optimization method selects the distinctive properties from the voltage and current signals for faster ANN computation and better detection accuracy. This new characteristic shows different behaviors in different error conditions. The Harris Hawks optimization algorithm reduces the volume of training data, improves training, and solves the divergence problem. In this method, the benchmark function is a comparison among several probabilities. This function can detect the error state from the normal state. Another advantage of this approach is that the error detection algorithm does not need to select threshold values. Since it is based on the error signals' statistical characteristics and does not require a specific criterion function, this method will be evaluated by simulating different error modes.

The proposed method uses the offline systems, which has the disadvantage of being ineffective with online systems.

The MMC-HVDC sample network will be modeled using the MATLAB-Simulink simulation package. The evaluation's findings will show specificity, accuracy, $F1$ score, and sensitivity in identifying various MMC-HVDC system problems. The confusion matrix (with examples of specificity, accuracy, $F1$ score, and sensitivity) was used to evaluate the results.

So far, several algorithms have successfully identified problems in power systems, enabling more protection and simplified maintenance. For example, traveling wave methods record the reflected signals at both ends after sending an electrical pulse in the line. They are as follows:

(1) An analytical method is used based on frequency measurements, like impedance. The return time of the pulse after traveling through the fault location tells how far away it is. This method collects the signals at the line's ends and identifies its periodic fundamental component after and before a fault by applying electrical magnitudes. Handling such crucial elements leads to problem identification.

(2) Knowledge-based techniques (AI tools) investigate how machines can mimic human thoughts and behaviors. They include numerical and symbolic calculations.

Making rational decisions is only one aspect of artificial intelligence; it also includes the capacity to deal with incomplete data and change course in response to changing conditions.

Three prominent families of artificial intelligence (AI) approaches are believed to be used in the automation and control of modern power systems:

(1) Fuzzy logics

(2) Expert systems

(3) Synthetic neuronal systems.

In areas like load forecasting, control systems, defect detection, and pattern categorization, neural network research has much potential. It may be employed in a networked environment and can learn, generalize, and tolerate errors.

Using an ANN and the Harris Hawks Optimization algorithm, faults can be localized, identified, or categorized in MMC-HVDC transmission lines.

For this study, a bipolar overhead MMC-HVDC TL type with a length of 1200 km and a rating of 70 kV has been chosen. Postfault MMC-HVDC TL values are coupled to prefault DC and AC (current and voltage) at the inverter stations and rectifier as inputs to the mentioned algorithm and ANN. The most frequent bipolar MMC-HVDC TL power faults may be reliably identified and characterized in this study, and their locations can be specified with a tolerable level of imprecision. To analyze neural networks, neurons per hidden layer and numbers of hidden layers validate the HHO's selection based on features of the voltage and current signals and ANN at each stage. According to simulation data, ANN-based techniques help detect, classify, and locate faults in MMC-HVDC transmission lines [22].

In previous research studies [23–29], the wavelet feature has been used to detect errors in HVDC. This study uses signal processing features and metaheuristic methods to find optimal signals, and then uses a support vector machine (SVM) machine learning model to achieve high-performance results in detecting faults in HVDC.

The main contribution of this research is the application of a novel technique for fault identification and classification in MMC-HVDC systems utilizing the Harris Hawks Optimization algorithm based on ANN. With this method, the features of the voltage and current signals are recovered from the signal over a significantly shorter amount of time using faulted and nonfaulted signals.

2. Material and Method

The faulty and nonflawed signals were developed in this study to assess the MMC-HVDC fault detection. Multiple signals were constructed for this purpose, each with a unique set of AC and DC faults. From these signals, the characteristics that depend on voltage, current, and their constituents are derived. Some of these traits are inappropriate for ANN training, and when included, the accuracy of detection and classification will be decreased. The best and most accurate features should be chosen as a result. So, for feature selection, the Harris Hawks Optimization approach is employed. As mentioned, Harris Hawk's optimization has been applied for the best feature selection from the feature matrix from the voltage and current signals obtained from the faulty and standard signals. The selected feature trains the ANN for high accuracy and fault detection performance [30, 31]. This optimization algorithm is a group intelligence method that enables the population members to take advantage of the group's information and the situation and try to solve an optimization problem. Metaheuristic algorithms mainly utilize a group intelligence method to show the group's hunting behavior. Individuals of the population circle the prey or the current ideal position and try search around it, and attack the victim at its weakest point. Group hunting is a habit many creatures display in nature, for example, arthropods, mammals, and insects. Harris Hawks Optimization method was developed in 2019 [32] and modeled as an example of this type of system. Group intelligence systems can incorporate the behavior of numerous creatures that cooperate, and their number may not be significant. Usually, groups of up to 6 birds fly around the prey and engage in cooperative hunting of an animal. Figure 1 depicts this tendency.

Figure 1: Hunting mechanism based on group intelligence in the HHO algorithm (source: figure is reproduced from Heidari et al. [32]).

It is evident from these animals' behavior that a small number of them went hunting first, and then other group members joined them. They all cooperated and participated in the group hunt. In this form of hunting, the prey or ideal solution is surrounded by all the hawks or issue resolutions, and one of the birds hunts it. This method demonstrates how the prey is initially detected before being surrounded and attacked. Each hawk in this algorithm represents a potential solution to a problem, and the hawks fly toward the rabbit, where the current best answer is located. These algorithms start by searching the problem space for the target before attacking it. The falcon's random and initial search activity can be modeled using equation (1) [32]:

$$X(t+1) = \begin{cases} X_{rand}(t) - r_1\left|X_{rand}(t) - 2r_2.X(t)\right| & rand \geq 0.5, \\ \left(X_{rabbit}(t) - X_M(t)\right) - r_3\left(LB + r_4(UB - LB)\right) & rand < 0.5. \end{cases} \quad (1)$$

Here, $X(t)$ is the hawk's current position, $X(t+1)$ is the position of a hawk in the new iteration, $X_{rand}(t)$ is a random position, r_1, r_2, r_3, and r_4 are random numbers from 0 to 1, $X_{rabbit}(t)$ is the most optimal solution's position, $X_M(t)$ is the falcon population's gravity point, and LB and UB are the solution's lower and upper limits, respectively. To calculate $X_M(t)$, equation (2) is used, and there is N number of hawks [32]:

$$X_M(t) = \frac{1}{N}\sum_{i=1}^{N} X_i(t). \quad (2)$$

In this equation, $X_M(t)$ is considered the gravity point of the population, and $X_i(t)$ is the solution's position (the i-th falcon). The energy coefficient in the falcon optimization algorithm changes the falcons' behaviors from searching to hunting over time, and equation (3) shows this behavior. Moreover, in this context, the parameter E value constantly reduces (like 2 to 0). Figure 2 shows a change in parameter E in terms of repetition.

Here, E_0 is the initial energy value, T is the algorithm's maximum iteration, and t is the number of current iterations [32]:

$$E = 2E_0\left(1 - \frac{t}{T}\right). \quad (3)$$

These behaviors were used later for choosing the optimal features for the feature matrix generated from the voltage and current signals from the MMC-HVDC model. Shahin's optimization technique includes a collection of behaviors used to solve the problem and direct the crowd.

Figure 3 depicts the flowchart of the process for choosing and using the features in the ANN.

The training of the ANN has been done by Levenberg–Marquardt training algorithm. There are various benefits to using the Levenberg–Marquardt algorithm. It is more computationally efficient than the Gauss–Newton approach and converges more quickly than the steepest descent method.

2.1. Model. The back-to-back MMC-HVDC modular multilevel converter that provides electricity to a passive network serves as a model. The MMC rectifier and inverter, which have 51 levels, are similar in starting settings. 66 kV is the connection voltage. For a steady state modulation index of 0.8, the DC voltage is 135 kV. The converter has a 220 MVA rating.

The model uses the modular multilevel converter's aggregated modeling technique to boost the model's computational effectiveness while preserving the critical dynamics and details. For example, every submodule capacitor of an arm of the MMC is modeled as a standard virtual capacitor, which implies that the model assumes perfect capacitor voltage balancing. However, this is merely a physical characteristic of practical design; it does not affect the simulation's outcomes.

Voltage source converters (VSCs) are employed in modern HVDC, although thyristors are used in the model for this study. The literature has well-established and established protection methods for thyristor-based two-

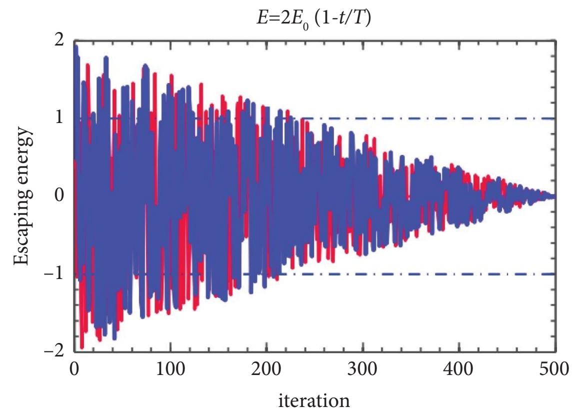


FIGURE 2: Reduction of the E index according to the repetition of Shahin's optimization algorithm (source: figure is reproduced from Heidari et al. [32]).

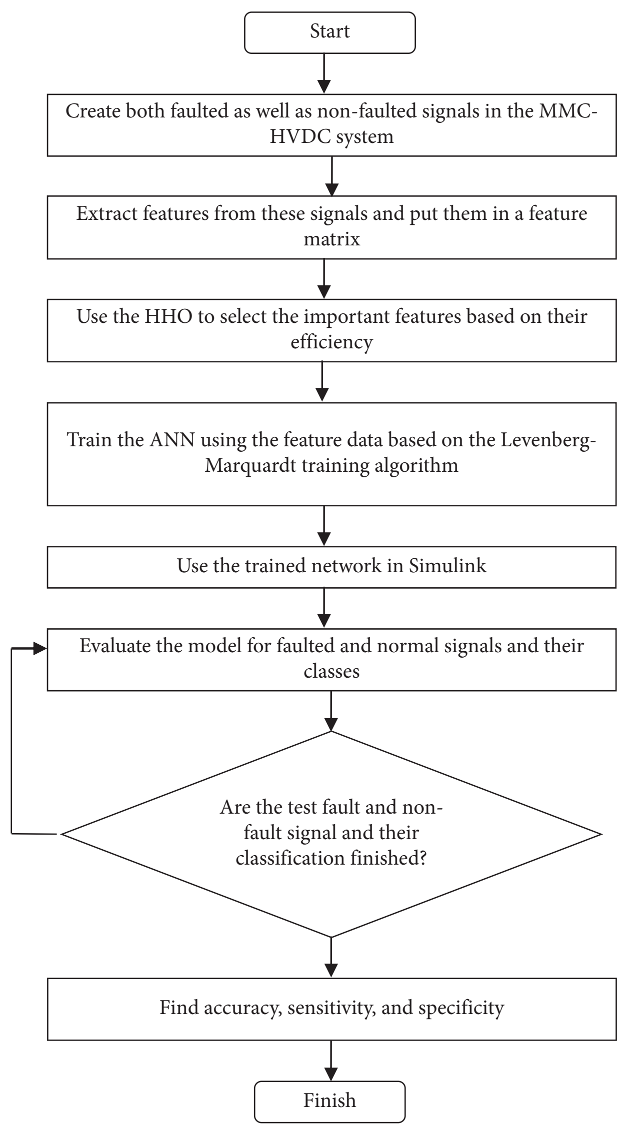


FIGURE 3: Flowchart for the proposed method's fault detection and classification.

terminal HVDC systems [33–35]. VSC-based systems, and specifically multiterminal DC systems, are the subject of the present protection problem. The HHO approach is utilized in this work to assess the features and choose the optimal voltage and current signal, which is its key contribution. In addition, authors advise employing HVDC systems based on VSC in simulation experiments in future investigations.

The importance of large training data in machine learning is crucial for enhancing accuracy and resilience in protection techniques, despite challenges like heightened computational costs [36]. To overcome these challenges, strategies such as data compression and distributed training algorithms are suggested [37]. The benefits of large training datasets include improved accuracy and increased robustness to noise and outliers [38], as models trained on such datasets can better comprehend intricate data relationships [36]. The neural network model and Simulink model that were utilized to evaluate the system are seen in Figures 4(a) and 4(b), respectively.

With a source of voltage harmonics on the DC side and a source of current harmonics on the AC side, respectively, the HVDC converter is used in both AC and DC systems. The output harmonics are arranged in accordance with the number of converter valves (P), where k is an integer and $n = \mathrm{kP} \pm 1$ for AC current harmonics and $n = \mathrm{kP}$ for DC voltage harmonics, respectively. For this reason, AC filters are placed on either side of the rectifier and inverter to cancel out the current harmonics on the AC side. The equations for the power system and the control/protection system were solved during the simulation using a sampling time of $\mathrm{Ts} = 50\,\mu\mathrm{s}$. As additional primary controls for HVDC, power control on the inverter side and rectifier control on the rectifier side are used.

When a valve is operating normally, the differences in thyristors' properties might put a lot of strain on it. The voltage on all of a valve's thyristors will drop as a result of each pole's improper operation, abruptly reducing the transmitting power. The HVDC converter must therefore be safeguarded as a standalone device.

The start unit of the protection block is the fault detection. Therefore, the MMC-HVDC protection systems' flaws must be found using a quick and accurate technique. To acquire a quick response to fault detection in this study, machine learning (ML) is applied. The learning phase of the ML method takes time, but once complete, the trained network is ready for fault detection. ML is much faster than logic algorithms at fault discovery during testing.

The inverter and rectifier types of failures in MMC-HVDC converters are introduced separately in this paper. The rectifier's dynamic behavior, simulation, and appropriate controller are then investigated using MATLAB software. The HHO is then used to identify the best features, and the prospective ML is trained by stripping the fault signal and the nonfault signal of the traits of the best features.

3. Results and Discussion

This section discusses fault detection, categorization, and classification scenarios. The signals have been separated into faulty and nonfaulted signals for fault detection. The voltage and current signals yielded characteristics employed in the ANN with 0 and 1 target numbers. In this case, "0" is used for nonfault signals, and "1" is used for the faulted signals.

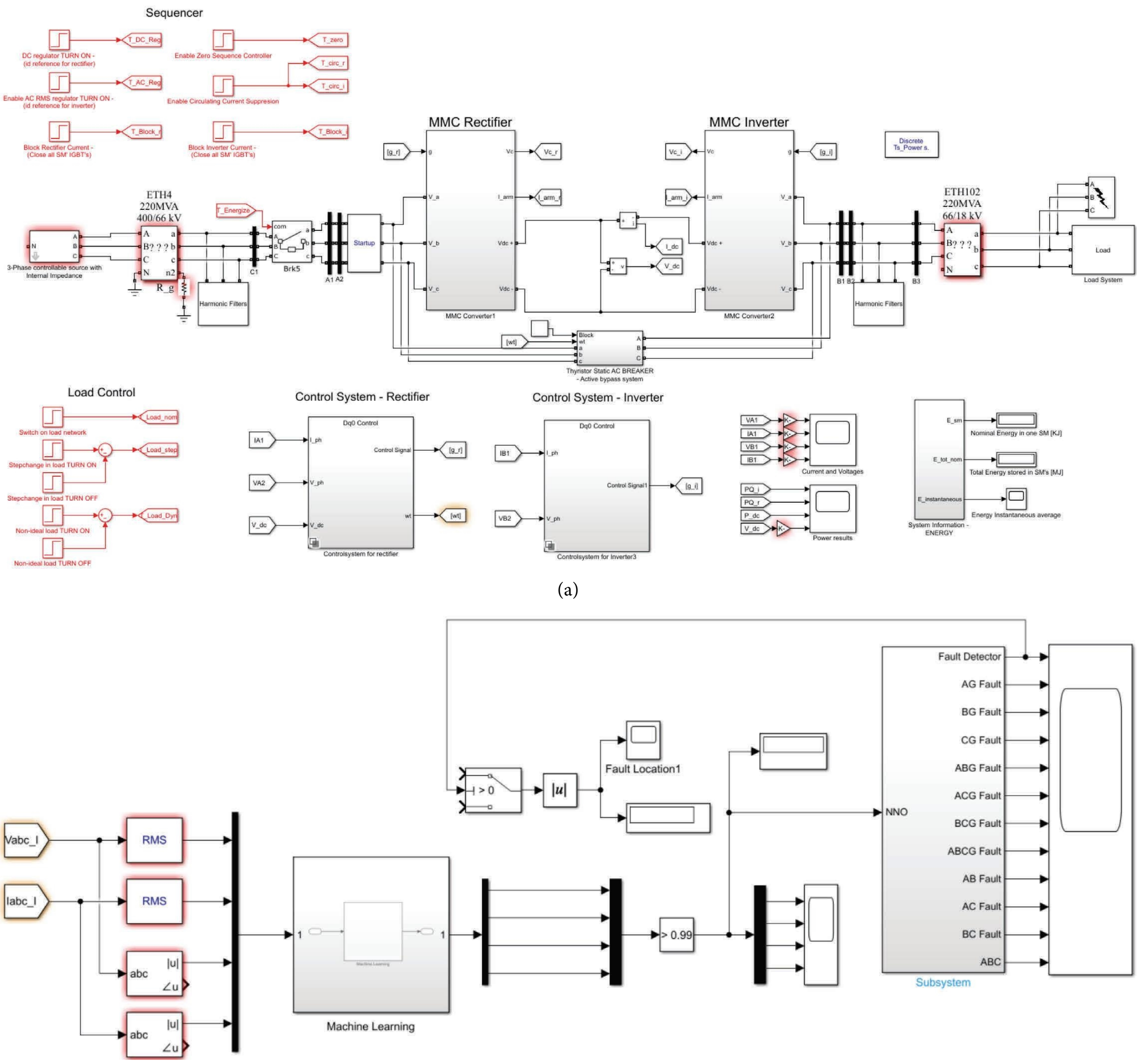
3.1. Fault Detection. Six inputs are given to the neural network during the fault detection procedure. Three voltages from the corresponding three currents and phases are the inputs. The supplied voltage and current values are normalized based on the prefault values. The data set was created considering the ten distinct errors and no-fault conditions. The training set consists of 8,712 input and output samples, comprising 6 inputs and a single output for every input-output pattern (means 792 for no-fault conditions and 792 for each of the 10 faults). The neural network's output, a yes or no form, or 1 or 0, tells us whether the defect has occurred. Five layers make up the designed artificial neural network architecture. A 6-12-6-4-1 neural network architecture was selected after running simulations, which showed that it had three hidden layers with 14, 8, and 4 neurons, respectively. Figure 5 shows satisfactory neural network training performance. The trained neural network's total mean squared error (MSE) is less than 0.0001, but after the network's training, it was 5.8095e 005. As a result, the ANN was trained using the final architecture for the provided input and output for this data set.

After training a neural network, a linear regression plot was generated to evaluate its performance that links the objectives and outputs, displayed in Figure 6.

The correlation (R) shows the neural network targets' ability to follow the output changes (0 depicts total correlation, and 1 means no correlation). This study shows a correlation coefficient of 0.99982, indicating an excellent connection. Plotting the confusion matrices for the different kinds of mistakes on the trained neural network encountered is another method of evaluating the neural network's performance. Figure 7 shows the confusion matrix (training, testing, and validation).

The successfully classified and incorrectly classified cases of the neural network are indicated by green and red diagonal cells, respectively. Each matrix's final dark gray cell displays the successfully categorized cases in green and the opposite in red. Obviously, the selected neural network detects faults with 100% accuracy.

3.2. Fault Classification. The classifier neural network's creation and development follow the procedure used in fault detection. As previously described, the constructed network accepts the six input sets (three-phase voltage and current normalized based on prefault values). The neural network has four outputs: an output for the ground line and three outputs for each of the three phases' fault conditions. Consequently, the outputs are either 0 or 1, indicating a fault or no fault in any of the A, B, C, or G lines. Here, G represents the ground, and A, B, and C stand for the transmission line's three phases. Because of this, each of the different flaws can be represented by one of the many possible permutations. The suggested neural network must accurately identify the



(a)

(b)

Figure 4: (a) The Simulink model and (b) the neural network model.

ten potential error categories. Table 1 indicates the ideal result for each flaw. The training set's 7,920 input and output patterns (792 for each type of fault out of 10 faults) have six inputs and a single output in every input-output combination. The number of neurons in each hidden layer and combinations of hidden layers in back-propagation networks were examined. The neural network (6-38-4) consists of six neurons in the input layer, 38 in a hidden layer, and 4 in the output layer. It was only the one that operated satisfactorily. The trained neural network's total mean square error is 0.036043, and Figure 8 shows testing and validation curves with similar properties, which shows the effectiveness of training.

Two methods are used to gauge how well the trained neural network performs. The first method involves a linear regression among the targets and outputs, as displayed in Figure 9. In this instance, the correlation coefficient was 0.93788, indicating an acceptable target-output connection. Figure 10 demonstrates the trained neural network's ability to determine the fault type (78.1%). In addition, the neural network can distinguish among the ten transmission line defects.

Table 2 displays the ANN fault detection's accuracy. The output network is split into fault and normal categories. Table 2 shows a 100% detection accuracy for testing proportions (0.1, 0.5, and 0.7). At a 0.9 testing proportion, the detection accuracy is 99.7%, meaning that only 0.3% of fault instances are mistakenly labeled as normal.

Table 3 contrasts the MMC-HVDC fault classification system as a whole between the suggested approach and other methods, as well as sensitivity, accuracy, Jaccard, precision, and $F1$ score.

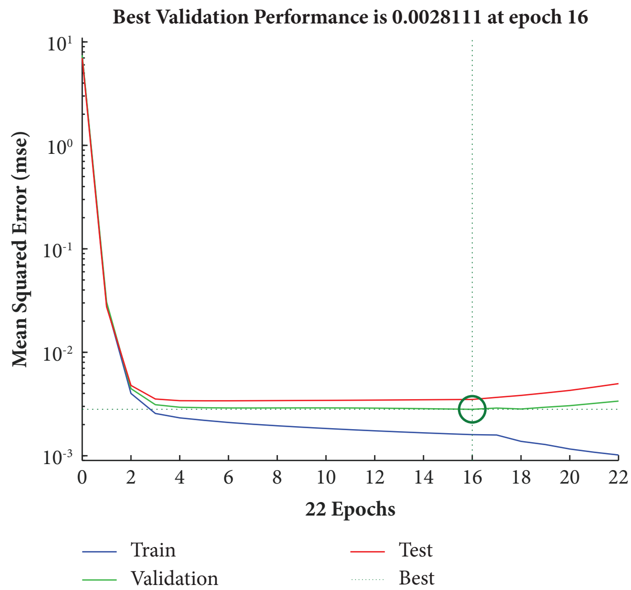


Figure 5: The network's error performance.

The $F1$ score (machine learning evaluation metric) assesses a model's accuracy, combining the model's precision and recall ratings. The accuracy statistic determines the frequency of correct predictions throughout the entire dataset.

Contrary to the simulated annealing (SA), genetic algorithm (GA), particle swarm optimization (PSO), and principal component analysis (PCA), the suggested method uses the HHO to choose the best features from the currents, voltages, and their derivatives. The trials showed that, for sensitivity, accuracy, Jaccard, precision, and $F1$ score, respectively, GA, PCA, PSO, SA, and the suggested technique (HHO) had accuracy values of 95.23%, 97.33%, 93.46%, 97.79%, and 99.26. Compared to other approaches, the accuracy of the suggested method was the highest because, when feature selection and HHO were applied, the accuracy rose to 99.26%.

The computational and hardware requirements of this approach are not examined in this paper because of the length of time needed to remove the fault. The detection and classification accuracy rate are the main aim of this study. The processing time of the training and testing and timing of the MMC-HVDC systems protection is not considered in this study.

The accuracy, sensitivity, and specificity of the fault classification system are contrasted with alternative approaches in Table 4.

The paper introduces an innovative fault detection technique for HVDC systems, utilizing a fusion of comparative analysis, metaheuristic optimization, and machine learning. A thorough evaluation of its efficacy necessitates both quantitative and qualitative comparisons with established techniques. Drawing from the details in the paper and the data in Tables 5 and 6, let us provide a comprehensive analysis:

3.3. Quantitative Comparison. The quantitative assessment reveals that the proposed technique outperforms existing methods across various metrics. In comparison to Table 5, it is evident that the new technique demonstrates superior accuracy, sensitivity, precision, Jaccard, and $F1$ score. These improvements highlight its quantitative edge over the established techniques, suggesting a more precise and reliable fault detection capability.

3.4. Qualitative Comparison. Higher accuracy: the novel technique uses metaheuristic optimization for feature selection, achieving higher accuracy than traditional methods (Table 6).

Simplified design: integration of fault localization within the model simplifies the overall system design, offering a more streamlined approach.

Adaptable and robust: the technique's high adaptability to unknown faults and robustness to noise makes it versatile and reliable for real-world applications.

The combined quantitative and qualitative comparison highlights the promising nature of the novel fault detection technique for HVDC systems. Its quantitative superiority, coupled with qualitative strengths such as metaheuristic optimization, fault localization integration, adaptability, and robustness, positions it as a compelling choice for advancing fault detection capabilities. However, the discussion also recognizes the trade-offs, urging further exploration into practical feasibility and interpretability.

3.5. Analysis

(i) The HHO technique achieves significantly better performance across all metrics compared to existing techniques.

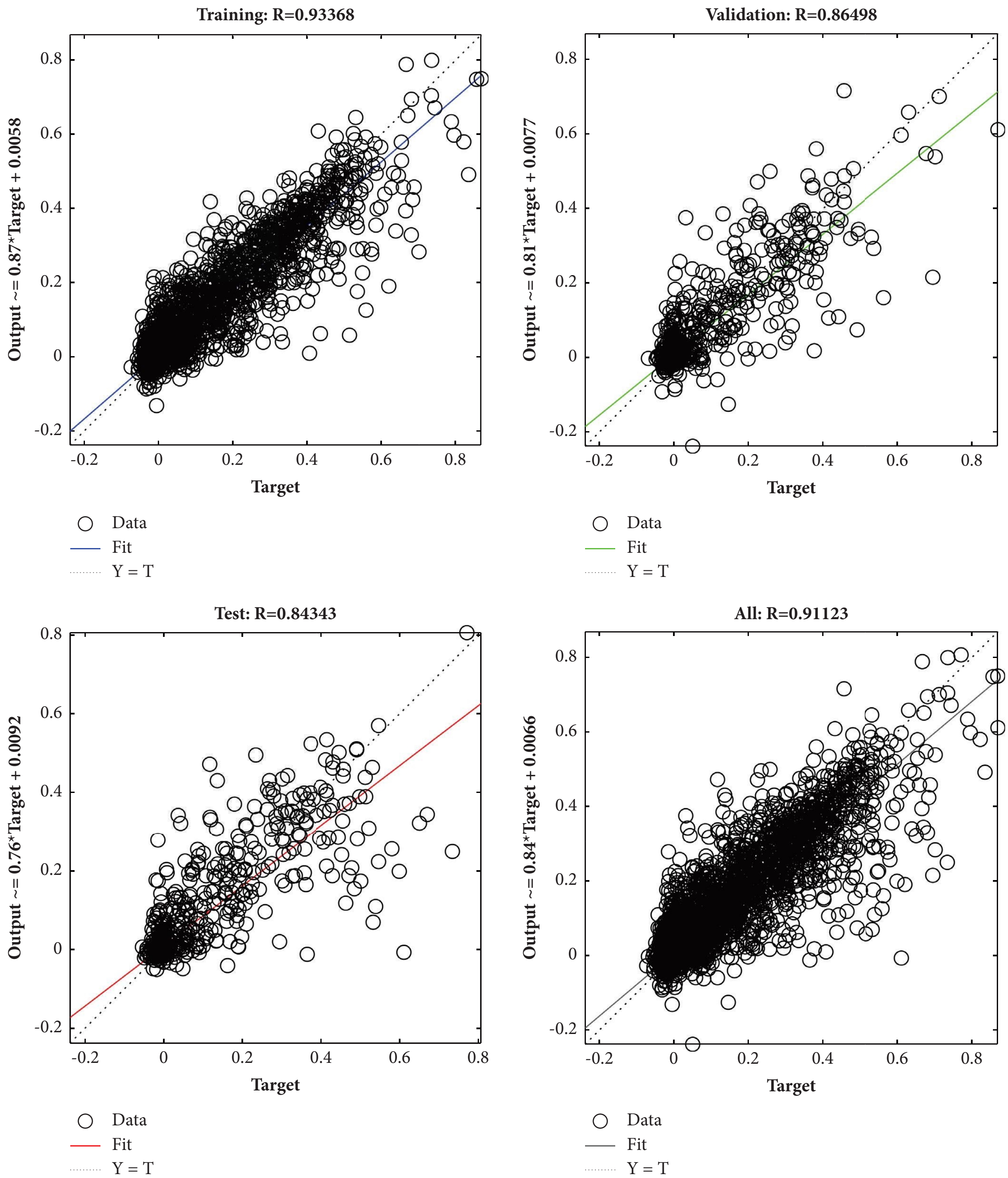


FIGURE 6: The regression fit for the outputs vs. the network targets.

(ii) The HHO technique utilizes a metaheuristic algorithm for feature selection, which improves its accuracy by focusing on the most informative features.

(iii) The HHO technique integrates fault localization within the model, simplifying the overall system design.

(iv) The HHO technique demonstrates high adaptability to unknown faults and robustness to noise, making it suitable for various real-world scenarios.

(v) Existing techniques, while less accurate, offer lower computational complexity and potentially lower cost-effectiveness.

3.6. Summary. The proposed HHO technique presents a promising solution for accurate and efficient fault detection in HVDC systems. Its superior performance, adaptability, and robustness make it a valuable tool for enhancing grid reliability and reducing maintenance costs.

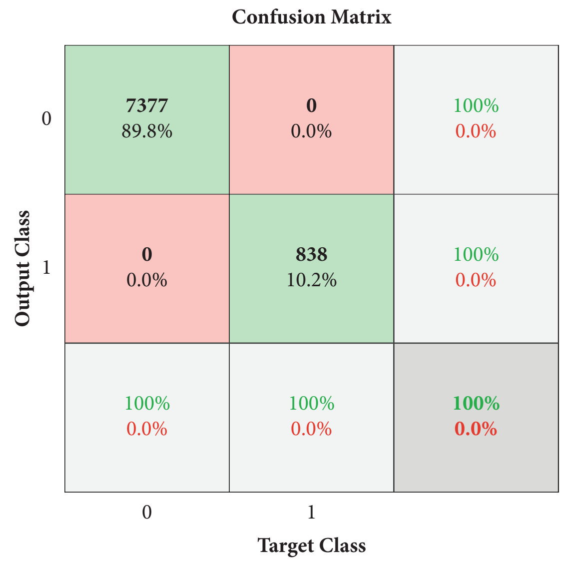


Figure 7: Confusion matrix for training, testing, and validation.

Table 1: Fault classifier ANN outputs for different faults (Table 1 is reproduced from Jamil et al. [39]).

	Phases			
Fault type	*A*	*B*	*C*	Ground
AG	1	0	0	1
BG	0	1	0	1
CG	0	0	1	1
AB	1	1	0	0
BC	0	1	1	0
AC	1	0	1	0
ABG	1	1	0	1
BCG	0	1	1	1
ACG	1	0	1	1
ABC	1	1	1	0
DC	1	1	1	1

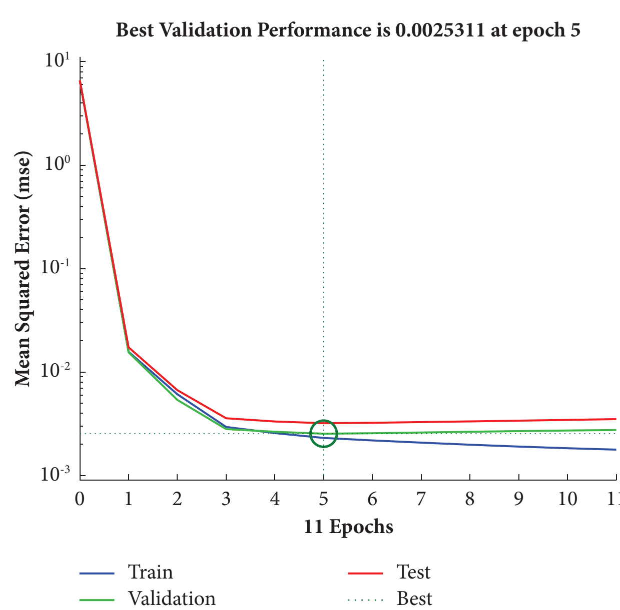


Figure 8: The network's mean-square error performance.

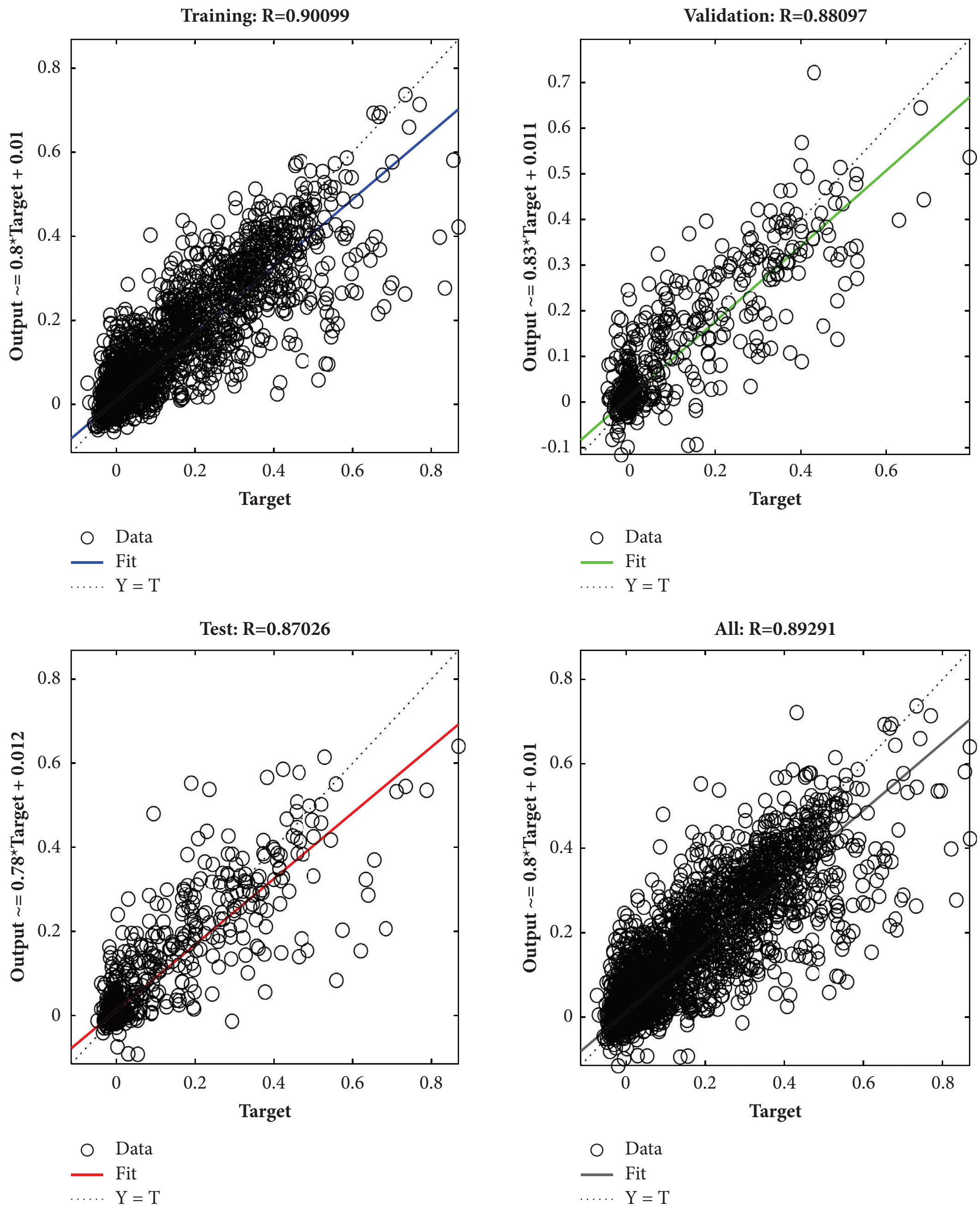


Figure 9: Regression fit curve for the proposed ANN's outputs vs. targets.

However, further research is needed to evaluate its practical feasibility and interpretability.

4. Future Research Direction

Future work can focus on the following areas to further advance fault detection and localization in HVDC transmission systems:

(i) Fusion of data from multiple sources: in addition to traditional voltage and current measurements, future fault detection systems could benefit from fusing data from multiple sources, such as optical sensors, acoustic sensors, and temperature sensors. This would provide a more comprehensive and nuanced view of the system, enabling more accurate and reliable fault detection and localization.

(ii) Use of artificial intelligence (AI): AI techniques like deep learning can revolutionize fault detection and localization in HVDC transmission systems. AI algorithms can be trained on large datasets of historical data to learn complex relationships between system parameters and fault signatures. This

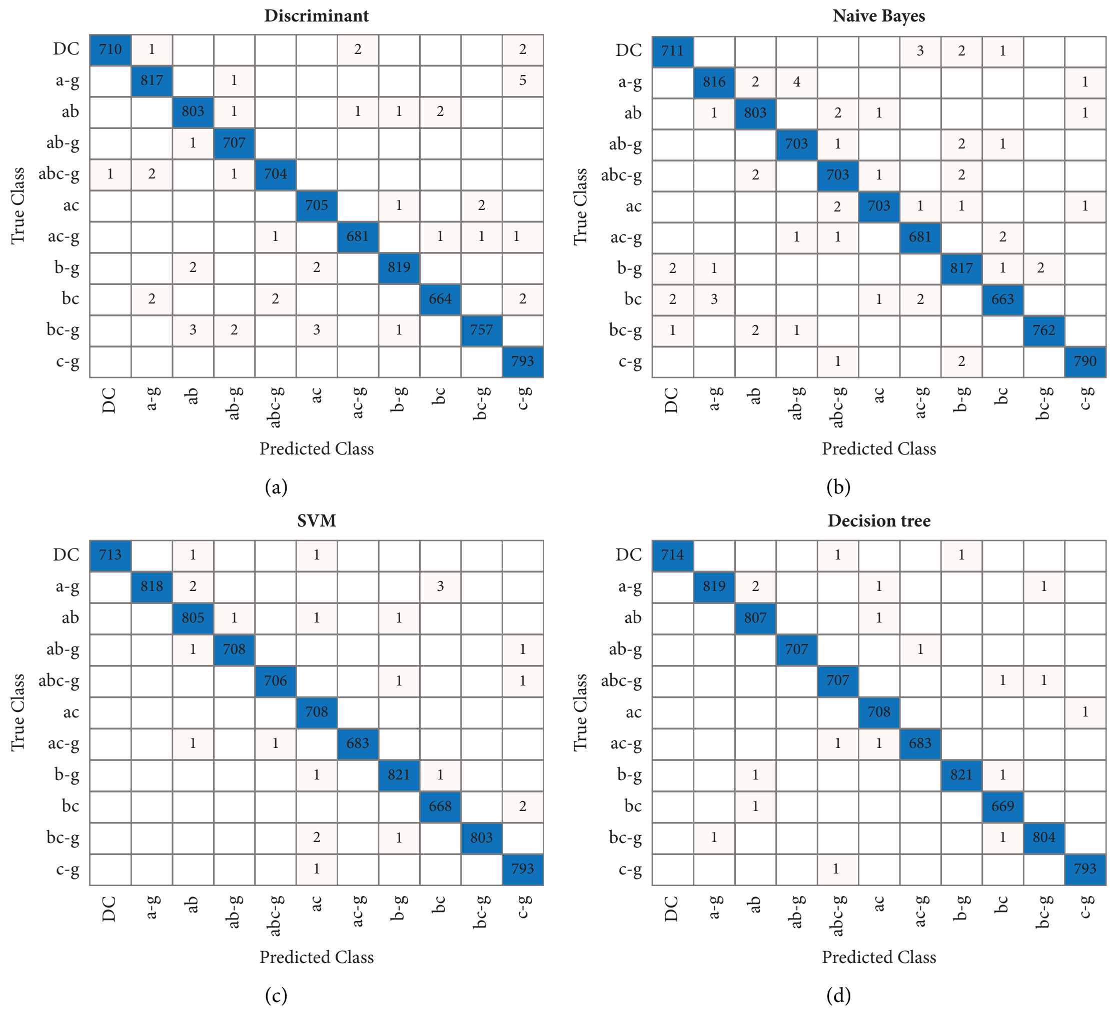


FIGURE 10: Confusion matrix (training, validation, and testing): (a) discriminant classifier, (b) Naive Bayes, (c) SVM, and (d) decision tree.

TABLE 2: Fault detection accuracy of ANNs.

Testing data proportion	0.15	0.25	0.35	0.45	0.55	0.65	0.75	0.85	0.95
Detection accuracy (%)	99.9	100	100	99.98	100	99.89	98.96	98.91	98.88

TABLE 3: The suggested method's accuracy, Jaccard, sensitivity, precision, and *F*1 scores.

Method	Accuracy	Sensitivity	Precision	Jaccard	*F*1 score
GA	97.33	97.35	97.45	96.89	97.64
PCA	95.23	95.12	95.34	93.36	95.24
PSO	97.79	97.25	97.68	95.69	97.90
SA	93.46	93.11	93.78	88.24	93.79
HHO	99.26	99.48	99.89	98.56	98.68

TABLE 4: Comparison between proposed method and other studies.

Method	Accuracy	Sensitivity	Precision
Gray wolf optimization [40]	99.00	99.24	98.74
Ant colony based on wavelet transform [41]	99.45	99.13	99.77
Particle swarm optimization [42]	98.74	98.5	97.85
Cat swarm optimization [42]	98.58	98.01	97.51
HHO	99.26	99.48	99.89

Table 5: Quantitative comparison.

Metric	Proposed technique	Existing technique
Accuracy	0.9901	95–98%
Specificity	0.9869	90–95%
$F1$ score	0.9864	92–95%
Sensitivity	0.9867	85–90%
Convergence time	Faster	Slower
Data requirements	Moderate	High
Computational complexity	Moderate	High

Table 6: Qualitative comparison.

Feature	Harris Hawks Optimization	Existing techniques
Feature selection algorithm	HHO	Simulated annealing (SA), genetic algorithm (GA), particle swarm optimization (PSO), principal component analysis (PCA)
Strengths	High accuracy, sensitivity, precision, Jaccard, and $F1$ score; adaptively selects the most informative features	Lower performance compared to HHO
Weaknesses	Computational and hardware requirements not explored	Lower accuracy, sensitivity, precision, Jaccard, and $F1$ score

knowledge can then be used to develop fault detection systems that are more accurate, robust, and scalable than traditional methods.

(iii) Cybersecurity: as HVDC transmission systems become increasingly interconnected and digitized, it is important to consider cybersecurity threats. Future fault detection systems must be designed to be resilient against cyberattacks and other malicious activities. This includes implementing security measures to protect data confidentiality, integrity, and availability.

5. Conclusion

This research examined how artificial neural networks can identify and categorize problems in three-phase transmission line systems. The established process uses three-phase currents and voltages as inputs to neural networks. Depending on their prefault values, the inputs were normalized. Only the line with ground fault is the subject of the results presented in this research. The development of ANN's other fault types, such as double line-to-ground, symmetrical three-phase, and line-to-line faults, can be investigated. The back-propagation neural network architecture has been used in all artificial neural networks examined here. According to the simulation results, all the suggested neural networks have shown adequate performance and are practically implementable. This work emphasizes the importance of selecting the ideal ANN configuration to maximize network performance. This study used a sampling frequency of 1,000 Hz to sample the voltage and current waveforms.

Data Availability

No data are available for this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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