



# Fault Detection and Classification for VSC-HVDC Systems by Using Different Swarm Optimization Algorithms-Based Neural Network

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## Abstract

In high voltage direct current (HVDC) systems, detecting faults has gained a lot of importance. Due to bulk power transmitted through the system where any faults not detected or properly treated will cause to loss of a huge amount of energy and maybe lead to a fall in the transmission system. Fault detection in HVDC transmission systems is crucial to prevent system failure. Voltage source converter (VSC-HVDC) transmission technology is expected to be heavily used in future power systems, but it is more prone to faults than Alternating Current (AC) transmission. This paper aimed to investigate algorithms to enhance fault detection accuracy in VSC-HVDC transmission lines. The authors used Grey Wolf Optimization (GWO), Particle Swarm Optimization (PSO), and Cat Swarm Optimization (CSO) optimization algorithms to select the best features of fault signals to train Artificial Neural Networks (ANN)s for detection and classification. The models were then combined to maximize system reliability. Implementing these models using MATLAB yielded positive results, with GWO providing the highest accuracy of over 99%. The combination of these algorithms resulted in a highly accurate and reliable fault detection and classification system.

**Keywords:** HVDC; VSC-HVDC; Fault detection; HVDC faults.

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## 1. Introduction

Electrical engineering witnessed a revolution in the 20<sup>th</sup> century due to the advancements made in the electrical power grid. The electrical power grid can successfully convert primary energy sources into electrical energy that can be transmitted across large distances. The use of electrical energy alters and enhances every area of human life. As a result, a secure and consistent source of electricity must be provided.<sup>[1]</sup> Improving techniques for identifying and categorizing faults in high voltage direct current (HVDC) transmission lines also advances society by making the power grid more trustworthy, safe, and efficient. Given the rising demand for electrical power, it is challenging to ensure that consumers can access electricity, especially during peak hours.<sup>[2]</sup> Since every

industry and aspect of our daily life depends heavily on electricity, there is always a need to modernize current systems or technology.<sup>[3]</sup>

Given various concerns, such as the increase in energy consumption, utilizing fuel cells in conjunction with alternative energy sources like wind and solar is considered a practical solution. Because of contamination and the shortage of traditional energy sources (like coal and fossil fuels), combined wind farms have been suggested as a solution to the issue above.<sup>[4]</sup> In the case of high-power rating, HVDC transmission systems show superior performance compared to High Voltage Alternative Current (HVAC). However, due to increasing resistance, inductance, and capacitance, there is a direct relationship between the losses of HVDC transmission lines and the power's traveling distance through these transmission lines.<sup>[5]</sup>

Using the HVAC to transmit bulk power leads to efficiency degradation in the case of long-distance transmission, besides other drawbacks such as corona loss and skin effect.<sup>[6-9]</sup> Various advantages made the HVDC transmission system preferable over HVAC transmissions, such as its reliability, low losses, controllability, ability to be connected to non-

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synchronized grids, and high efficiency, even when transmitted to remote sites.<sup>[10]</sup> Nevertheless, HVDC fault detection is one of the essential aspects of this transmission line system, *i.e.*, the HVDC.<sup>[11]</sup>

The significance of HVDC fault detection derives from the possibility that the breakdown of the entire system might result from the fault current continuing without being discovered. If the right technique is not employed, it is hard to distinguish between a flawed system and its healthy components.<sup>[12,13]</sup> Restoring system stability and preventing economic losses require identifying transmission line faults as quickly as feasible.

In this paper, the HVDC model being considered for fault detection is HVDC-VSC. The HVDC-VSC is a self-commutating converter that uses Insulated Gate Bipolar Transistor (IGBT) valves as switching components. The VSC technology employs the same transformer as the conventional AC system.<sup>[14]</sup> VSC systems require 40% - 50 % less site land than HVDC-LCC systems. In addition to black start capabilities, these systems can self-commutate.<sup>[15]</sup> One of the key benefits of VSC technology is that it utilizes Pulse Width Modulation (PWM) for switching control, which provides a high degree of control over the system's amplitude, phase angle, and active and reactive power.<sup>[16]</sup> In case of a fault, regardless of HVDC classification, a short circuit current, also known as a fault current, is produced, resulting in a large amount of current flow within the system. This high current can significantly impact the insulation of the system's equipment, causing power surges that destroy equipment or charge devices such that when they are touched, an electric shock is delivered, often resulting in death.<sup>[14]</sup> The high-level fault current can influence the sending end bus, transmission line, and generating unit in the event of asymmetric faults. Due to faults, the generator can be overstressed beyond its specified limitations. In contrast, the fault current is confined when faults occur on HVDC power systems. Depending on where the fault is, the fault current does not flow through the

generator system or the load, allowing for safer, more effective systems.

To solve the challenges mentioned above, many researchers have taken action to propose solutions that ensure better HVDC transmission system protection. For HVDC transmission, in the literature, various methods for identifying and categorizing faults have been developed; these techniques are outlined below and are depicted in Fig. 1.

According to references.<sup>[17-19]</sup> Fuzzy logic is used for fault identification for the HVDC transmission line besides wavelet singular entropy. However, fuzzy logic suffers some drawbacks regarding fault classification and detection. First, it is challenging to find precise membership functions and fuzzy rules; second, considerable hardware testing is needed for the performance evaluation and validation of fuzzy-based systems. In addition to decision trees and ANN-based fuzzy techniques, other techniques for fault detection includes measurements of local current decision trees and Wavelet Transform (WT). In Ref. [20] fault categorization is achieved by running a sequence analyzer to detect negative and zero sequence components. Another work in Ref. [21] has applied a decision tree for fault detection to detect and classify different DC faults; in this work, the Teager-Kaiser Energy Operator (TKEO) method is combined with decision trees for fault classification. Discrete Wavelet Transform (DWT) has also been proposed in Ref. [22] where fault localization, classification, and identification are achieved using Taguchi-ANN-based technology and multi-resolution DWT analysis. By merging WT and wavelet neural network (WNN), a novel approach for defect diagnostics is proposed.<sup>[23]</sup> A protection system based on Mathematical Morphology (MM), which uses traveling waves, is proposed in Ref. [21]. The suggested technique delivers speedy fault detection since MM technology only performs small additions and subtractions. However, traveling wave-based techniques need very high sampling-rate measurement equipment.

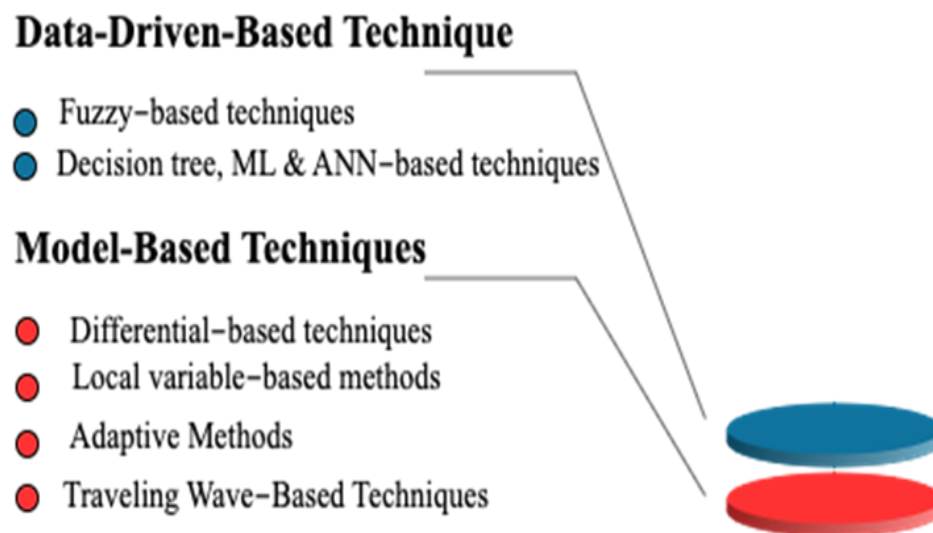


Fig. 1 Approaches for identifying and classifying faults in HVDC systems.

These processes are efficient and precise, but the advantages are greatly diminished when high sample rate measuring devices are used. In Ref. [24] Machine Learning (ML) contributes to fault detection. The authors propose fault detection using ML and Deep Learning (DL) techniques to differentiate between internal and external faults that happen in the DC section. However, the researchers concluded that LSTM-based relays perform better than ML methods. The robustness of LSTM has also been demonstrated in Ref. [25] Another paper<sup>[11]</sup> presented an integrated multi-ML system architecture to protect bipolar HVDC transmission lines that used ML for HVDC fault detection. A range of ML models, such as K-Nearest Neighbors (KNN) and Support Vector Machine (SVM), are used for fault detection and classification. The extraction of features is applied in Ref. [26] using the Principal Component Analysis (PCA), next, for classification, two techniques are employed: multi-class SVM based on Error-Correcting Output Codes (ECOC) and multinomial logistic regression (MLR). Finally, after reviewing previous works, we can conclude that Artificial Intelligence (AI) has an important role in HVDC transmission line fault detection. The

present study examines the faults that may occur in Bipolar VSC-HVDC systems utilizing three Swarm Optimization algorithms (Gray wolf, Particle Swarm, and Cat) based on ANN, namely GWO, PSO, and CSO. The study first employs each of these algorithms to extract the most significant features of the fault voltage and current signals. Subsequently, these features are utilized for training ANN models. The performance of the three trained ANNs are then analyzed through relevant metrics. The study combines and tests the three ANN models to further enhance the fault detection and classification process. This paper presents two key contributions. The first is introducing an advanced fault detection and classification model with high accuracy. The second contribution is the proposal of a novel Artificial Neural Network (ANN) based multi-swarm optimization algorithm model designed to improve the dependability of fault detection and classification.

In addition, this paper is an extension of our published article that discussed the fault detection of monopole LCC HVDC.<sup>[27]</sup>

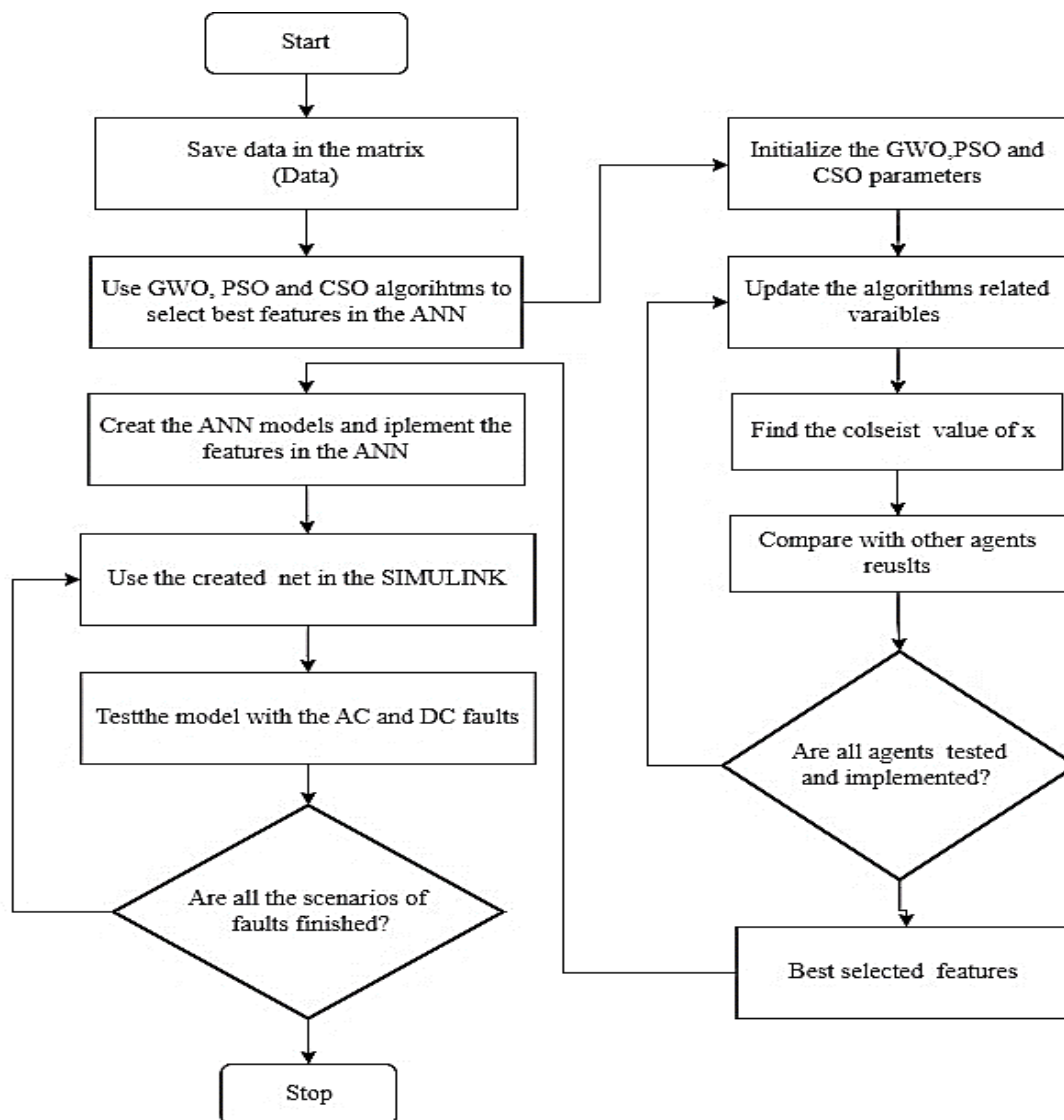


Fig. 2 ANN-based SOA technique proposed a flow chart for fault type detection and location prediction.

The organization of this paper is as follows: In the introduction, the background and purpose of the study are presented. Section 2 of materials and methods explains proposed fault detection and classification. Section 3 discusses the general VSC-HVDC Simulink’s model and methods, including the system’s specifications and parameters. Section 4 covers the details of the ANN-based SOA, including the SOAs used for ANN training, including GWO, PSO, and CSO. The proposed Simulink model is reviewed in Section 5. Finally, the results and discussion are presented in Section 6.

**2. Materials and methods**

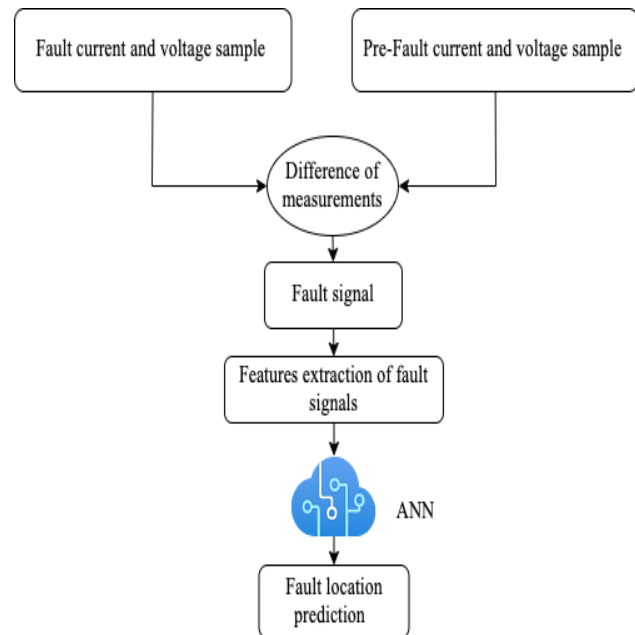
This paper utilizes ANN-based Swarm Optimizing Algorithms (SOA) to detect faults in a VSC-HVDC transmission system. Three types of SOA are employed, namely: Particle Swarm Optimization (PSO),<sup>[28]</sup> Gray Wolf Optimization (GWO),<sup>[29]</sup> and Cat Swarm Optimization (CSO)<sup>[30]</sup> algorithm. The effectiveness of these algorithms is evaluated and compared to one another. The diagram in Fig. 2 shows the steps involved in detecting and classifying faults in the HVDC transmission line system, where the voltage and the current of the detected fault are put into the SOA. The voltage and current values are then used for feature extraction and subsequently fed into ANN. Additionally, the flowchart in Fig. 3 shows the detailed process for predicting the location of the fault.

**3.1 VSC-HVDC simulink models**

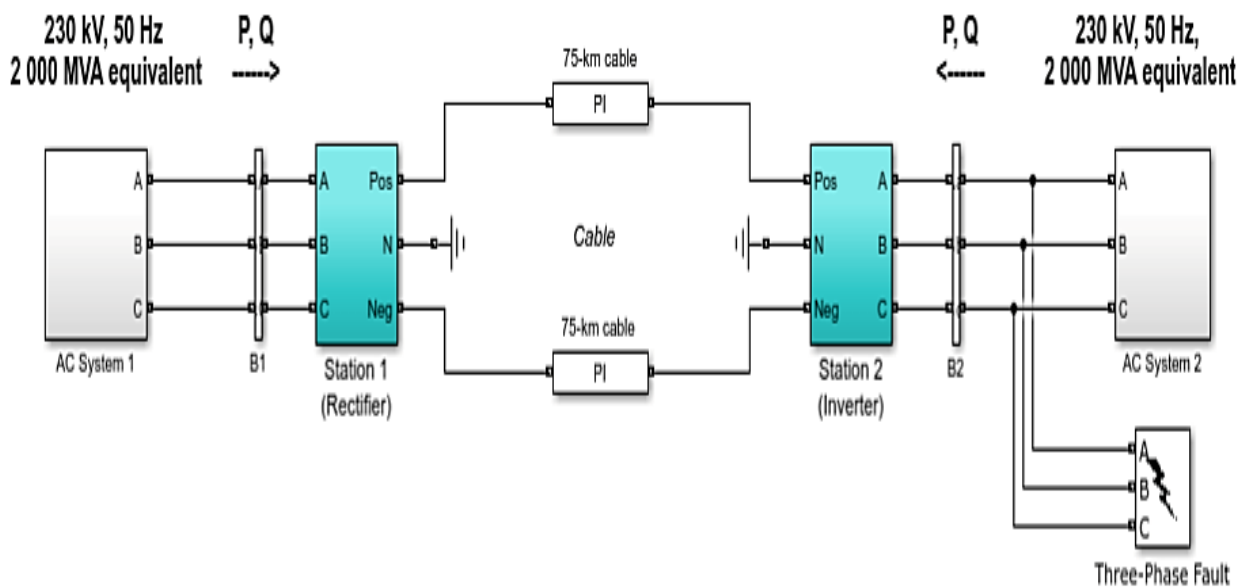
A 200 MVA VSC with a voltage of 100kV is used in a grid test system configuration to transfer bulk power through a process known as forced commutation. The HVDC connection is used to receive 2000 MVA of power at 230kV and 50Hz from an AC system, as illustrated in Fig. 4. The rectifier and inverter of the VSC-based HVDC transmission system are constructed from a voltage source converter with three levels and a neutral point clamp that includes IGBTs and diodes, and employing sinusoidal pulse width modulation (SPWM) at a frequency of

27 times the fundamental frequency. A stepped-down Yg-D configuration transformer, AC filters, and a converter reactor are installed on the AC side of the converter.

Capacity and DC filters are used on the converter's DC side. The system also employs high pass-tuned shunt AC filters of 40MVAR that have been adjusted to filter out dominant harmonics at the 27th and 54th positions. The phase and amplitude of the output voltage of the VSC in relation to the voltage in the point of common coupling may be influenced by the leakage reactance of the converter reactor and transformer and by DC capacitors connected to the VSC terminals. The third harmonic frequency is the leading harmonic in both the positive and negative pole voltages. Two 8mH smoothing reactors and a 75 km long wire composed of two pi sections connect the rectifier and inverter.



**Fig. 3** Flowchart for the detailed fault location prediction process.



**Fig. 4** VSC-Based HVDC Transmission Link.<sup>[31]</sup>

### 3.2 Methods

The illustration in Fig. 5 displays the design of the proposed ANN-SOA fault location estimation model, which consists of three primary components. The first block shows the VSC-HVDC system investigated. The second section deals with feature extraction, in which the pertinent features from the fault voltage-current signals are extracted and then transferred to the estimator. The third part comprises an ANN-based SOA estimator that uses the features from the second step to determine the fault location in the HVDC system accurately. Furthermore, three SOA approaches were applied to train ANN: GWO, PSO, and CSO. The feature extraction process applies these three SOA strategies to extract the essential features from the fault voltage and current signals. Lastly, the estimator block will take the fault current and voltage data as input to ANN, allowing the model's accuracy to be evaluated.

### 3.3 Procedure

This study investigates the various faults that can appear in VSC-HVDC transmission lines, such as rare ungrounded DC faults (P1P2) and the more common earthed DC faults (P1G, P2G).<sup>[32]</sup>

Pole-to-ground faults (P1G and P2G) are more likely to appear in DC lines due to potential flashovers, which dust, impurities, or high voltage can cause. All the potential DC faults (P1P2, P1G, P2G) that can arise in VSC-HVDC transmission lines are illustrated in Fig. 6. Figs. 6a, 6b, and 6c depict a pole-to-ground fault with pole 1, pole 1, and pole 2 being grounded respectively. Data were collected to train and test the proposed model; the model was first run with no fault to record the AC and DC current and voltage signals.

Subsequently, the MATLAB Simulink was used to create various DC faults and collect the voltage and current data for fault detection and location.

### 4. ANN-based SOA

This section presents a comprehensive examination of ANN and SOA, focusing on three specific SOA implementations under consideration. Using ANNs is imperative in identifying faults and determining their precise location. Within the realms of Artificial Intelligence, Machine Learning, and Deep Learning, ANNs empower computer systems to discern patterns and arrive at solutions to complex issues by mimicking the human brain's neural processes. The complexity of the task at hand generally decides the number of layers in a neural network. Neural networks have four main stages: initialization, activation, weight training, and iteration - which are all utilized to resolve the classification issue. In this study, backpropagation (BP) is used, in which connections travel from the output neuron to other nodes. Each connection has a numerical value and a weight that connects it to the output. A perceptron is a collection of all connected links. An activation function is created when the input connections have been weighted individually.<sup>[33]</sup>

In this paper, the optimal feature for training ANN was extracted using SOAs, based on Mean Square Error (MSE) value as indicated in Equation 1.

$$RMSE = \sqrt{\sum_{i=1}^n \frac{(\hat{y}_i - y_i)^2}{n}} \quad (1)$$

where  $\hat{y}_1, \hat{y}_2, \dots, \hat{y}_n$  are predicted values and  $y_1, y_2, \dots, y_n$  are observed values  $n$  is the number of observations.

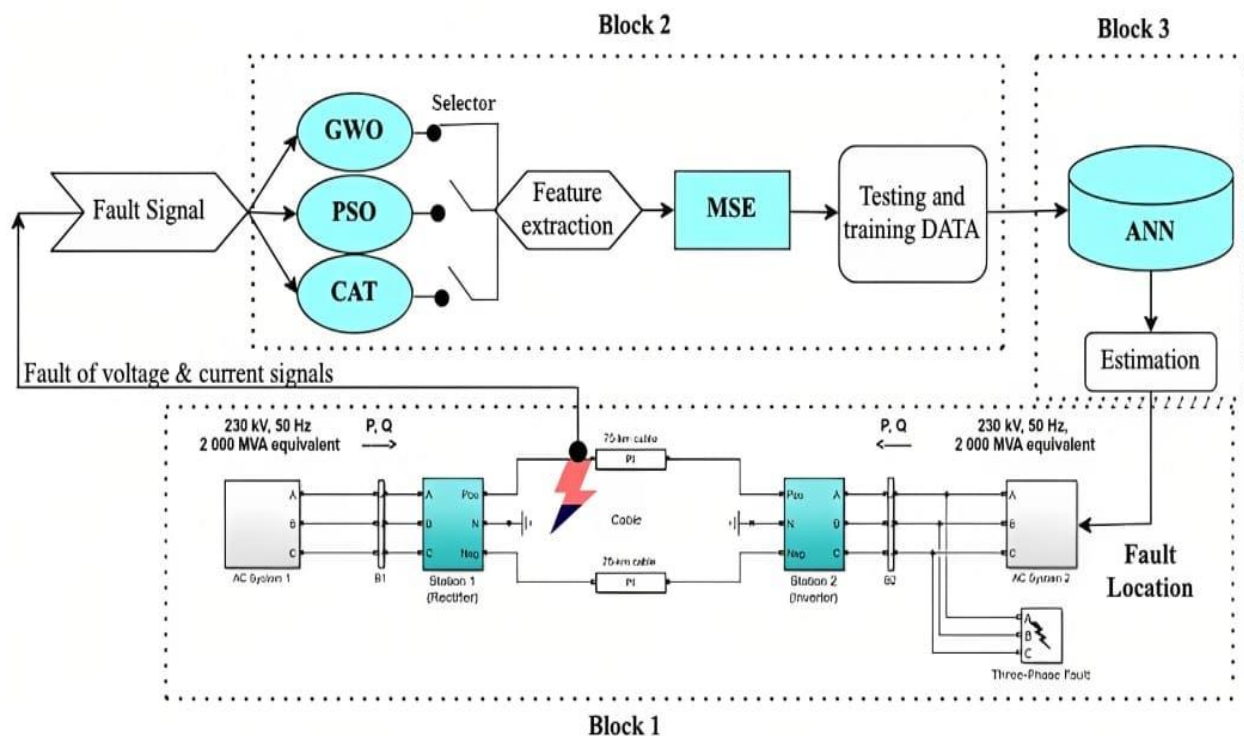


Fig. 5 The three blocks of fault detection and location.

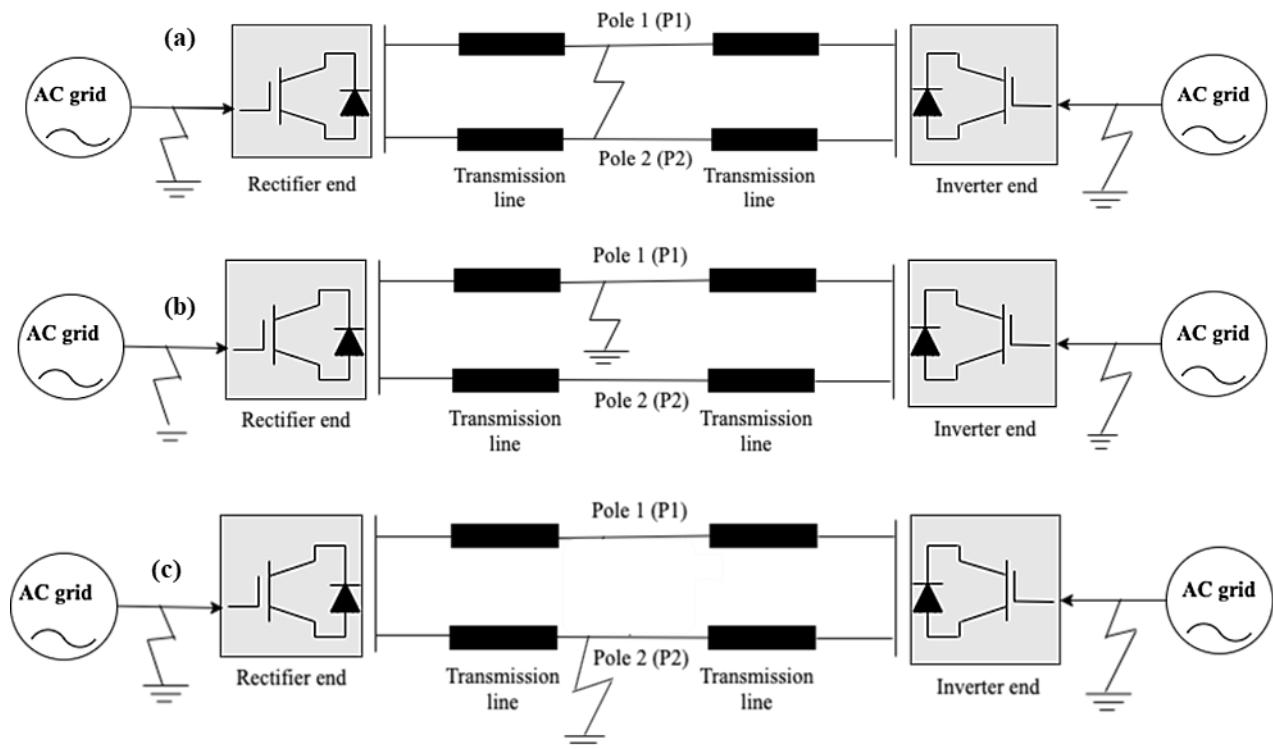


Fig. 6 HVDC and AC fault scenarios.

MSE is a typical loss function for artificial neural networks during training. MSE calculates the average of the squared deviations for all training samples between the actual output and the predicted output.<sup>[34]</sup> Training ANN aims to decrease the MSE by changing the network's weights and biases. An optimization method like SOA, which continually alters weights and biases to reduce the MSE, is typically used to achieve this goal. In this approach, the network learns to generate accurate predictions for the training set. Once trained, the network may also be used to make predictions about data that has not yet been observed. The following part will review each optimization method and its mathematical model briefly.

4.1 SOA for ANN training

The SOA can be used to optimize the parameters of ANN for a specific task, such as fault detection of a HVDC system, as shown in Fig. 7 (modified from the Ref. [35]). To apply SOA to the training of ANN, we define the optimization problem in terms of the weights and biases of the network and use the SOA algorithm to find the values of these parameters that minimize the error between the predicted and actual outputs of ANN on the training dataset (MSE). The specific steps involved in the SAO algorithm depend on the specific implementation being used. Still, the general idea is to use a random search to explore the space of possible solutions and gradually refine the solution by making small, random changes to the parameters of ANN.

4.1.1 GWO

A group of potential solutions, known as wolves, are utilized by the GWO algorithm to find the best solution to a specific

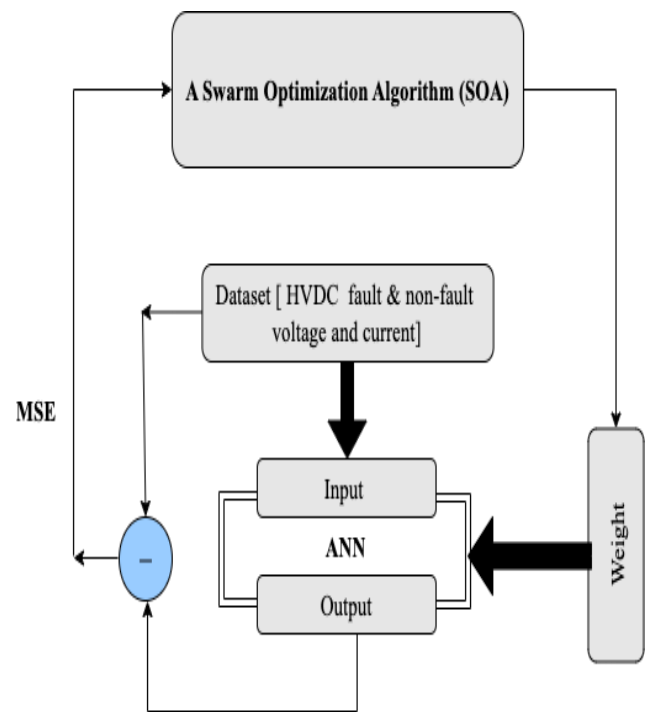


Fig. 7 ANN training the SOA.

problem.<sup>[36]</sup> A vector of real-valued variables represents the positions of the wolves  $X = \{x_1, x_2, \dots, x_n\}$ . The fitness function  $F(X)$  is used to evaluate the quality of solution X. At each iteration, the positions of the wolves are updated based on their neighbors' positions and their solutions' fitness values. The algorithm uses three types of wolves: alpha, beta, and delta. The alpha wolf is the pack's leader and has the highest fitness value, while the beta wolves follow the alpha wolf and the

delta wolves explore the search space. The position of the  $i^{th}$  wolf at time  $t$  is updated as follows:

$$Xi(t+1) = Xi(t) + a1 \text{ rand}() (X \text{ alpha}(t) - Xi(t)) + a2 \text{ rand}() (Xbest(t) - Xi(t)) \quad (2)$$

where  $X \text{ alpha}(t)$  is the position of the alpha wolf at time  $t$ ,  $Xbest(t)$  is the best solution found so far, and  $\text{rand}()$  is a random number between 0 and 1. The constants  $a1$  and  $a2$  are coefficients controlling the wolves' movement.

The algorithm continues until a stopping condition is met, such as reaching a maximum number of iterations or achieving a certain fitness level. The final solution  $X$  has the highest (or lowest) fitness value, depending on the optimization problem.

In the subject of HVDC fault detection and locating, several works in the literature have used this algorithm, for example, in our previous works<sup>[27,37-39]</sup>

#### 4.1.2 PSO

In 1995, Kennedy and Eberhart developed the Particle Swarm Optimization algorithm,<sup>[40]</sup> which utilizes a group of potential solutions, called particles, to find the optimal answer to an optimization problem. The algorithm is based on the cooperative behavior of fish schools and bird flocks, where individuals adjust their movements based on the actions and positions of those around them. In PSO, the particles move throughout the search space and change their position based on their own experiences and those of their neighboring particles. The initial positions of the particles are randomly determined, and the algorithm utilizes specific equations to update the particle positions at each iteration.

$$vi(t+1) = wvi(t) + c1 \text{ rand}1(pi(t) - xi(t)) + c2 \text{ rand}2 (pg(t) - xi(t)) \quad (3)$$

$$xi(t+1) = xi(t) + vi(t+1) \quad (4)$$

where  $vi(t)$  is the velocity of the  $i^{th}$  particle at time  $t$ ,  $xi(t)$  is the position of the  $i^{th}$  particle at time  $t$ ,  $pi(t)$  is the best position that the  $i^{th}$  particle has ever encountered,  $w$  is the inertia weight,  $c1$  and  $c2$  are acceleration constants, and  $\text{rand}1$  and  $\text{rand}2$  are random values between 0 and 1.  $pg(t)$  represents the best position that any particle in the swarm has found.

The algorithm runs until a stopping condition is satisfied, such as completing a predetermined number of iterations or attaining a predetermined fitness level. Depending on the optimization issue, the best solution is the one with the highest (or lowest) fitness value. PSO has been used in a number of optimization contexts and has demonstrated its ability to find effective solutions. It has also been used in conjunction with other optimization algorithms to enhance performance further. However, it has also been utilized for HVDC fault detection.<sup>[41-45]</sup>

#### 4.1.3 CSO

CSO (Cat Swarm Optimization) is a population-based optimization algorithm that was proposed in 2014 by Zhang *et al.*<sup>[46]</sup> It is inspired by the behavior of cats when they are hunting prey. In CSO, a group of potential solutions, called cats, move through the search space and update their positions

based on their own experience and the experience of their neighbors. Cats are initialized randomly, and their positions are updated at each iteration according to the following equations:

$$vi(t+1) = wvi(t) + c1 \text{ rand}1 (pi(t) - xi(t)) + c2 \text{ rand}2 (pg(t) - xi(t)) \quad (5)$$

$$xi(t+1) = xi(t) + vi(t+1) \quad (6)$$

where  $vi(t)$  is the velocity of the  $i^{th}$  cat at time  $t$ ,  $xi(t)$  is the position of the  $i^{th}$  cat at time  $t$ ,  $pi(t)$  is the best position that the  $i^{th}$  cat has ever encountered,  $pg(t)$  is the best position encountered by any cat in the swarm,  $w$  is the inertia weight,  $c1$  and  $c2$  are acceleration constants, and  $\text{rand}1$  and  $\text{rand}2$  are random numbers between 0 and 1. In addition to the standard PSO equations, CSO introduces a new parameter called the *hunting step size*, which determines the distance that the cats move during each iteration. The hunting step size is adjusted based on the fitness values of solutions, with larger step sizes being used when the fitness values are lower and smaller step sizes being used when the fitness values are higher. It helps the cats to explore the search space more effectively and avoid getting stuck in local minima.

The algorithm will keep running until a certain point is reached, such as when the maximum number of iterations has been completed or when a specific fitness level has been achieved. The final solution is the one with the highest (or lowest) fitness value, depending on the optimization problem. CSO has been used to tackle various optimization problems and has demonstrated its ability to identify satisfactory solutions. It has also been used in combination with other optimization algorithms to improve performance further. However, to the best of our knowledge, no work in the literature has used this algorithm for HVDC fault detection and location.

### 5. The Proposed simulink model

This study uses the MATLAB Simulink model, shown in Fig. 8, to create different types of faults between pole 1 (P1) and the ground. Additionally, the study employs ANN to recognize and categorize DC and AC faults that occur in the VSC-HVDC transmission system using three optimization algorithms: GWO, PSO, and CSO. The Simulink model in Fig. 9 is used to evaluate the system using three proposed models, and the signals from these models are used to train the three neural networks. As shown in Fig. 10, these three trained ANNs are integrated and used to identify and classify faults in the system, with the goal of improving fault detection and classification reliability. The function block in Fig. 10 is described in pseudocode. This block's functionality shows a fault's location when at least a dual of the ANNs classified the fault in the same location, *i.e.*, produce the same value of the specific type of fault assigned during ANN training. However, one of the challenges is that sometimes ANN output is not an integer, making it difficult to match the output of these ANNs. Thus, we add the round block to the Simulink model to ensure a more reliable classification.

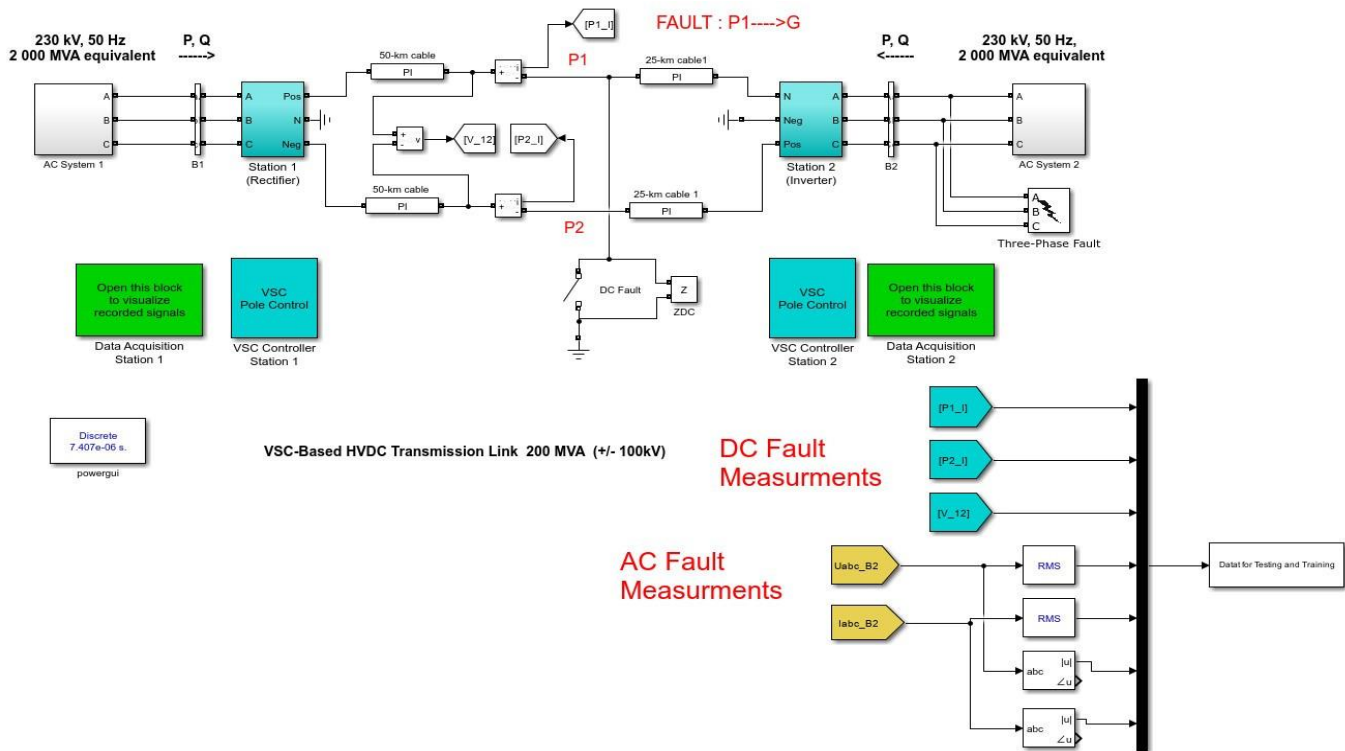


Fig. 8 Fault creating Simulink model.

ANN networks were trained using all of the produced faults. Thus, the features of the signals chosen by the three techniques under study were employed as neural network inputs. The protective mechanisms in this investigation respond to all kinds of faults.

Function block pseudocode

START

//Input Values: ANN-GWO, ANN-PSO, ANN-CSO

//Output: y

if ANN-GWO == ANN-CSO

y = ANN-GWO

else

if ANN-PSO == ANN-GWO

y = ANN-PSO

else if ANN-CSO == ANN-PSO

y = ANN-CSO

else

y = 0

end if

end if

END

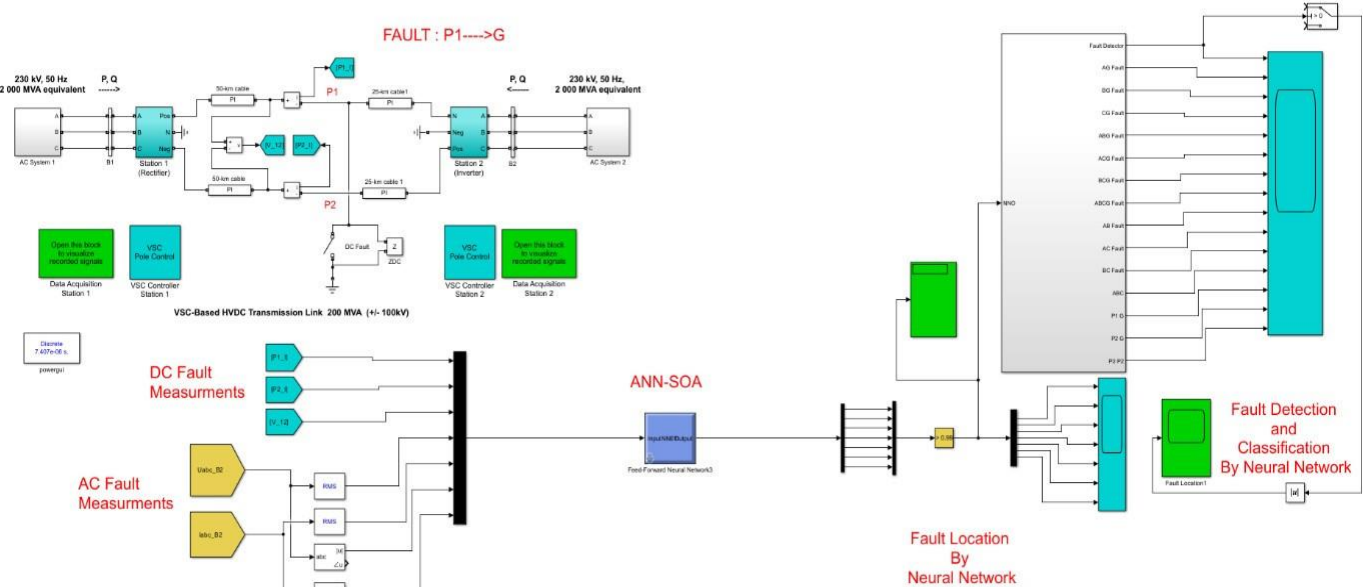


Fig. 9 Simulink model for testing the trained ANN models.



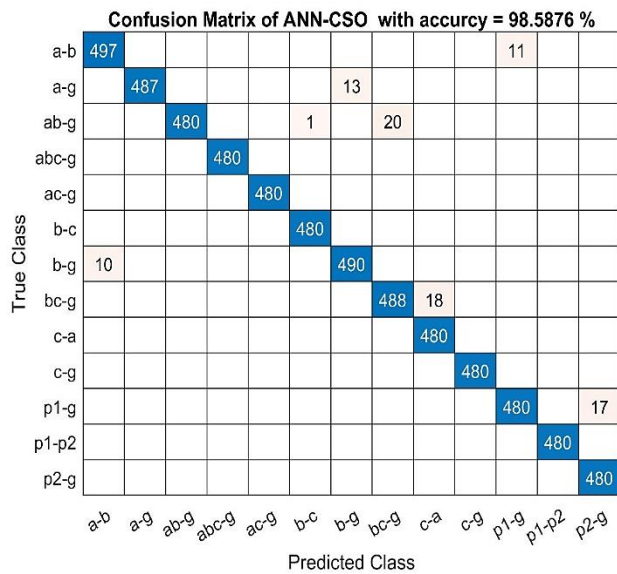


Fig. 11 Confusion Matrix for ANN-CSO Model.

to evaluate the proposed models. The overall performance of strains 1-3 of the proposed device was simulated using various system setups and operation modes, and this performance is illustrated in Figs. 11, 12 and 13, where these Figs provide graphs illustrative of these outcomes.

For example, the ANN-GWO confusion matrix shown in Fig. 10 describes the system after examining the a-g fault 500 times and identifying it accurately 495 times. ANN-GWO did not identify only five instances of this kind of fault. For the faults a-b, b-c, abc-g, and DC faults, there were no faults in p1-g and p1-p2. This scenario illustrates that the chosen characteristics were optimal for building and testing the network.

However, the average accuracy did not provide detailed information on the model's performance. The F1 Score was used to evaluate the overall performance of the categories in order to analyze the classifier's behavior throughout error

training. The F1 score parameter is a measure of accuracy, sensitivity, recall, and precision and is best when equal to 1 and worst when equal to 0. The findings of accuracy, precision, recall, and F1 score are shown in Table 2.

Figures 14, 15, 16 present the results of Accuracy, Precision, and Sensitivity (Recall) for the three ANN-Swarm algorithms GWO, PSO, and CSO.

The performance of the overall HVDC fault classification system using the proposed methods is evaluated using metrics such as accuracy, sensitivity, precision, Jaccard coefficient, and F1 Score. The results are listed in Table 3. The proposed method chose the most effective features from voltage, current, and their derivatives using the GWO, PSO, and CSO algorithms. The tests showed that ANN-GWO, ANN-PSO, and CSO were accurate. Comparing ANN-GWO to the other two algorithms, it is clear that it provides the best results. In

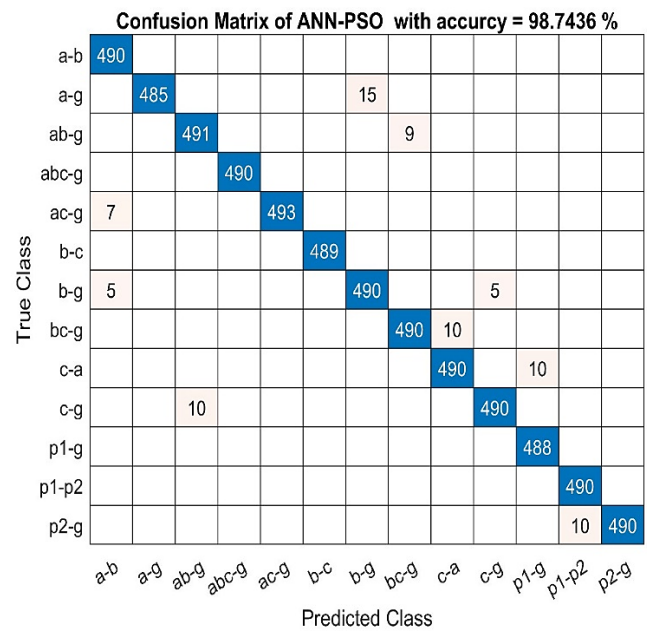
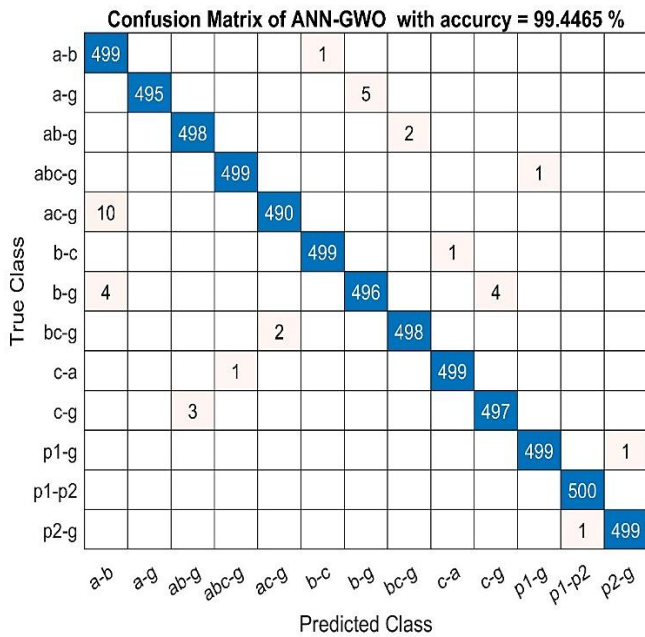


Fig. 12 Confusion Matrix for ANN-PSO Model.

Table 2. Accuracy (%), Precision (%), sensitivity (%), and F1-Score results for the three models.

Fault class	Accuracy (%)			Precision (%)			Recall (%)		
	ANN-GWO	ANN-PSO	ANN-CSO	ANN-GWO	ANN-PSO	ANN-SCO	ANN-GWO	ANN-PSO	ANN-SCO
a-g	99.93	98.851	98.371	99.514	98.855	98.972	99.845	98.831	98.618
b-g	99.207	98.733	98.743	99.121	98.732	98.371	99.158	98.765	98.743
c-g	99.801	98.856	98.618	99.314	98.953	98.743	99.932	98.842	98.371
ab-g	99.067	98.827	98.743	99.234	98.873	98.618	99.518	98.7867	98.743
bc-g	99.222	98.752	98.371	99.932	98.755	98.371	99.384	98.653	98.618
ac-g	99.920	98.806	98.743	99.933	98.868	98.743	99.698	98.732	98.743
a-b	99.344	98.629	98.618	99.047	98.794	98.743	99.484	98.857	98.371
b-c	99.908	98.932	98.371	99.073	98.652	98.618	99.903	98.759	98.743
a-c	99.296	98.853	98.743	99.982	98.903	98.371	99.025	98.956	98.618
abc-g	99.538	98.782	98.618	99.967	98.757	98.743	99.186	98.663	98.371
p1-g	99.939	98.851	98.371	99.795	98.89	98.618	99.444	98.855	98.317
p2-p2	99.945	98.76	98.743	99.946	98.754	98.743	99.945	98.637	98.743
p2-g	99.923	98.852	98.743	99.987	98.832	98.371	99.493	98.853	98.618



**Fig. 13** Confusion Matrix for ANN-GWO Model.

the accuracy test, GWO scored 99.44% compared to 98.74% for PSO and 98.58% for CSO. It is worth noting that CSO performs well in tests involving small amounts of data, but its performance decreases as more data is used. As a result, ANN developed by GWO has exceptional fault detection and classification performance.

Figure 17 displays an example of the fault detection system.

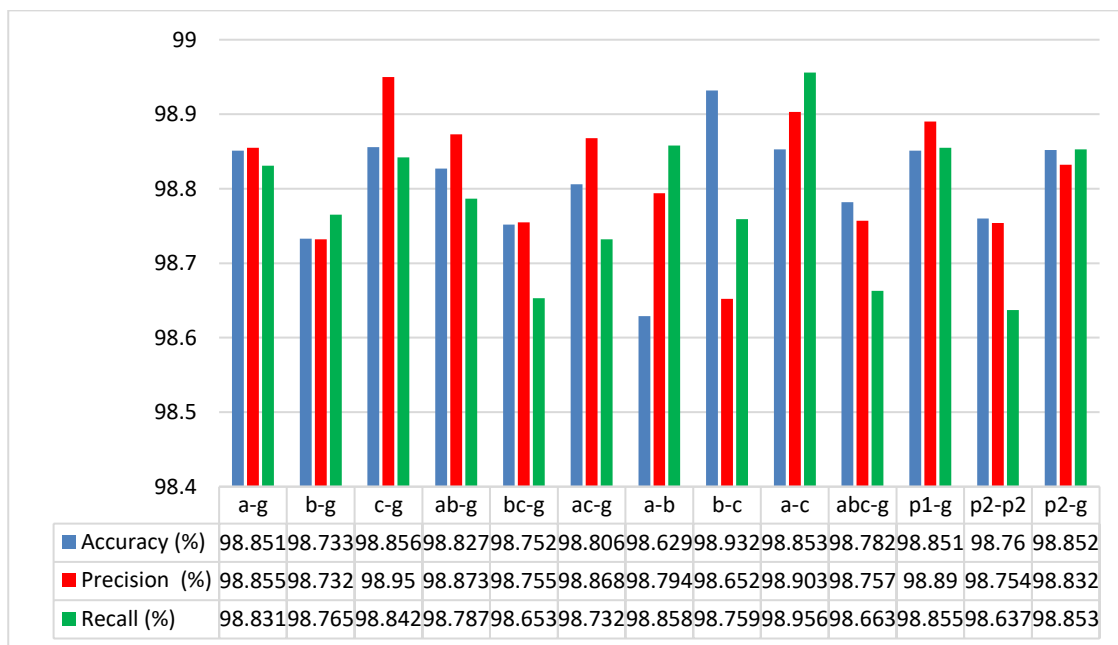
As shown in Fig. 17, the neural network accurately identified the c-g fault that was presented to the system.

The features of this signal were first extracted, and the GWO method was used to choose the best and most appropriate features for the neural network's input. The fault category was then determined in relation to the chosen features by the trained neural network. The confusion matrixes seen in Figs. 11, 12, and 13 were produced after the model underwent several tests. Variable fault resistances in the faulty signals were evaluated, and features were retrieved from various resistance values. To extract the features from the signals, the input signals were fixed, just the resistances were altered, and the scenarios of the faults were varied. This approach's computational and hardware requirements were not examined in this research because of the time needed to remove the fault. DC fault detection and classification experiment used the same methods discussed before. The aggregate performance of the three models in Fig. 18 shows how robust the proposed model classified in identifying and classifying the DC fault. The most common faults in the HVDC transmission line are identified and categorized in the diagram as P1-G and P2-G.

Finally, to evaluate the combined model shown in Fig. 10, we have run the model for all 13 fault types around 50 times for each fault type. Table 4 depicts the experiment results from the table; it is obvious that the combined model provides the ultimate performance by identifying and classifying the fault and its location. However, this empirical result does not reflect the theoretical accuracy values measured in the previous work.

**Table 3.** Accuracy, sensitivity, precision, Jaccard, and F1 Score of the proposed method.

Method	Accuracy	Sensitivity	Precision	Jaccard	F1 Score	TP	TN	FP	FN
ANN-GWO	99.44	99.21	98.63	98.16	99.01	98.20	99.33	1.27	0.73
ANN-PSO	98.74	98.5	97.85	97.57	98.86	98.14	99.12	1.4	0.8
ANN-CSO	98.58	98.01	97.51	97.03	98.7	98.03	99.06	1.3	0.86



**Fig. 14** The ANN- PSO Simulation results as a graphical illustration for Accuracy, Precision, and Recall.

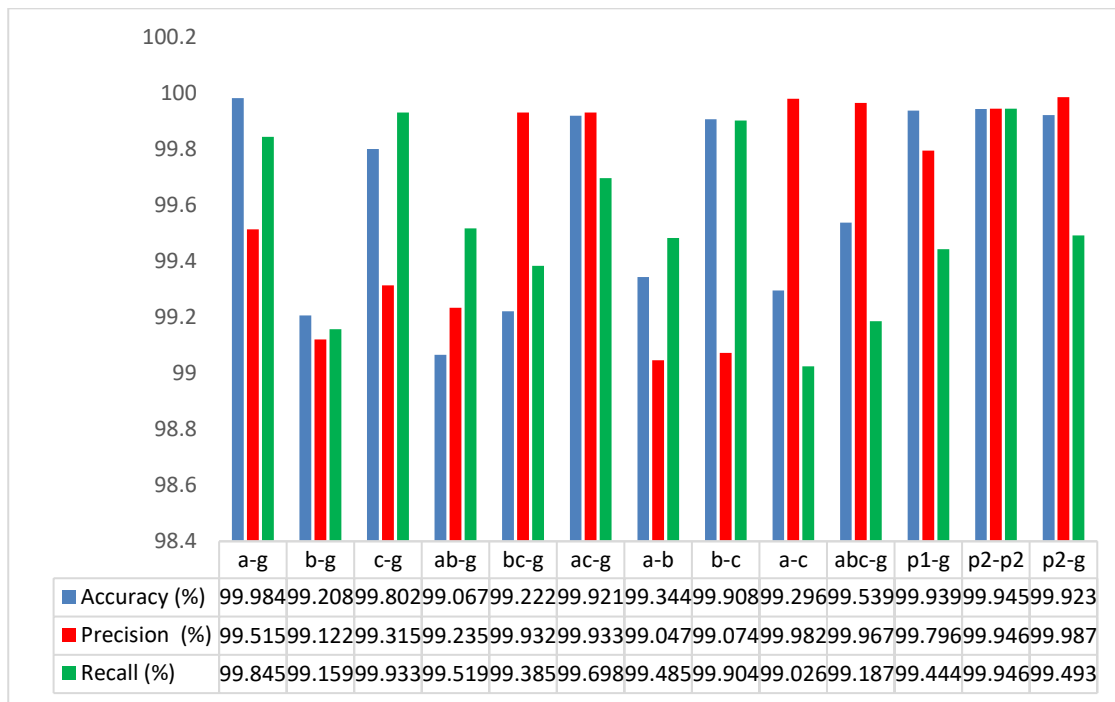


Fig. 15 The GWO Simulation results as a graphical illustration for Accuracy, Precision, and Recall.

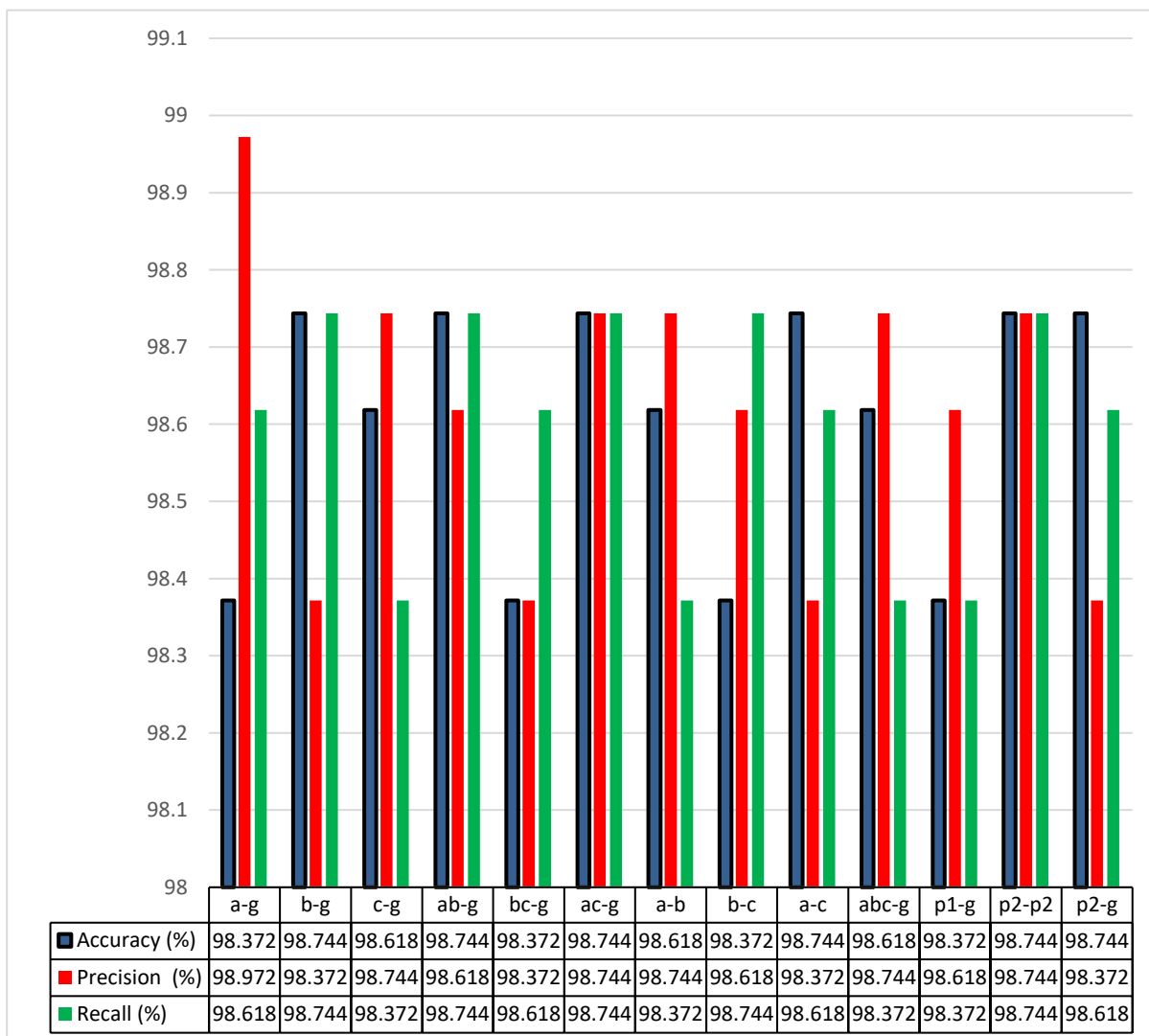


Fig. 16 ANN-CSO Simulation results as a graphical illustration for Accuracy, Precision, and Sensitivity (Recall).

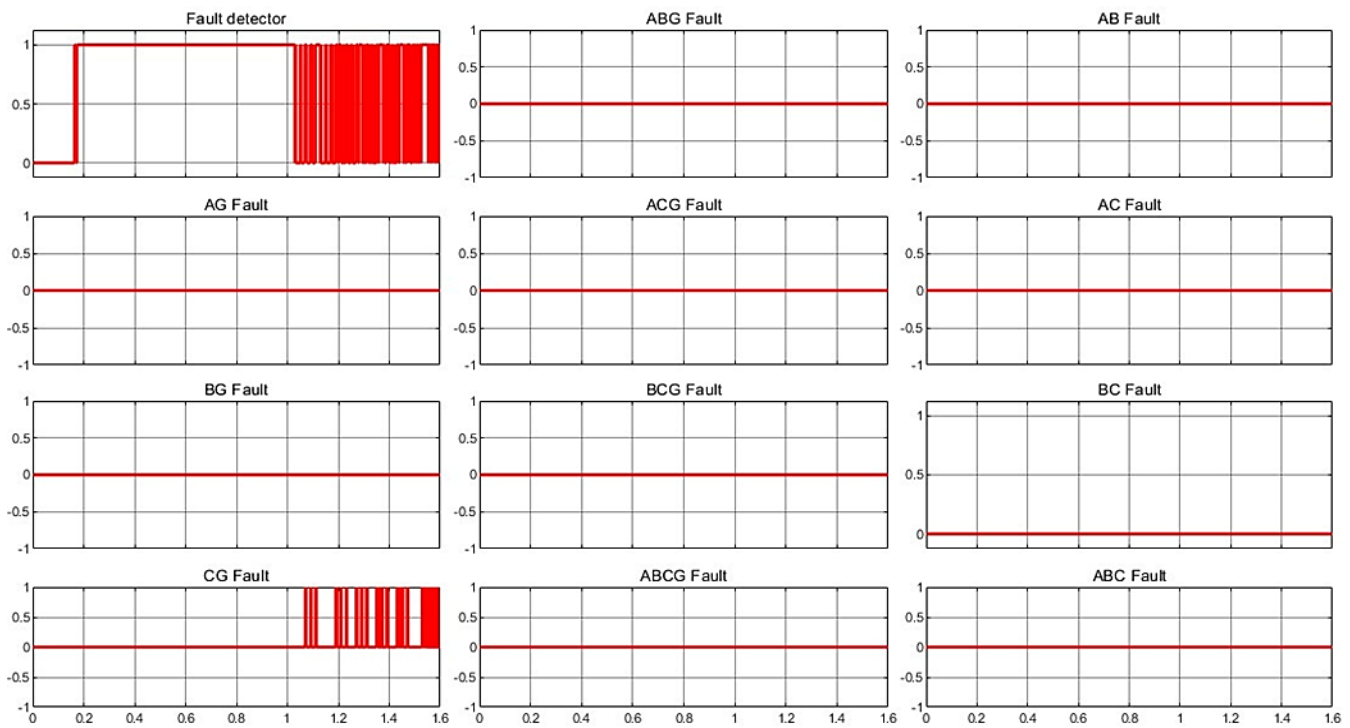


Fig. 17 c-g Fault detected.

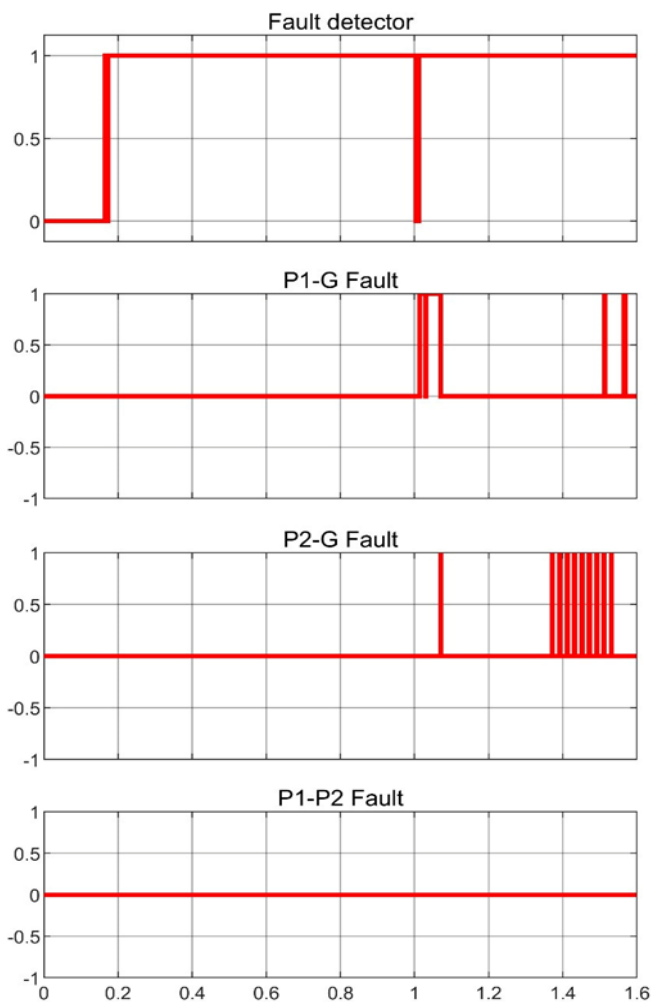


Fig. 18 p1-g and p2-g faults detected.

Table 4. Empirical experiment for the combined model.

Fault class	Accuracy (%)
	Combined model
a-g	100
b-g	100
c-g	100
ab-g	100
bc-g	100
ac-g	100
a-b	100
b-c	100
a-c	100
abc-g	100
p1-g	100
p2-p2	100
p2-g	100

### 7. Conclusions

A new approach for identifying faults in HVDC transmission lines is presented in this study. The proposed technique utilizes the primary characteristics of voltage and current, measured on one side of the line, to detect faults. The detection method relies on the correlation between voltage and fault current signals, as determined by trained neural networks when the protection system's initiation unit confirms the presence of a fault. The study first generates voltage and current signals, which are used as input features. Three algorithms are employed to select the most effective features - GWO, PSO,

and CSO. The results show that the GWO algorithm selects the optimal features for training ANN. When a large dataset is used for training and learning, the ANN-based GWO algorithm can accurately locate faults. As a result, the GWO algorithm, which is based on ANN, is becoming increasingly popular. The data was also used to simulate various fault types at different locations to predict the outcomes of unknown fault sites. Moreover, the three trained ANNs have combined to ensure more reliable fault detection and classification. The results of this combination recorded full score accuracy, which can enhance fault detection and classification.

In this paper, the authors suggest that future work includes investigating other machine learning algorithms, such as Random Forest or SVM, for fault detection in HVDC lines and comparing the results to the proposed ANN-based algorithm. Additionally, the authors recommend developing a real-time implementation of the proposed algorithm and testing it on actual HVDC line data to evaluate its performance in a real-world scenario. Another suggestion is to combine the proposed algorithm with other existing fault detection methods to improve the overall accuracy and robustness of the system. Furthermore, incorporating additional features, such as weather data or line condition information, could improve the algorithm's accuracy. Additionally, developing a method for early fault detection by monitoring the system's health state and identifying potential issues before they occur could be a valuable area of research. Finally, the authors propose investigating the use of deep learning models for fault detection and comparing their performance to traditional ANNs.

### Conflict of Interest

There is no conflict of interest.

### Supporting Information

Not applicable.

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