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Fault Monitoring and Analysis of Distributed New Energy Grids Using Simulation Data Models

Hao Bai[1], Weichen Yang[1], Ruotian Yao[1], Lifang Wu[2], Liwen Qin[2] and Xiaoyong Yu[2]

[1] Electric Power Research Institute
China Southern Power Grid
Guangzhou, 510663 Guangdong (China)
E-mail: **baihao@csg.cn**
[2] Electric Power Research Institute
China Southern Power Grid
Nanning, 530023 Guangxi (China)
E-mail: **13557019675@163.com**

ABBREVIATIONS	
DNN	Deep Neural Networks
CNN	Convolutional Neural Networks
ESS	Energy Storage System
1D-CNN	One-dimension CNN
FLI	Faulty Line Identifier
FCT	Fault Class Types
FLE	Fault Locations Estimator
LSTM	Long Short-Term Memory
ANFIS	Adaptive Neuro-Fuzzy Inference System
ROC	Receiver Operating Characteristic
WPT	Wavelet Packet Transform
EOA	Equilibrium Optimizer Algorithm
SAE	Stacked Autoencoders
LVDGs	Low-voltage Smart Distribution Grids
FDR	False Discovery Rate

Abstract. Data analysis is essential for fault identification and detection in smart grids in order to maintain grid monitoring. Many DL algorithms have been developed recently for data analysis applications related to smart grids. To resolve these challenges, the study suggests a Deep Neural Network (DNN) for data-driven fault location detection and type of fault classification by exploiting the Modified Sand Cat Swarm Optimization (MSCSO) optimization. Here, the DNN is used to diagnose the faults and determine the position of the sites. Numerous synthetic field data sets derived from simulated models of different transmission line types are used for training and testing. The position and type of faults are predicted by the DNN classifier based on the fault signal features, in which the DNN weights are ideally tuned using a novel MSCSO optimization method that is the improved concept of Sand Cat Swarm Optimization (SCSO). Lastly, MATLAB/Simulink is used to implement the suggested DNN-based method for fault classification and its localization in transmission line. An intellectual IEEE 6-node network model is utilized to confirm the efficacy and reliability of these methods. The outcomes demonstrated its effectiveness in giving the system operator precise and detailed analytics for fault identification.

Key words. Distribution Grid, Deep Neural Network, Fault Detection, Fault Location Identification, Optimization.

1. Introduction

With wind energy being one of the world's most promising RES, wind generation systems are expected to provide a sufficient amount of electricity and integrate well with the grid [1], [2]. Wind power production systems require more complex, distinctive, and reliable control approaches for achieving a more stable controller functioning and boosting the system's efficacy. The extraction of energy from water yields large volumes of sustainable, pure energy. However, only 30% of this energy has been produced [3]-[5]. When compared to alternative RES, hydropower, particularly hydropower plants, is more economical, efficient, and ecologically friendly. Hydropower facilities are extremely automated and operate at a low cost. The major parts of the power system need to be periodically checked and protected which helps to sustain the quality and trustworthiness of the power source. This duty is carried out by the system for collecting, observing, and protecting data. Short circuits and anomalous conditions must be protected against turbines. A system failure occurs when there is a sustained disturbance in its ability to perform the required function under specific circumstances [6], [7]. An unapproved divergence of at least one system feature or characteristic from the accepted or usual state is referred to as a defect [8]-[10]. ML models often face the issue of training a decision model with a large amount of prior data. This size necessitates that the controller possesses both powerful computing and storage abilities. Many devices cooperate in an actual network to ascertain whether a node is reachable. If the controller forecasts and monitors each piece of equipment, it will be burdened with a very large amount of data. It is crucial to use an ML method that can train a very accurate model with limited information.

Large volumes of data are analyzed using data mining and ML models in which the data-driven strategies help to identify and categorize faults. Model-driven approaches locate and identify faults by using mathematical system models. Since every technique has a unique mix of benefits and drawbacks, choosing the best one will rely on the particular application and the data that is available. Although the smart grid increases efficiency, flexibility, and dependability by utilizing cutting-edge communication and information technology, it is prone to malfunctions that could cause power outages. Smart grid maintenance requires the important duties of problem detection, classification, and localization, which enable prompt defect identification and power restoration. Due to their independence from system structure, data-driven methods like methods that use machine learning might be helpful in identifying faults in highly nonlinear systems [11], [12]. Real-time defect detection has found great potential in data-driven methodologies due to the rapid developments in parallel computing hardware and deep learning. Additionally, data-driven algorithms show good resistance to noise, which makes them very useful for solving challenging classification issues. The potential of DNNs, including ANNs and CNNs, has been shown through fault detection and classification tasks [13]-[15]. DL strategies have the capability to undergo training using labelled fault data, enabling them to autonomously identify, categorize, and pinpoint faults within the smart grid in real-time applications [16]-[18].

The major encouragements of this study are enumerated below:

Presents a novel approach for identifying both the type and distance of faults occurring in transmission lines utilizing Deep Neural Network (DNN) classifier.

The DNN weights are tuned optimally by a novel meta-heuristic technique named modified Sand Cat Swarm Optimization (MSCSO) technique.

The performance of presented method is contrasted over several prevailing methods in terms of classification accuracy, precision, specificity, sensitivity and so on.

The paper is organized as follows: an overview of standard schemes is represented in Section II. Section III outlines the process of identifying and classifying faults in distribution grids using Deep Neural Networks (DNN). Section IV introduces the weight tuning through the MSCSO method. The outcomes of the implemented system are detailed in Section V, and Section VI delivers a summary and conclusion for the paper.

2. Literature Survey

A. Related Works

Rizeakos et al. [19] created a data-driven application in 2023 for the identification of fault location and type of fault categorization. It is based on CNN that has been optimally tuned through Bayesian optimization and continuous wavelet transformation. High-resolution measuring equipment is widely available in distribution networks, which is considered a benefit for this application. It has the ability to identify short-circuit faults precisely and categorize them into eleven distinct types. By understanding the spatial and temporal properties of the three-phase voltage and current time series measurements derived from field devices, its intrinsic models enable operators to see their networks in real-time. The outcomes demonstrated its effectiveness in giving system operators accurate and detailed analytics for fault identification.

The architecture of a GEO-based controller was devised by Kailash Kumar et al. [20] in 2023 which has been integrated into a grid-connected microgrid and has the capacity to store energy. The controller's objective is to minimize power transfer among the main grid and microgrid and control the ESS rate of charge and discharge to reduce end-user operating expenses. The proposed method calculates the ESS charge and discharge rates on a rolling horizon by reducing the load, the ESS charging state, as well as the electricity cost from the obtainable sources of energy. The suggested controller can minimize energy exchange and achieve reduced operating expenses as compared to earlier controllers with comparable goals.

DNN was introduced by Nikolaos Sapountzoglou et al. [21] in 2020 and are suggested for fault identification and localization in LVDGs. Portugal's LV distribution grid has been taken into consideration for evaluating the method's robustness and examining its key characteristics. Additionally, the accuracy of the method has been tested against various impacts to evaluate its resilience. The presented model is demonstrated to be highly effective in fault detection and localization based on the experimental findings. Also, it is demonstrated that the suggested method can achieve an equivalent or higher performance than cutting-edge techniques when the accuracy is contrasted with different techniques found in the literature.

In 2023, Xiaofeng Ren et al. [22] introduced a fault localization model depending on the travelling wave modulus's time difference. Initially, the attenuated zero-mode travelling wave transmission was analyzed which helps to assist a zero-mode time-of-arrival calibration method for the optimal frequency range. After, defining the relative wave velocity, examine the quantitative affiliation among the zero-mode, aerial-mode wave velocity and the modulus transmission time variance that helps to generate equations by constraining the connection among the transmission distance, relative wave velocity, and modulus transmission time difference. The PSCAD simulation findings show that the suggested approach in this study can determine faults easily and accurately and has better accuracy, strong error tolerance, and great adaptability.

In 2023, Ahmed Sami Alhanaf et al. [23] developed a novel fault detection approach with ANNs and 1D-CNNs. Shortening the fault identification method reduces the pre-processing stages, feature engineering, and signal conversion may provide an efficient model. In addition, it enhances the dependability and efficacy of smart grids by precisely detecting the FLI, FCT, and FLE using DNNs. As a result, DL deliberates as a potential method for enlightening fault classification and identification in smart grids by providing better performance.

In 2020, Yordanos Dametw Mamuya et al. [24] focused on identifying and classifying faults in radial distribution networks that have an individual source at the sending end. The ML tools were executed via knowledge-based approaches. Relevant data was extracted from the observed current signal utilizing wavelet decomposition along with statistical measurements. The NN were trained by utilizing those characteristics. A basic radial distribution network with balanced and unbalanced load circumstances was used to test the suggested methodology. Thus, the effectiveness of the suggested fault-localizing approach was assessed using error metrics, demonstrating that the DWT combined with ML provide a precise and consistent way for fault localization and classification under a balanced and unbalanced radial system.

In 2023, Camille Franklin Mbey et al. [25] introduced a DL model made of LSTM and ANFIS for detecting faults in smart DGs supported by smart meter data. Initially, these extracted data samples from the smart meters were trained using LSTM. Next, an ANFIS approach is examined for identifying and detecting the fault. In the end, a fault with high precision was found. The IEEE 13-node bus is utilized to assess the efficacy and toughness of the suggested method in terms of various features, including accuracy, precision-recall, F1-score, ROC curve, and complexity time. The findings show that the suggested DL method performs 99.99% accuracy for identifying and classifying the fault when compared with the existing DL methods.

In 2022, Moath Alrifaey et al. [26] developed a hybrid DL approach that helps to attain the automated real-time fault identification and classification of a PV system. This study utilizes WPT as a data preprocessing tool that helps to manage the gathered PV signal voltage and fed as input into an integrated DL structure that includes EOA and LSTM-SAE approaches. According to computational time, accurate fault detection and noise resilience, the simulation findings confirm the effectiveness of the suggested model.

In 2023, a new general approach to fault detection in smart grids was introduced with the help of a combined model that consists of deep learning structures, namely graph neural networks (GNN) and reinforcement learning (RL). This method uses the concept of topological structure and is less sensitive to variations in power networks. The studies found that the proposed methods of using GNN and RL had less fault detection time and greater fault detection accuracy as compared to conventional techniques, which means that these approaches could be used to improve the reliability of the grid [27]. The second recent work under study was based on the context of smart grids and dealt with the efficient control of wind and solar power stations. To deal with the fluctuating energy sources they also proposed an improved EMS based on deep reinforcement learning (DRL). Hence, as concluded in [28], the proposed DRL-based EMS provided better control of the grid stability and lower operating expenses as compared with standard optimization methods.

In 2022, for smart-grid ML-based predictive maintenance system was developed. Finding out when equipment is likely to fail is achieved through historical data of faults as well as real-time data acquisition. The application of the predictive maintenance methodology was very effective in enhancing the frequency of the grid system, and at the same time, it also ensured that the costs for frequent maintenance and the rate of system downtimes were minimised. Based on the conclusions of the study, it is evident that proactive fault management should use machine learning to ascertain the functionality and constructiveness of powering today’s complex systems [29]. Further, in 2022, applying blockchain with a smart grid for a secure and transparent approach to fault management was studied. Through the implementation of the blockchain-based system, the fault data is more reliable and can be traced back easily thus allowing for quick and accurate diagnosis of the fault. To detail, the integration of blockchain technology in fault management can tackle the following weaknesses: Including security issues and trust deficits among the grid stakeholders [30].

These advancements show that fault detection and integration of renewable energy sources into smart grid are the areas of constant development, which layout the foundation for the proposed research.

B. Problem Definition

Table 1 shows the reviews Review on DL-based fault detection and classification for smart grids. A CNN + Bayesian optimization is developed in [19], which is highly effective and provides accurate fault diagnosis. However, it needs a lot of information for training that is not frequently accessible, when it comes to genuine data. The GEO model is introduced in [20], in which power oscillations due to unpredictable RES get reduced. However, the distribution network reliability is not considered here. Moreover, a DNN classifier was developed in [21], which is highly accurate, and reliable and performance will be superior. However, it may cause less computational cost and converge locally at bad minimum values. In addition, the PSO approach was introduced in [22], which offers high precision with robust adaptability. Nevertheless, the computational complexity of the model is very high. ANN+1D-CNN model is introduced in [23], which is highly accurate and provides system reliability. However, computation time may not remain the same. Furthermore, ANN & ELM methods were developed in [24], which are reliable, effective and accurate. However, training ML models are complex. Likewise, LSTM & ANFIS techniques were introduced in [25], which are effective, robust and provide 99.9% accuracy. Here, data analysis may not cause a voltage drop. Similarly, the EOA & LSTM approach was developed in [26], which provides better accuracy with less computation time. Nevertheless, feature extraction and selection are considered the major challenges.

Table 1. Review on Methods of Fault Detection and Classification for Smart Grids

AUTHOR/ CITATION	METHODOLOGY	FEATURES	CHALLENGES
V. Rizeakos, et al. [19]	CNN + Bayesian optimization	Highly effective. Accurate fault diagnosis	For training, it needs a lot of information that is not frequently accessible, when it comes to genuine data.
Kailash Kumar et al. [20]	GEO model	Power oscillations due to unpredictable RES are reduced.	Distribution network reliability is not considered here.
Nikolaos Sapountzoglou et al. [21]	DNN classifier	Accurate, reliable Performance is superior.	Low computational cost. Converges locally at local minimum values.
Xiaofeng Ren et al. [22]	PSO approach	High precision. Robust adaptability	Computationally complex
Ahmed Sami Alhanaf et al. [23]	ANN + 1D-CNN models	Better precision System reliability is high.	Computation time may not remain the same.
Yordanos Dametw Mamuya et al. [24]	ANN & ELM methods	Effective Reliable and accurate	Training ML models are complex.
Camille Franklin Mbey et al. [25]	LSTM & ANFIS	Effective and robust Accuracy is 99.9%	Data analysis may not cause a voltage drop.
Moath Alrifaey et al. [26]	EOA & LSTM approach	Better accuracy Less computation time.	Manually, feature extraction and selection are considered the major challenges.

3. Identifying Location and Classifying Type of Fault Using DNN in Distribution Grid

A. Collected System Data

While evaluating several power systems analysis and control approaches, electrical engineers commonly employ the IEEE N-bus power system. A mathematical model is constructed depending on the system's acquired information that helps to develop a data-driven system model using MATLAB. The IEEE 6-bus system, consisting of three conventional voltage sources with 132kV voltage rating and 60Hz frequency is seen in Figure 1 in a single-line configuration. In addition, Data information was collected using different scenarios by varying anticipated load patterns. Furthermore, data were gathered in scenarios in which the distributed sources, like variable wind turbines or solar systems are present. The major purpose was to improve the research findings' robustness and dependability.

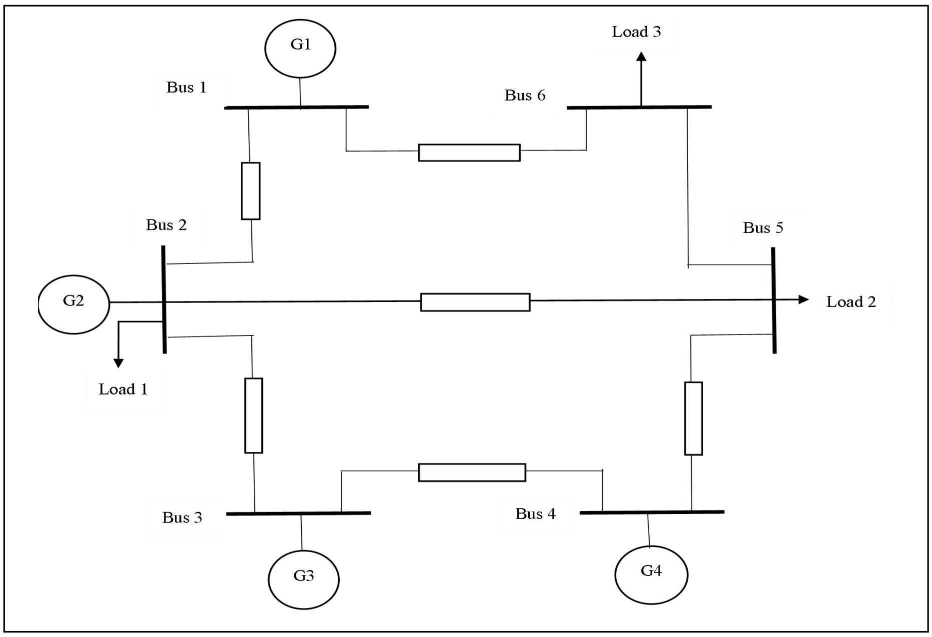
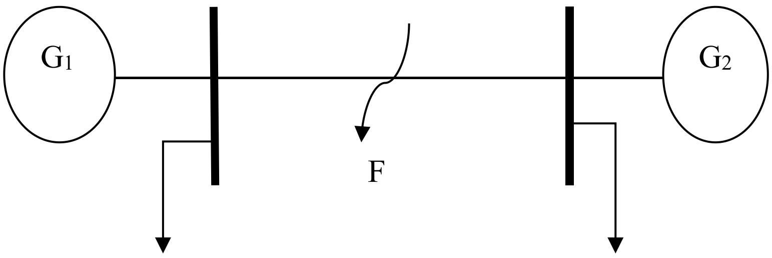


Figure 1. Diagram of a Single Line IEEE 6 Bus System

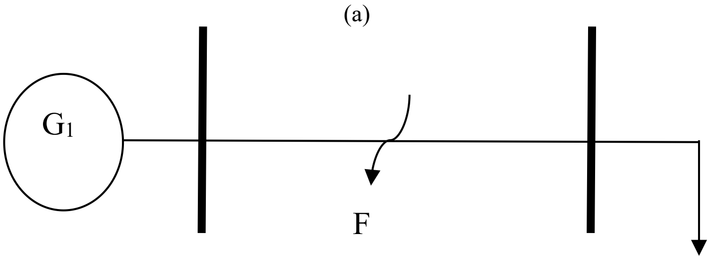
An elementary estimation of the distributed power system is illustrated in the IEEE 6-bus system which includes six buses, three loads, four generators, and 7 transmission lines. The transmission lines with three-phase systems are demonstrated as medium lines. In addition, the system with three loads is present at buses 2, 5, and 6 which require both active and reactive power. To determine the fault type, a three-phase fault block is utilized. The fault type could be adjusted by choosing phases (A, B, C) and ground G and it is capable of setting the type of fault, even if voltage and current were gathered from both transmission line ends. In order to alter the fault's position in the simulation process, the system line model is categorized into two segments with the objective of varying the resistance and inductance values in certain ways. The line data, load data and generator data of the IEEE 6 bus system are collected from [23].

B. System Model

For the classification of fault type and identifying its fault location, the system model is replicated as a single-line transmission model which comprises generators, loads, buses and transmission lines [31]. As a consequence, the transmission line system model with the Line-Line (L-L), Line-Ground (L-G) faults and single transmission line with 2 generators are depicted in Figures 2(a), 2(b), and 2(c).



(a)



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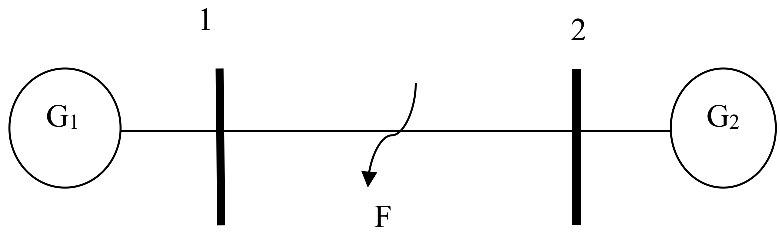


(c)
Figure 2. System Model of (a) L-L (b) L-G (c) Single Transmission Line with 2 Generators

C. Fault Location Identification

A fault's resistance value is simply one factor that determines its consequences and characteristics; another factor is the fault's type. Different impacts of balanced and imbalanced faults can be seen on the grid voltage, particularly in the negative and zero sequence components where unbalanced faults will clearly show deviations from normal operating conditions [32]. Therefore, the system performance comparison is made towards the 4 fault types under consideration in order to assess its accuracy and robustness. Nonetheless, a fault type is used to group the data points. Again, three and four hidden layers as well as positive, negative, and zero voltage components are taken into account for the DNN complexity and voltage measurements.

D. Type of Fault Classification

One of the crucial components of the protection relay is the fault-type classification. Over a decade, researchers primarily created robust, accurate, and new fault classification algorithms and procedures. As a result, classifier models drawn from learning theory are used in the majority of classification procedures [33]. The values of the voltage and current samples in this proposed work are different depending on when the fault occurs before and after and are determined by the fault categorization. As a result, the DNN model needs the faulty data from the previous analysis in order to identify the fault type. Faults can also be detected by the patterns of voltages and currents that arise from transmission lines. As a result, A-G, B-G, C-G, A-B, B-C, and C-A, respectively, are the characteristics that were used to detect the defect.

E. Data Pre-processing

The measured values are processed depending on the instant current and voltage in each phase R, Y, and B prior to inputting the voltage and current signals into the DNN. Through the division of the fundamental current and voltage, it is probable to calculate the IO current and voltages, representing the transition from post to pre-fault fundamental current and voltage states. Besides, earth-related faults are detected using the zero-sequence current component [34].

F. Proposed Deep Neural Network

Two sets of input feature spaces make up the training and testing datasets. These characteristic spaces are made up of high-dimensional vectors that are formed from the actual values of three-phase current and voltage signals that are calculated at different positions. According to this research, DNNs are now a reliable model for statistical modeling that isn't linear, especially when it comes to fault identification and classification.

A DNN framework consists of input, hidden, and output layers. Figure 3 displays a representation of the DNN framework. Each nodal layer is systematically coupled to entire nodal layers below it. The I/O layers are usually a single layer, but the hidden layers might have two or more layers. After the hidden layers have prepared the data features supplied into the input layer as data features, the forecasting elements are obtained from the output layer. Every single hidden-layer’s node activation method turns the weighed sum of terminals into accessible outputs. This activation technique computes the expected outcomes as well as the average weighted number of terminals. ReLU generates a value which is equal to the input if the terminals' weighed computation is larger than or equal to zero; if not, it generates zero. In general, ReLU is the most frequently utilized activation function in regression analysis.

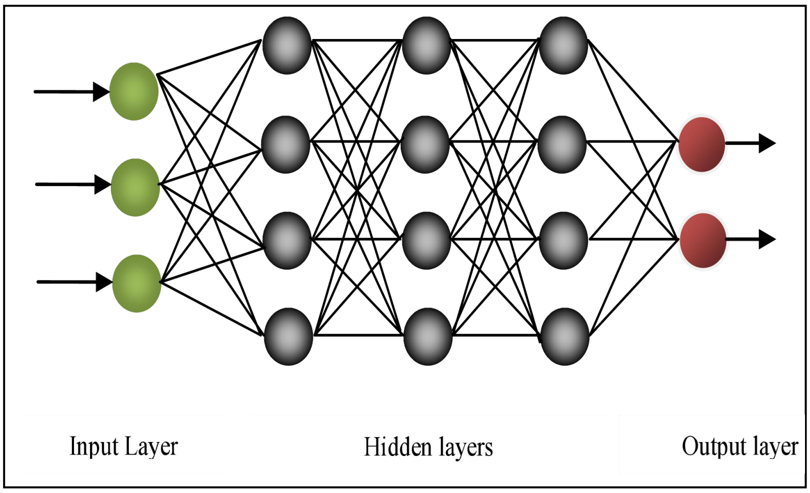


Figure 3. DNN Model Structure

In order to forecast values, ReLU continuously adjusts the weights throughout each DNN training model session. This weight adjustment is applied towards the back, from the output to the input layer, using backpropagation till the cost function is minimized and it can be defined by adding the squares of the modifications among the expected and actual values. The correlation for evaluating the cost function J is illustrated in Equation (1). Now, n represent the arbitrary nodes in the output, x_l and $\hat{x}_l$ define the observed and projected output values at l^{th} a node, congruently. Equation (2) signifies the manner in which the following load can be taken to equalize the discrepancy amongst the prior weight as well as the partial derivative error function. Now, p denotes the nodal count in the prior layer, $q\ t$ specifies the nodal digit in the subsequent layer, W_{pq} suggests the weight at the time t and λ represents the learning rate [33].

$$J = \sum_{l=1}^{n} \left(x_l - \hat{x}_l \right)^2 \tag{1}$$

$$W_{pq}{}^{t} = W_{pq}{}^{t} - \lambda \frac{\partial J}{\partial W_{pq}{}^{t}} \tag{2}$$

In this suggested work, to estimate the performance of the suggested method, the actual and predicted values of the tested data are related and the weights of the DNN are tuned optimally by a novel meta-heuristic algorithm named Modified-SCSO technique.

4. DNN Weight Tuning via MSCSO Strategy

A. The Objective Function

To maximize the model's performance and to attain optimal outcomes, the developed strategy plans to identify the faulty location and classify its fault type by means of a DNN such that the weights are optimally tuned using the Modified-SCSO algorithm.

B. Proposed MSCSO Algorithm

The MSCSO Algorithm is a recently developed metaheuristic technique for optimization. All sand cats are encouraged to hunt, and they all attempt to catch larger prey. Sand cats have a specific frequency at which they fight or hunt for prey. As a result, the sand cat will seek an improved location to find more prey. By giving the SCSO technique [35] a large potential for exploitation, each sand cat will gradually come closer to its target. However, as the SCSO scheme develops, each sand cat has a higher probability of hitting the ideal site, preventing it from migrating to a better spot to improve the sand cat's mobility and the method's exploratory potential. As a result, a modification is made in this study, and hence, it is called the Modified SCSO algorithm.

1) Population Initialization

In the instance of dimensional optimization, each sand cat is an $1 \times d$ array, as it stands for the problem's resolution. Each value Q will be within a set of variable values, namely $(Q_1, Q_2, \ldots. Q_d)$ such that each value Q must be within the upper and lower limits. During the initial stage, depending on the magnitude of the issues $(n \times d)$, an initiation matrix is generated. Moreover, every repetition yields a suitable outcome. If the resulting output value is better than the previous method, the previous method will be dropped. If the next iteration does not identify a superior result, the previous iteration's result will not be stored.

2) Food Searching (Explored Phase)

The location of every single sand cat is defined by the value of Q_i. The superior lower-frequency hearing of sand cats is exploited by the MSCSO approach. All sand cats have a low-frequency hearing range of less than 2 kHz. The sensitivity ranges for the dune cat are from 2 to 0 kHz as equation (3) specifies the sensitivity in computational models. Furthermore, the technique's ability for seeking and exploiting is handled, and the variable H is calculated in equation (4).

$$V_g = C_s - \left(\frac{C_s \times t_i}{T_{\max}} \right) \tag{3}$$

$$J = 2 \times C_s \times rnd(0,1) - V_g \quad (4)$$

Where $C_s = 2$; t_i defines the present numeral iteration; $T_{\max}$ describes the maximal iterated count.

Every sand cat will randomly select an unfamiliar location inside their sensitive area when they look out for food. This method works better for investigating and using new techniques. To avoid slipping into the local ideal condition, each sand cat has a distinct sensitive limit S_l. Thus, V_g is employed for guiding the S_l variable, as depicted in equation (5).

$$S_l = V_g \times rnd(0,1) \quad (5)$$

During the investigation, the prey's location will be ascertained using the ideal candidate positioning (Q_{bc}), current location $(Q_c(t_i))$, and sensitive limit (S_l) connected with each sand cat. The specific equation is shown in equation (6).

$$Q(t_i + 1) = S_l \times \left(Q_{bc}(t_i) - rnd(0,1) \times Q_c(t_i)\right) \quad (6)$$

3) Attacking the Prey (Exploited Phase)

Equation (7) represents the distance (Q_r) between the victim and the sand cat, simulating the sand cat attacking its prey. Consider the sand cat has a sensing range of a circle, and that its path selects an arbitrary inclination by means of the Roulette Wheel selection method. The randomly selected value of the angle (δ) ranges from 0^0 to 360^0 and falls within the bounds of -1 and 1. Each sand cat may move in this way, following an alternate circular route within the search region. The target then makes an attack with equation (8). In a similar manner, the dune cat may rapidly approach its feeding location.

$$Q_r = \left|rnd(0,1) \times Q_b(t_i) - Q_c(t_i)\right| \quad (7)$$

$$Q(t_i + 1) = Q_b(t_i) - S_l \times Q_r \times \cos(\delta) \quad (8)$$

The flowchart in Figure 4 and accompanying pseudocode in Algorithm 1 show the MSCSO implementation process.

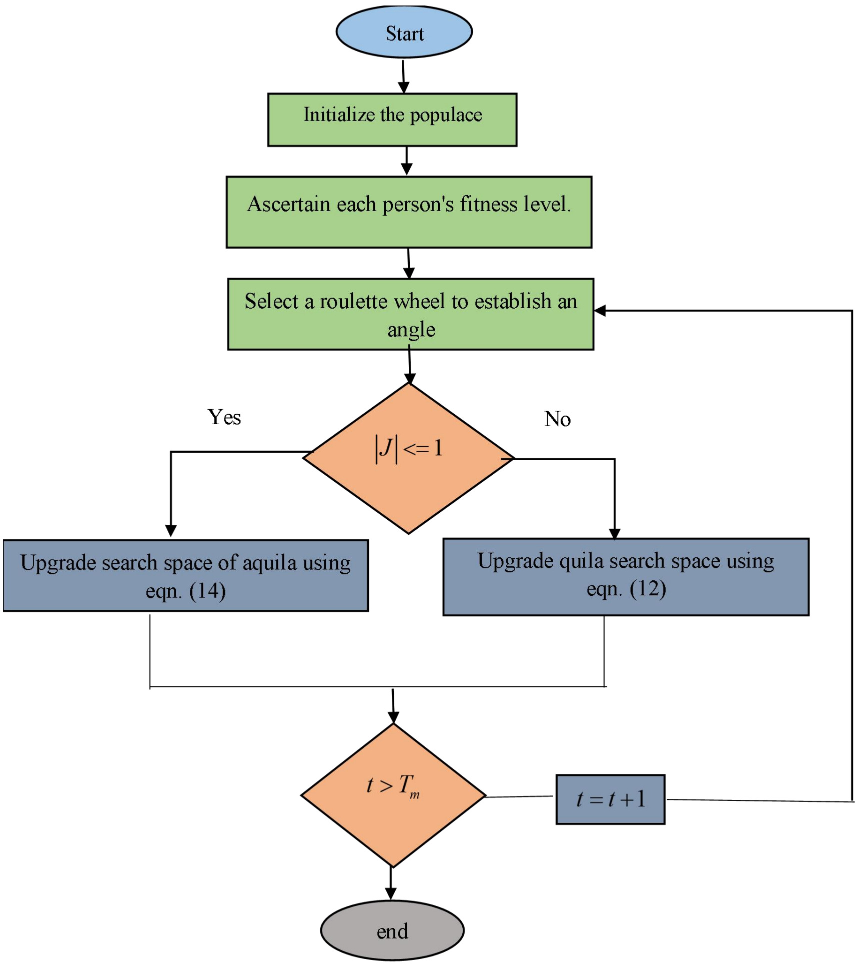


Figure 4. Flowchart of MSCSO Approach

Algorithm 1: MSCSO Approach

MSCSO Approach
Set the initial populace data
Using the OF, compute the fitness function.
Set the variables V_g, S_l and J
While $\left(t_i \le T_{\max}\right)$
For every search agent
Achieve a haphazard angle regarding the Roulette Wheel Selection $(0^\circ \le \delta \le 360^\circ)$
If $\lvert J \rvert > 1$
Update searching agent spot using eqn. (6)
else
Update searching agent spot utilizing eqn. (8)
end
$T_{\max} = t_i + 1$
End

The MSCSO Algorithm is a new optimization solution that is of a metaheuristic nature and has been developed relatively recently. All members of the sand cat population are active hunters, and they all try to capture the larger meals. Fight or hunting frequency in sand cats has also its own frequency rate. Thus, the sand cat will look for a better area where it gets more prey. Thus, attributing a large potential for exploitation of the SCSO technique, each sand cat will over time approach its goal. But, as the agglomeration of the system of cooperative sites progresses with the scheme of SCSO, each sand cat indeed possesses a lesser chance of shifting to the optimal site, which otherwise would denigrate to a superior site leading to enhanced mobility of the sand cat and exploratory range of the method. Therefore, a change is introduced in this study, and thus, it becomes the Modified SCSO algorithm.

The MSCSO algorithm proposed in this paper adds to the SCSO algorithm by improving the exploration and exploitation powers of the algorithm. But in the standard SCSO, a problem of high tendency to fast convergence towards the best solution, the part can converge to local optima and get stuck at the lower level. In the first step, both the sand cats choose a random zone within their hearing distance, which changes according to the value of ‘iteration’. This adjustment also suppresses the tendencies of the agents to focus on one point and drives them to explore a larger area of the solution space. To achieve this, the range of each sand cat is changed with a defined frequency function; where in earlier iterations, the emphasis is on exploration, and subsequently, the search space is refined around promising regions in the later iterations.

MSCSO uses shift hunting to indicate that sand cats can base their hunting on the quality of the solutions in the environment. If a sand cat discovers a better solution, it focuses more on that area, and it increases exploration and exploitation of the options more equally. Actual change of the particle’s location in the search space also allows the sand cats to avoid getting stuck in local optima, and actually change the behaviour in the process – adding to the overall reliability of the algorithm. In the exploitation phase, the distance from the sand cat to the prey is computed in a better distance formula taking into consideration the position of the sand cat at the time and the limit of sensitivity of the sand cat. The MSCSO also includes a Roulette Wheel Selection method to define the direction of the move and comes with an element of probability that is crucial in ensuring the spread of competence in the population does not stagnate.

In the case of dimensional optimization, each sand cat is an array since it refers to the problem’s resolution. Each value will be within a set of variable values, particularly such that every value has to be within the maximum and minimum values. In the first stage based on the scale of the concerns, an initiation matrix is created depending on the size of the issues. Also, there is an appropriate return each time there is a repetition. If the generation output value is higher than the previous method, the previous method will be eliminated. If the next iteration does not locate a better solution, then there will be no storing of the previous iteration of the result.

Each sand cat’s position when and where can be described by the value of. Hearing capability is another area where the sand cats are superior to the other animals, especially at lower frequencies, and this is what is harnessed in the MSCSO approach. Every sand cat has a low-frequency hearing range not exceeding 2 kHz. The ranges of sensitivity for the dune cat as far as concerned are 2 to 0 kHz as equation (3) Designates the sensitivity in structural models. Further, handling of seeking and exploiting nature of the technique is done and the variable H is computed from equation (4). Where, (;) points to the present numeral iteration, describes the maximal iterated count. Each sand cat at a particular time of the day will go look for food in a location that is random and outside the known or familiar area in their sensitive area. It is more efficient to solve a problem or explore a new method by using the new technique. To prevent each of the sand cats from falling prey to the local ideal condition they have different sensitive limits. Hence, it is used for leading the variable as represented in Equation 5 above.

The coordinate location of the – prey when revealed will be determined by the ideal candidate positioning the current location and the sensitive limit associated with each sand cat. The specific equation is indicated by the equation (6). Distance between the victim and the sand cat is represented by equation 7 which imitates the sand cat attacking its prey. Let it be assumed that the sensing range of the sand cat has a circular shape and the path that it chooses is determined by an arbitrary inclination with the help of the Roulette Wheel selection scheme. The randomly selected value of the angle is an integer laid between 0 and 360 and is quantized in the range of -1 and 1. Every sand cat may move in this fashion, in an opposite circular route within the search area. The target then counterattacks with equation (8). Likewise, the dune cat can move quickly toward the feeding area, At the same time, the steepness of the slope, or the rate of the increase in height per unit of distance.

5. Results and Discussion

A. Simulation Procedure

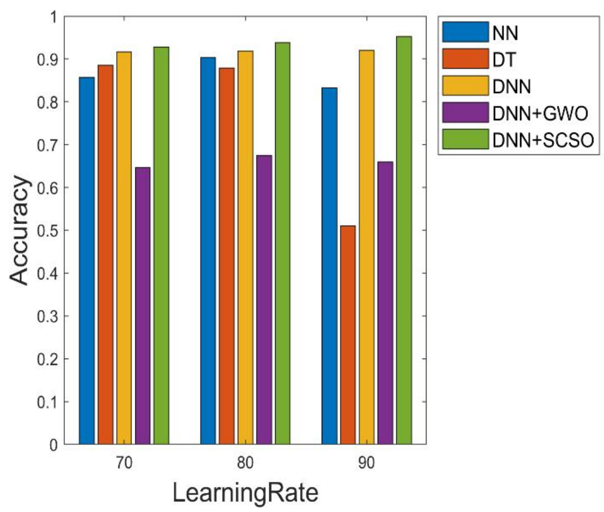
The recommended DNN-based MSCSO technique for detecting the fault type and its location was simulated in MATLAB/Simulink and their equivalent outcomes were attained. Transmission line models were taken into consideration during the research, from which artificial data based on fault type and distance was gathered. Lastly, an analysis and comparison are made between the performance of the suggested DNN model based on the MSCSO algorithm and the conventional models, like NN [24], DT [36], DNN [21] and DNN+GWO [37] algorithms.

B. Evaluation Metrics

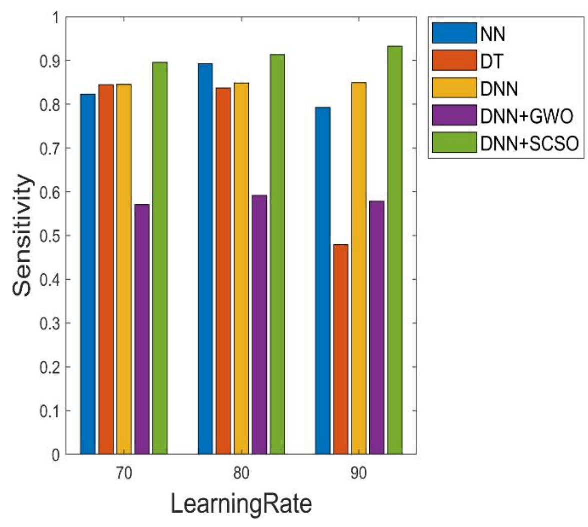
The proposed approach's effectiveness is simulated by employing performance indicators such as accuracy, sensitivity, precision, F1-score, specificity, FDR, FPR, FNR, NPV, and Mathews correlation coefficient (MCC).

C. Analysis of Positive, Neutral and Negative Metrics

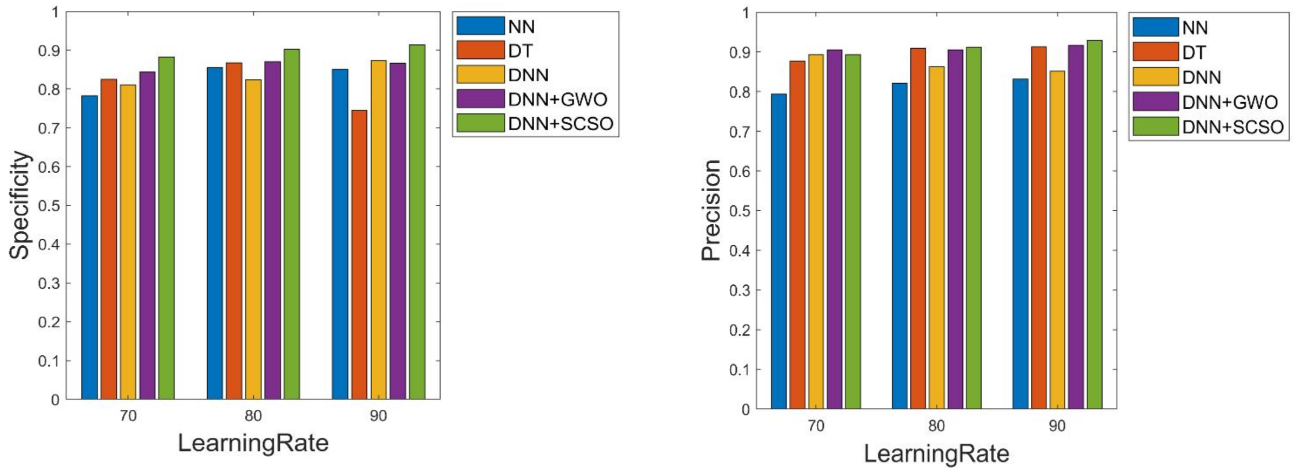
The suggested DNN-based MSCSO approach is proven to outperform the traditional algorithms when its performance is compared by employing the previously stated criteria. Figure 5 compares the methods in regard to the percentage of positive measures, such as accuracy, sensitivity, specificity, and precision that are trained. Figure 6 depicts an overview of the methods' training percentages in relation to objective metrics like the F1-score and MCC. Figure 7 also shows an assessment of the training proportions for the different techniques for the four negative metrics such as FDR, FNR, FPR, and NPV.



(a)

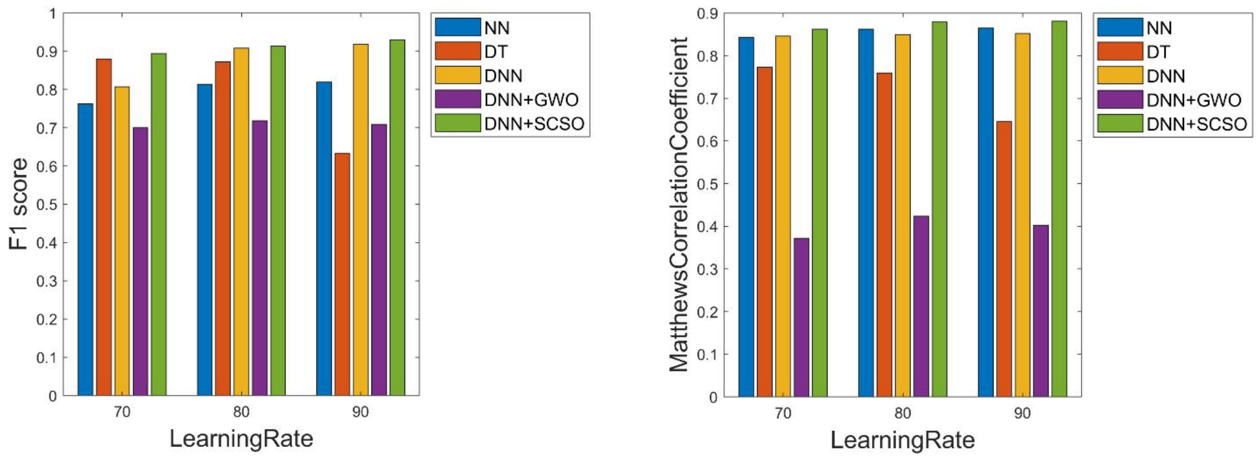


(b)



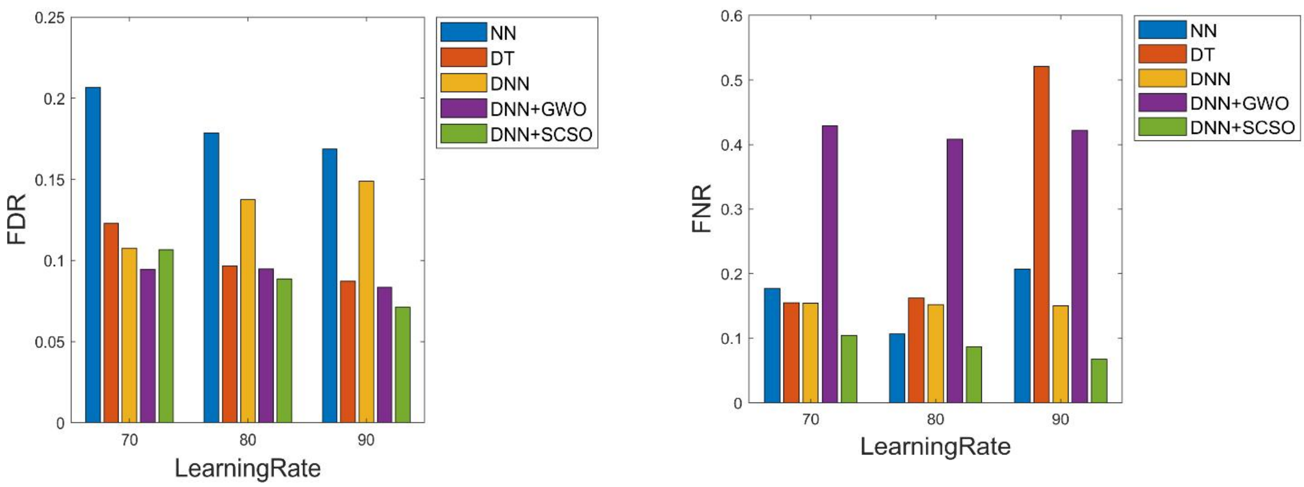
(c) (d)

Figure 5. Performance Assessment Regarding Positive Measures

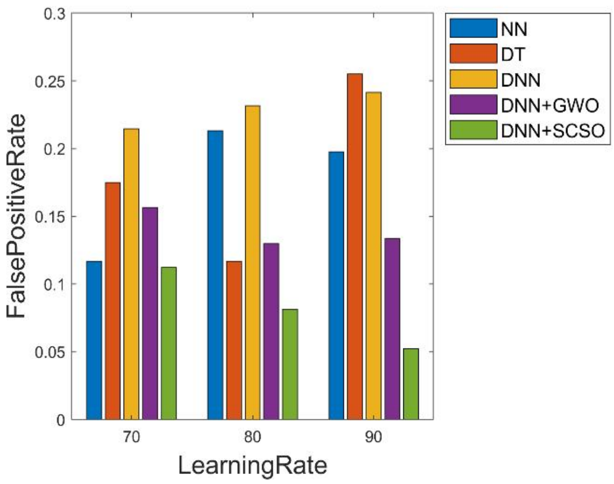


(a) (b)

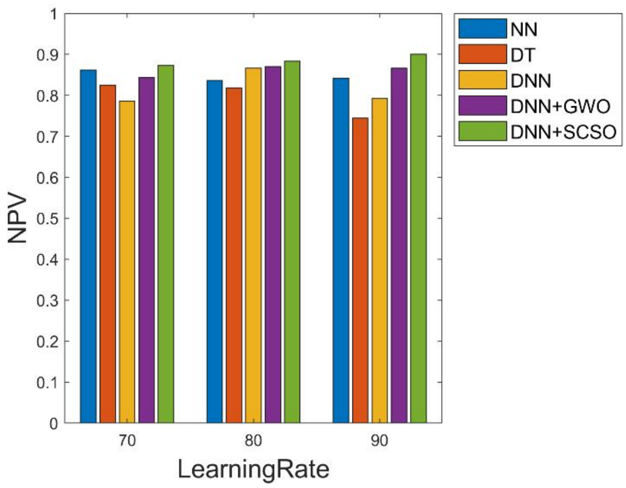
Figure 6. Performance Assessment Regarding Neutral Measures



(a) (b)



(c)



(d)

Figure 7. Performance Assessment Regarding Negative Measures

Table 2. Metrics Based on Fault Detection and Classification

METRICS	TRAINING PERCENTAGE=70%				
	NN	DT	DNN	DNN+GWO	DNN+SCSO
Accuracy	0.8566	0.88533	0.91673	0.64613	0.928
Sensitivity	0.82315	0.8449	0.84575	0.5709	0.8952
Specificity	0.78235	0.82506	0.81024	0.84348	0.88215
Precision	0.79325	0.8772	0.89237	0.90537	0.89327
FPR	0.11698	0.17494	0.2145	0.15652	0.11245
F1 score	0.76215	0.87957	0.80643	0.70025	0.89354
MCC	0.84241	0.77286	0.84627	0.37188	0.86241
FNR	0.17685	0.1551	0.15425	0.4291	0.1048
NPV	0.86202	0.82506	0.78635	0.84348	0.87302
FDR	0.20675	0.1228	0.10763	0.094626	0.1067
	Training percentage=80%				
	NN	DT	DNN	DNN+GWO	DNN+SCSO
Accuracy	0.90322	0.8786	0.9186	0.6743	0.9379
Sensitivity	0.89326	0.83745	0.84808	0.59155	0.91325
Specificity	0.85478	0.86735	0.82364	0.87008	0.90255
Precision	0.82133	0.90933	0.86253	0.90505	0.91133
FPR	0.21325	0.11672	0.23154	0.12992	0.08132
F1 score	0.81383	0.87191	0.90779	0.71857	0.91383
MCC	0.86205	0.75923	0.84944	0.42367	0.87905
FNR	0.10674	0.16255	0.15192	0.40845	0.0867
NPV	0.83655	0.81867	0.86598	0.87008	0.88328
FDR	0.17867	0.09669	0.1375	0.0949	0.0887
	Training percentage=90%				
	NN	DT	DNN	DNN+GWO	DNN+SCSO
Accuracy	0.8326	0.5108	092	0.6598	0.9526
Sensitivity	0.79313	0.47911	0.84974	0.57824	0.93254
Specificity	0.85041	0.74497	0.87256	0.86643	0.91407
Precision	0.83142	0.9128	0.85102	0.91645	0.9288

METRICS	TRAINING PERCENTAGE=70%				
	NN	DT	DNN	DNN+GWO	DNN+SCSO
FPR	0.19759	0.25503	0.24154	0.13357	0.05215
F1 score	0.81941	0.63306	0.91877	0.70908	0.92951
MCC	0.86449	0.64587	0.85182	0.40244	0.88049
FNR	0.20687	0.52089	0.15026	0.42176	0.0675
NPV	0.84216	0.74497	0.79236	0.86643	0.90041
FDR	0.16858	0.0872	0.14892	0.08355	0.0712

Table 2 examines the performance of the suggested strategy and the conventional models based on the evaluation measures, such as accuracy, sensitivity, precision, Specificity, F1-Score, MCC, NPV, FPR, FNR and FDR. The table clearly shows the fact that the recommended approach prevails over alternative methods with regard to overall effectiveness. From the results, it seems that the proposed method attains superior value. Table 4 examines the computational time attained by the suggested method over existing NN, DT, DNN and DNN+GWO approaches under 70%, 80% and 90% training percentages.

Subsequently, cross-validation was carried out so as to test the stability of the proposed DNN-derived MSCSO method under differential noise and or external factors. In an effort to challenge the flexibility of the algorithm, various levels of Gaussian noise were added to the data and diverse types of external interference likely tampering with fault detection as well as classification were also introduced. The primary goal of the experiment was to determine how the noise levels that ranged from 0% to 10% of the signal amplitude affected the algorithm. Through computational analysis, findings showed that DNN-based MSCSO enhanced the recognition performance and stability, especially under higher noise levels. At a signal-to-noise ratio level of 5% for instance, it was observed that the accuracy only declined by 2%. As observed, with an increase in the noise level to 5%, the accuracy decreased to only 5%, and at a 10% noise level, the accuracy dropped down to only 5% less than that of the highest noise level. This is due to the fact that the MSCSO algorithm is capable of adjusting its hunting as well as exploration patterns during the training mode so as to successfully segregate the signals of the faults from noises.

The effects of external perturbations like power loads, random fault resistances, and variations in transmission line characteristics were also brought about to check the versatility of the model. The DNN-based MSCSO model achieved high AUC, G-mean, accuracy, and DSC compared to three scenarios for consistent fault detection and classification results. For example, when the values of fault resistances change from 0 to 100 ohms, the sensitivity and specialness are both more than 90%. It establishes the versatility of the algorithm, making it suitable for real-world applications regardless of the condition under which it will be employed.

The proposed method for analysing noisy images proved fairly accurate and sensitive even when noise and other interferences were introduced. This may suggest that the model has some amount of tolerance or resilience against changes in the input data. In comparison to classical algorithms such as NN, DT, and standard DNN used in the context of this work, the DNN-based MSCSO approach performed better overall and was more robust under noisy and disturbed conditions. The utility of the proposed method can be readily seen from the higher values of accuracy, precision, and MCC metrics over the datasets at all levels of noise and any underlying factors. The MSCSO algorithm also used a lower amount of time to compute which makes it suitable for real-time use where timely detection of faults is essential. The breakdown of the data serves to further demonstrate that the application of DNN to MSCSO is quite resilient and adaptive against noise and other influencing factors. Due to the high accuracy it can detect and classify faults that occur in the transmission lines it is therefore highly recommended for use considering its high operational reliability and stability.

6. Conclusion

This paper presents a crucial aspect of smart grids and addresses the mission of identifying, classifying, and localizing the faults in multi-machine power systems. Deep learning techniques were used to carefully gather, preprocess, and classify simulated faulty data that were obtained from real three-phase voltage and current readings. An optimization-based DNN-based fault diagnosis technique for transmission lines is proposed. The DNN examines a variety of defects in the transmission lines, including L-L and L-G faults, in order to locate and detect faults. This is accomplished by utilizing a DL technique known as the DNN, which was accomplished by means of a variety of field data sets attained through the simulation of faults. As a result, a revolutionary MSCSO optimization technique precisely tunes the DNN's weights to identify the fault's type and location. Furthermore, an accuracy comparison of the suggested method with other methods from the literature demonstrates that it can achieve an equivalent or superior performance compared to prevailing approaches. By using the planned procedure, we hope to expand the future scope to include complex and varied network topologies. It is imperative to realize that the suggested strategy may be vulnerable to external noise or the impact of load switching. Lastly, the feasibility evaluation will be investigated in the suggested approach on larger systems to confirm its efficacy and robustness when used in more complicated and comprehensive circumstances.

A. Future Work

Include in the existing procedure the versatility of networks and incorporate in handling more sophisticated forms of structures such as multi-node and interconnected grids. Examine the capacity of the proposed DNN-based MSCSO approach in more extended power networks and the capability of performance of the technique in different networks.

Propose other complex noise elimination methods in order to improve the fault detection system against noise at different levels. Carry out extensive noise effect analysis to determine and reduce the effects of environmental and operation noise on the accuracy of fault diagnostics.

The proposed work on using DNN-based MSCSO is to partially or fully implement this method in actual real-time systems to assess its operation in real-world conditions and find ways of improvement. Embed them into the real-time monitoring and control systems for smart grids so that faults can be detected as well as localized in real time.

Provide methods for the DNN model's weight adjustment, which will enable the model to learn from the real-time data and other changing grid conditions. Examine how the technique used in the online learning process facilitates model improvement each time new data is obtained.

Run the algorithm on a broader variety of fault patterns and cases, rare and edge ones, to test the created algorithm's ability to work reliably. Examine the behaviour of the developed model in diagnosing and categorising faults at different load levels and during load changeover circumstances.

This work is to analyse the synergistic combination of the proposed DNN-based MSCSO method with additional AI approaches like reinforcement learning and ensemble methods for fault detection enhancement. Introduce new mix strategies where new approaches of AI are integrated into one system to provide more effective and efficient means to diagnose faulty systems.

Perform pilot studies that would involve a larger population to assess the effectiveness and stability of the suggested methodology under more comprehensive conditions. Check the outcomes of the model tests when they are carried out for a longer time and under different operation modes to ascertain the degree of efficiency of the product.

The subsequent work can be focused on the enhancement and subsequent enhancement of the performances of the method as well as its usability in the context of smart grids to not only detect but also, classify the faults.

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