Squaring and Lowpass Filtering Data-Driven Technique for AC Faults in AC/DC Lines

Arif Mehdi, S Jarjees-ul Hassan, Chul-Hwan Kim (Fellow, IEEE)

***Abstract*- Transient events that result from the incorporation of HVDC into the HVAC power transmission system make fault identification a difficult task. To minimize transient power outages, anomalies must be identified and categorized as quickly as feasible using robust schemes. In the proposed scheme, the multi-classification of AC faults in hybrid transmission lines is performed. A neural network has been employed for the correct recognition and classification of AC faults. The proposed scheme initially uses squaring and lowpass filtering techniques along with, transient energy, negative sequence of voltage, and current as features to pre-process the fault voltage and current signals. The extracted features are then used to form the neural network's input for training and testing. We performed a complete assessment study on the developed ac/dc test system employing MATLAB/Simulink software to ensure the stability and reliability of the presented technique. The technique is verified under noise-added data and compared with other schemes to ensure efficacy. The test result shows that the proposed technique has successfully classified the AC faults with an accuracy of 99.3% in ac/dc transmission lines.**

***Keywords*: Artificial Neural Network protection, Classification of faults, AC/DC protection, Squaring, and lowpass filtering.**

Nomenclature

HVDC	High voltage direct current
HVAC	High voltage alternating current
VSC	Voltage Source Controller
MMC	Modular multi-level controllers
AI	Artificial intelligence
KNN	K-nearest neighbor
SVM	Support vector machine
ANN	Artificial neural networks
ACF(a,b,c)	Autocorrelation coefficient of phases
Neg_Seqv (NSv)	Negative Sequence Voltage
Neg_Seqi (Nsi)	Negative Sequence Current
Teng (Te)	Transient energy
MSE	Mean square error
ROC	Receiver operating characteristic
TPR	True positive rate
FPR	False positive rate
SNR	Signal-to-noise ratio

I. Introduction

Modern power transmission networks have undergone a paradigm shift because of the integration of decentralized renewable energy resources. The development of a new transmission line has been stopped due to right-of-way, cost, and environmental issues, while electricity demand has increased steadily [1], [2]. Due to the advancement of power electronics, the current situation necessitates a reassessment of conventional power transmission based on new concepts that enable maximum usage of the existing transmission systems [3], [4]. Consequently, high-voltage DC integration into HVAC is gaining interest because of its high efficiency and to meet rising energy demands [5], [6]. The major objectives are employing simultaneous ac/dc transmissions and loading the line as close to its thermal limit [7], [8]. Hybrid transmission is an emerging concept; thus, the protection schemes are naive, and challenges are manifold. To ensure stability and longevity, transient faults should be removed as soon as possible in hybrid transmission lines to avoid power system failures and blackouts [9]. A protection scheme for hybrid transmission lines to identify the fault location using eigenvalue decomposition was proposed in [10]. The scheme has utilized distributed line parameters using the Bergeron model through eigenvalue decomposition to decouple the system. In [11] an ac fault detection scheme and analysis was proposed to overcome the interaction challenge of ac/dc. A voltage source converter (VSC) based fault protection scheme was proposed for the hybrid transmission system in [12]. The scheme has used a full-bridge module to handle the intersystem and line-to-ground faults in the ac/dc system. Modular multilevel converters (MMC) have been utilized in HVDC systems to further enhance protection issues [13].

Previously, various techniques were used to categorize faults in HVAC and HVDC transmission lines, but these schemes were not optimal for the hybrid system. Owing to the complexity and shortcomings, they may separate healthy parts and are not cost-effective for hybrid transmission lines.

Artificial intelligence (AI) techniques are being utilized to meet those challenges [14], [15]. Since AI methods have proved successful that are efficient, rapid, and adaptable, they may be the best option for managing complicated non-linear power systems. Therefore, to provide an un-interruption power supply a robust efficient, and accurate protection scheme is needed to continuously monitor the voltage and current signals in the

This work was supported by a National Research Foundation of Korea (NRF) grant funded by the Korean government (MSIP) ((No. 2 021R1A2B5B03086257) and Korea Institute of Energy Technology Eva luation and Planning (KETEP) and the Ministry of Trade, Industry & Energy (MOTIE) of the Republic of Korea (No. 20225500000110).

A.Mehdi, S.J Hassan, C.H. Kim is with the Department of Electrical Engineering, Sungkyukwan University, Suwon, South Korea (e-mail: mehdiarif@skku.edu, jarjees@skku.edu, chkim@skku.edu).

Paper submitted to the International Conference on Power Systems Transients (IPST2023) in Thessaloniki, Greece, June 12-15, 2023.

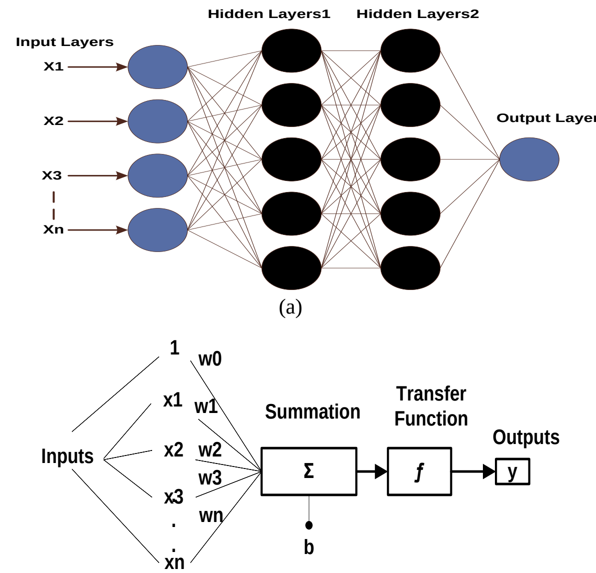
power transmission system [16]. A neural network-based scheme for the dc microgrid was presented in [17] to detect the faults. For AC/DC transmission lines, a fault identification and categorization method based on k-nearest neighbor (KNN) is given in this work [18]. The hybrid power transmission faults are identified using an SVM-based method [19]. The conventional AC and DC protection schemes do not apply to hybrid transmission lines, therefore it demands novel AI-based techniques to overcome the challenges of hybrid transmission protection. Even though most of the approaches listed above have shown positive outcomes, there is still a gap in the protection of hybrid transmission due to the transient nature of ac/dc faults.

To overcome the hybrid protection challenges, this study is focused on the identification and classification of AC faults using an artificial neural network with a combination of squaring and lowpass filtering envelope detection techniques. To investigate the faulty phase distortion, autocorrelation, and transient energy, a negative sequence of voltage and currents at the point of common coupling are employed. The standard deviation of the selected features is retrieved to make the dataset for the model. The extracted data has been used to train and test the proposed model. After successful AC fault detection in the hybrid system, the scheme further classifies each AC fault into 11 types: AG, BG, CG, AB, AC, BC, ABG, BCG, ACG, and ABC, ABCG. To verify the effectiveness of the scheme, the model is tested under noise addition of 30dB and 40dB SNR. The fault classification model is developed and performed in the MATLAB/Simulink environment.

The structure of the paper is arranged as: the theory and working principle of ANN are explained in Section II, and Section III explained the proposed classification scheme in detail. Section IV elaborates on the test system. The simulation results and discussions are explained in Section V. The detailed conclusion is further summarized in Section VI.

II. ARTIFICIAL NEURAL NETWORK

Artificial neural networks (ANNs) have been used to study how human brain neurons process information [20]. ANN is a highly connected, dynamically parallelized framework for neural computation units known as neurons that can learn and acquire information. The fundamental processing unit of an ANN is made up of several neurons. Each neuron has connections that connect it to other neurons. Each neuron gets a set of inputs that are influenced by weights. The synaptic weights either increase or diminish the signal that is subsequently arranged. The total of the summed values is processed into a non-linear function named a transfer function, together with a boundary value called bias, to create the final simulated value in the result. An ANN is constructed from several artificial neurons, or nodes, that are connected in layers to form a network. A multi-layer designed ANN is depicted graphically in Fig. 1(a). One of the key benefits of neural network models is their ability to provide a flexible mapping between inputs and results. Trial and error are frequently employed to determine the number of hiding layers and the nodes in each hidden layer. The working principle of the neural network is shown in Fig. 1(b).



(b)

Fig. 1 ANN (a) General ANN model, (b) Neuron computation principle

By summing inputs x, with the corresponding matching weights w_i, each layer unit generates a single value cutoff point. The neuron's total input value n is then calculated by multiplying this weighted value by the bias term b. The bias is applied to the total to move it away from the origin. After that, the total input value is fed into the transfer function f, which generates the neuron's final output **y**. The output equation of the ANN network is given in (1):

$$y = f\ [\sum_{i=1}^{n} w_i x_i + b] \qquad (1)$$

The most used transfer function is the sigmoid or logistic function, which limits the node's output to 0 or 1.

III. PROPOSED SCHEME

A. Parameter Selection

Hybrid power transmission lines face several transient issues due to nonlinear loads and the combination of AC and DC in the same structure. When faults occur in any of the transmission lines, the power system's stability is compromised. Therefore, timely detection and observing the hybrid environment to secure the transmission lines. Using extracted characteristics from faulty phase voltage and current, it can efficiently characterize and anticipate faults and non-linearity problems in the system [21]. The features selected for the data acquisition are envelope detection using squaring and lowpass filtering, as well as negative voltage and current sequences. The squaring and low-pass filtering technique has been utilized in power system protection based on the threshold setting [22], [23]. But due to the complexity of the hybrid microgrid, the threshold criteria are not feasible to adopt for fault identifications. Therefore, the autocorrelation function is used at the output to get the envelope detection features. Due to its fundamental characteristics of periodic signal amplification and noise removal, autocorrelation analysis is vital in the area of signal processing. It is common practice to employ autocorrelation to identify the periodic components masked by noise.

Autocorrelation is the correlation of a signal with a delayed replica of itself [24]. The features are obtained using a multi-scenario of faults in the proposed hybrid system as shown in Table I. Finally, the obtained data is being utilized for training and testing the ANN algorithm. The proposed scheme overcomes the threshold-based criteria using ANN in hybrid transmission protection. The squaring and lowpass filtering mechanisms are shown below in Fig. 2.

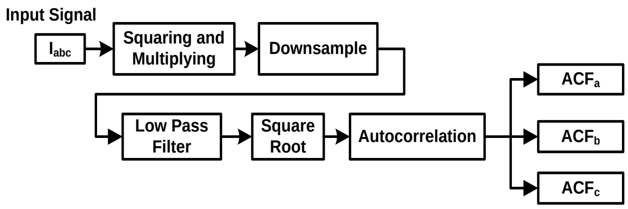


Fig. 2 Squaring and filtering working principle

TABLE I
FEATURES OF THE PROPOSED SCHEME

Parameters	Symbols	Features
ACF	acf_a	F_1
ACF	acf_b	F_2
ACF	acf_c	F_3
Neg_seq_V	NS_v	F_4
Neg_seq_I	Ns_i	F_5
T_{eng}	Te	F_6

B. ANN-based Fault Detection and Multi-Classification Scheme

The theoretical background and working principle of ANN are explained in Fig. 1. The flowchart of the presented detection and classification technique is shown in Fig. 3. The scheme considers the voltage and current data and pass into the feature extraction stage. The data retrieved from the features is first preprocessed to ensure the missing data. After that, the data is divided into train and testing, and validation. The proposed model is trained using the training data. After the model was trained, the unseen data is used to assess the performance of the model. After successfully identification of hybrid faults either AC or DC, the model further classifies each AC fault in the AC transmission line. The proposed model has classified all 11 AC faults of LG, LL, LLG, and LLL successfully into each category with high accuracy.

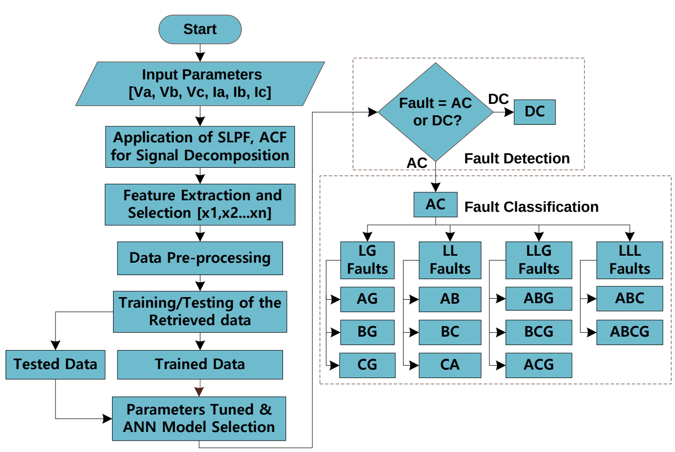


Fig. 3. Flow Chart of the proposed scheme

The presented ANN network is made of an input layer, hidden layers, and an output layer. The extracted features from the fault's signals are fed into the input nodes. The designed model has 15 neurons for the hidden layer. Output nodes classify the faults into 11 types. The designed ANN was trained in MATLAB 2020b using a neural network toolbox with the Levenberg-Marquardt algorithm. Iteratively, the MSE performance function between the predicted output and the expected values was learned out of the ANN to minimize it. The tuned parameters for the designed ANN model are shown in Table II. The proposed ANN model with tuned parameters is shown in Fig. 4.

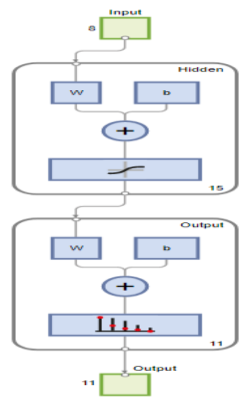


Fig.4. Simulated proposed ANN Model

The designed ANN model has 8 inputs with 15 hidden features. The model has successfully classified all 11 faults of the AC line in a hybrid network.

TABLE II
OPTIMIZED PARAMETERS OF ANN

Parameters	Value/Name
Hidden Layer Size	15
TransferFcn	tansig
TrainFcn	Trainlm
Epochs	1000

IV. SYSTEM UNDERSTUDY

We used the MATLAB/SIMULINK environment to simulate the developed hybrid transmission system. The system network studied has shown in Fig. 5. The test system has two lines, above one is the AC line, and below is DC with rectifiers at both ends. The overall length selected of the transmission line is 200km and generating plant (4200MVA) generators to an equal system (a short circuit level of 20 GVA). The source is connected to the AC system side through a transformer 13.8 kV/ 735 kV while for DC line 735kV/230 kV. The ac line has shunt-compensated by two 200 MVAR per line shunt reactors. The DC line uses a forced-commutated voltage-source converter (VSC) connection to transfer power. The rectifier and inverter both employ three-level neutral-point-clamped VSCs with almost insulated-gate bipolar transistor diodes. On the AC side are the phasedown Yg-D transformer, AC filters, and converter reactor, while on the DC side are the capacitors and DC filters. The details of the utilized hybrid transmission line model are shown in Table III.

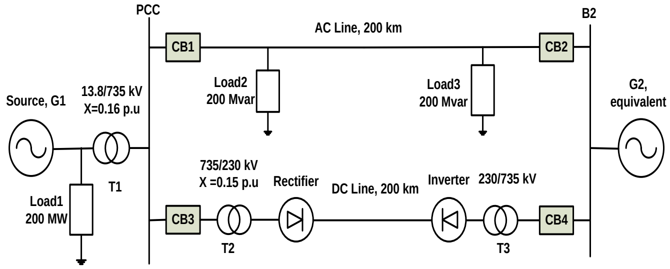


Fig. 5 Simulated test system

TABLE III
SIMULATED SYSTEM PARAMETERS

Equipment	Parameters	Ratings
AC Transmission line	Total Length TL	200 km
	AC line voltage	735 kV
	Frequency	60 Hz
	Resistance per unit length (Ohms/km)	0.01165/0.2676
	Inductance per unit length (H/km)	0.8679e-3/3.008e-3
	Capacitance per unit length (F/km)	13.41e-9/8.57e-9
DC Transmission line	Total Length TL	200 km
	DC line voltage	230 kV
	Resistance per unit length (Ohms/km)	0.015
	Inductance per unit length (H/km)	7.92e-04
	Capacitance per unit length (F/km)	1.44e-08

A. *Fault Data Generation*

As illustrated in Fig. 5, a 200 km hybrid transmission line having HVAC and HVDC parallel lines is fully examined to verify the robustness of the presented method. The sampling frequency is kept at 3.6 kHz for data extraction. To train the ANN appropriate fault data for different faults are crucial. Therefore, fault data for different cases of AC faults are simulated with varied conditions and attributes (as given in Table IV). In this table, 11 fault types, fault distance varied from (25-175) km, fault resistance varied from (0.1-90) ohms, and fault inception angle varied from (0^o , 45^o , 90^o , 270^o). Each fault data cases are 110, there are a total of 1210 fault data taken for the training and testing, and validation of the proposed ANN model.

TABLE IV
PARAMETERS GENERATION

S. No	Parameters	Set values
1.	Fault Types	SLG: AG, BG, CG DL: AB, BC, AC DLG: ABG, BCG, ACG TL: ABC, ABCG
2.	Fault's distance [km]	25-175
3.	Fault Resistance [ohm]	0.1-90
4.	Fault inception angle	0^o ,45^o ,90^o ,270^o

V. SIMULATION RESULTS AND DISCUSSIONS

A. *Behaviors of the parameter during Abnormality*

Hybrid ac/dc faults exhibit distinct anomalies in voltage and current. On the specified interval of faults in the proposed system, the voltage of that phase falls while the current of that phase rises. As a result, the measured voltage and current values of the faulty phase deviate from that of the healthy phases. Owing to that, we have considered the retrieved features in the form of standard deviation (STD) to detect the anomaly and accumulate the datasets for the model. When a fault occurs, the selected features exhibit abnormal behavior between 0.2 and 0.25 seconds of fault duration, as shown in the below results. The behavior of faults during a single line-to-ground is shown in Fig. 6. During the fault duration, the current observed the transient signal in Fig. 6(a), similarly the selected feature observed the abnormality successfully in Fig. 6(b) and (c).

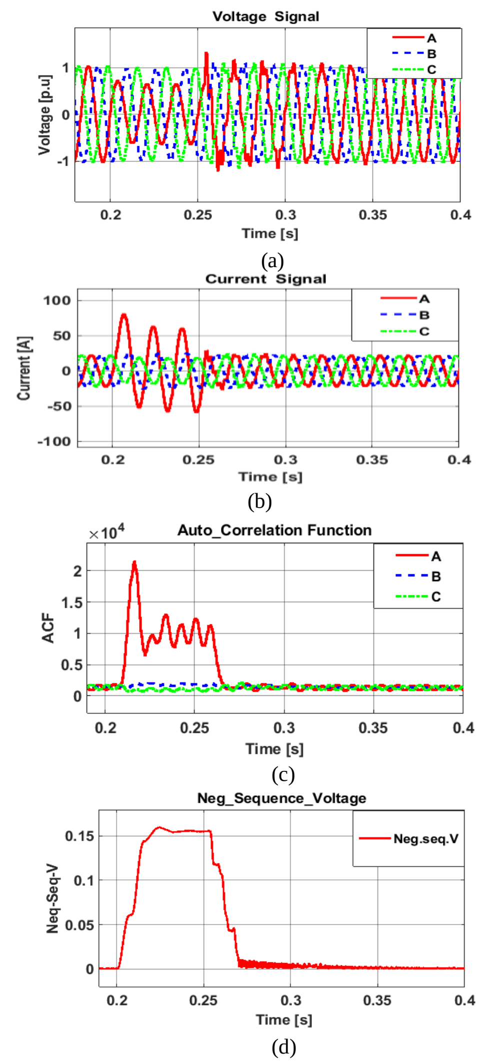
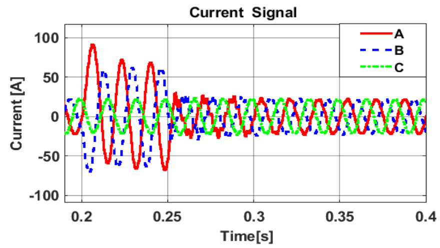


Fig. 6. Behavior of features (a) Voltage, (b) Current, (c) ACF of current, (d) Neg_seq_v during SLG fault at 100 km fault location.

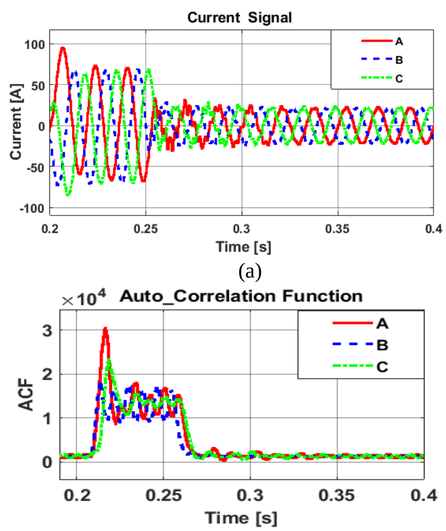
Similarly, double line-to-ground fault transient behaviors during hybrid ac/dc parallel transmission are shown in Fig. 7. The current and the selected feature have shown abnormality during the fault duration. Therefore, the feature has deducted the fault intervals successfully and used it for training the proposed algorithm.



(a)
(b)

Fig. 7. Behavior of features (a) Current, (b) ACF of current, during LLG fault at 100 km fault location.

The fault's transient nature is shown for the three-phase line-to-ground faults in Fig. 8. Due to the integration of ac/dc, the transient behavior is observed during fault events. We can see the distortion in the output of current outside the fault duration also, it is due to the ac/dc interaction during hybrid transmission. The transient events are observed in Fig. 8 (a) and (b).



(a)
(b)

Fig. 8. Behavior of features (a) Current, (b) ACF of current, during LLLG fault at 100 km fault location.

These features behaviors have shown that the ac/dc integration has introduced distortions in the form of transient events. These transient events need to be identified earlier and removed using filtering techniques. The proposed scheme also utilized the filtering technique to easily identify the transients and based on those extracted features ANN model was designed.

B. Validation of the Proposed Scheme

The performance metrics used for the validation of the proposed algorithm are the accuracy, receiver operating characteristic (ROC) curve, and histogram of the model. The mathematical formula for the accuracy is:

$$Accuracy = \frac{T_{correct}}{T_{total}} \quad (2)$$

Here, $T_{correct}$ shows total correct events while T_{total} for total events.

A confusion matrix is used to demonstrate the efficacy of the proposed strategy to overcome protection issues. After fault detection, the proposed scheme's fault classification confusion matrix is presented in Fig. 9.

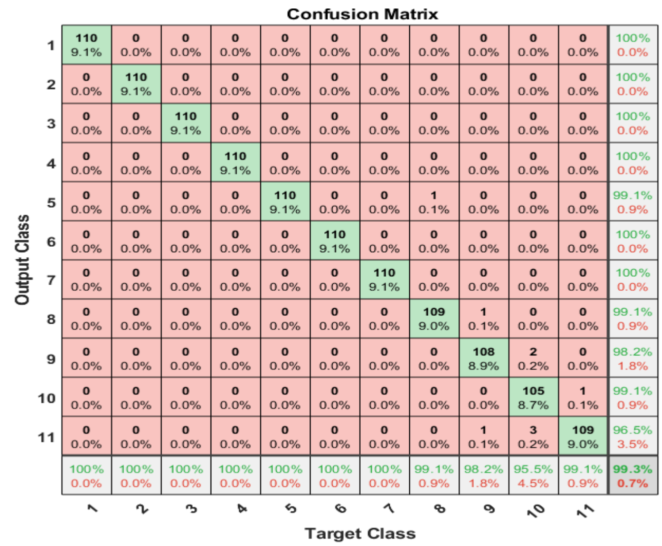


Fig. 9. Confusion matrix of the proposed scheme

Each type of AC fault has 110 data cases. The gathered data for the classification includes a total of 1210 fault cases. The extracted data has been divided into three categories training, testing, and validation sets. The data is divided into 70 % for training to build the model. The performance of the scheme is verified by using the 15 % for testing and 15 % validation data. According to the confusion matrix chart, the proposed technique correctly classifies all of the 11 AC faults based on the test results. During classification, all the faults of a single line-to-grounds are classified without any misclassification with 100 % accuracy. Similarly, 1 fault is misclassified in the case of phase BC line-to-line faults. In the case of double line-to-ground, one fault is misclassified in phase BCG and 2 in the case of phase ACG. Furthermore, 1 of the triple-line faults ABC and 4 of triple line-to-ground ABCG are misclassified. The overall accuracy of the validation confusion matrix is 99.3 %. In general, the suggested method has high performance in terms of accuracy.

The mean square error (MSE) and correlation coefficient were used to compare the performance of the different developed models. Following the training and validation, the network's generalization performance is assessed using test data that includes a mix of normal and all types of fault categories. The MSE performance of the proposed ANN model with datasets of training, testing, and validation are shown in Fig. 10. The best validation performance value obtained is 0.0029308 at epoch 80. After epoch 80 the performance remains constant. Therefore, the model has stopped at that value of epoch.

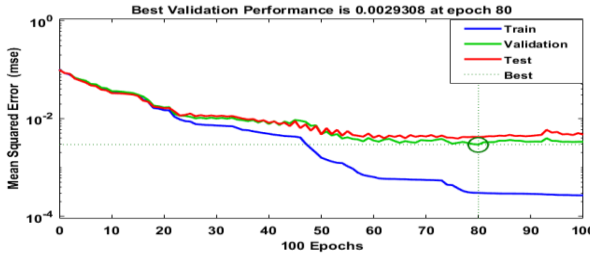


Fig. 10. Validation performance of the proposed scheme

The receiver operating characteristic (ROC) curve is frequently used to assess the performance evaluation of the classification models. Generally, it graphically represents the trade-off between the true positive rate (TPR) and the false positive rate (FPR) for different models.
ROC for the proposed ANN scheme for fault classification is shown in Fig. 11.

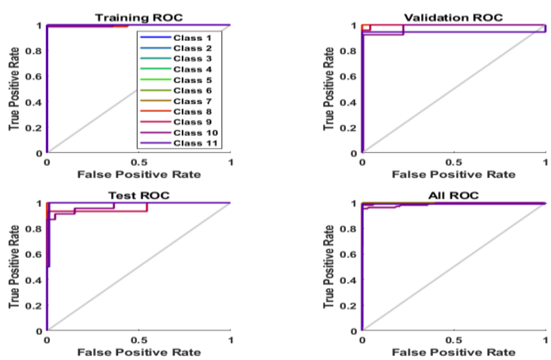


Fig. 11. ROC for the proposed scheme

The ROC is used to show the relations between input and output targets during training, testing, and validation of the proposed algorithm. The ROC of the scheme has efficiently discriminated the TRP and FPR by showing the curve that is close to the top left corner of the graph. Hence, ROC has proved the effectiveness of the proposed algorithm for the protection of hybrid transmission lines.
The performance of the proposed algorithm is further verified using the performance metric histogram. For ANN models, histograms may be used as a performance indicator to gauge the model's overall effectiveness, check the distribution of predicted outputs, and detect biases or imbalances in the predictions. The histogram plots with 20 bins show zero error for the proposed scheme in hybrid systems faults classification as shown in Fig. 12. Hence, it has proven the performance of the proposed algorithm by distinguishing between multi-classes.

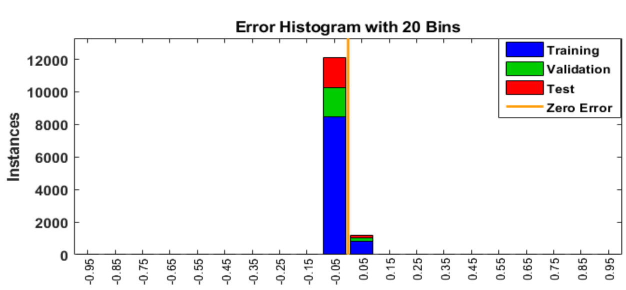


Fig. 12. Error Histogram of the proposed scheme

C. Performance Comparison of the Proposed Scheme

The proposed scheme is compared with a support vector machine (SVM), decision trees, and neighbor nearest (KNN) to verify the efficacy of the proposed scheme in the form of accuracy. The effectiveness of the proposed ANN-based technique is mature enough to overcome the transient events as compared to the conventional techniques in the hybrid transmission lines. The proposed scheme for the multiclassification of AC faults in hybrids transmission lines has the highest accuracy as compared with other schemes as shown in Fig. 13. This comparison graph demonstrates how the proposed ANN-based technique can be used to prevent the AC protection issues in hybrid transmission lines by having input characteristics to quickly identify abnormalities of HVAC and HVDC interactions.

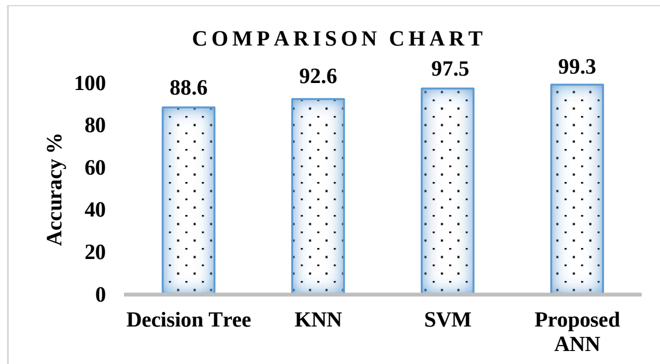


Fig. 13. Performance comparison with other schemes

D. Performance Under Noise

To ensure the efficacy of the proposed scheme, noise is added to the retrieved features data. The performance robustness of the model is demonstrated by the addition of (10dB, 20dB, 30dB, and 40dB) signal-to-noise ratio (SNR). The performance metric accuracy is used to show the model performance in the noise-added data. The proposed model has shown the variation of model accuracy according to the noise data. As we increase the noise level the performance is increasing gradually. This results that, accuracy and noise have direct relation during the performance measures. Table V has shown that with the addition of the noise ratio, how the proposed algorithm accuracy varies. With the addition of noise, the model has performed well. It means that an SNR of 10dB has high noise density than 20dB. Henceforth, the proposed ANN model using squaring and lowpass filtering features has proven effective mechanism to overcome the transient fault protection in a noisy hybrid transmission line.

TABLE V
PERFORMANCE UNDER NOISE

SNR	Accuracy%
10dB	93.6
20dB	95.3
30dB	95.7
40dB	96.9

Due to the amalgamation of multi-energy resources (AC and DC), several power transients and faults events occur in grid-connected and islanding modes. Due to the varying nature of transient events in hybrid lines, the existing AC or DC protection algorithms are limited to apply directly. Therefore, the proposed scheme is presented to ensure AC protection in hybrid ac/dc transmission lines. The scheme has utilized simple features and based on that ANN network is trained without any complexity. There is no need for any threshold requirements. The single-ended extracted features have no demand for any communication network to avoid any time delay. In the future, a unified scheme for both ac/dc faults is considered.

VI. CONCLUSION

A neural network-based approach for the detection and classification of AC faults in a hybrid transmission line is proposed in this paper. The proposed scheme is designed and simulated to create various fault scenarios depending on fault locations, fault resistance, fault inception angle, and fault classes based on faulty voltage and current parameters on MATLAB/SIMULINK. The scheme has utilized the squaring and lowpass filtering technique along with auto-correlation, transient energy, and negative and positive voltage and current sequences are used as a feature. The extracted data is utilized to train, test, and the validation of the proposed model. After successfully identification of faults, the scheme has shown tremendous accuracy for all the multiclassification of AC faults in a hybrid environment during transient events. The simulation results indicate that the proposed technique accurately and efficiently classifies all the 11 AC faults AG, BG, CG, AB, DC, AC, ABG, BCG, ACG, and ABC, ABCG with high accuracy of 99.3%. The scheme is further tested in a noisy environment. Based on these findings, it can be stated that the proposed method has provided very accurate and dependable hybrid AC protection mechanisms to avoid transient events in hybrid transmission and mitigate the interaction of ac/dc fault challenges.

VII. REFERENCES

[1] S. Mirsaeidi, X. Dong, S. Shi, and D. Tzelepis, "Challenges, advances and future directions in protection of hybrid AC/DC microgrids," *IET Renew. Power Gener.*, vol. 11, no. 12, pp. 1495–1502, 2017.

[2] R. G. F. Espinoza and M. C. Tavares, "Faulted Phase Selection for Half-Wavelength Power Transmission Lines," *IEEE Trans. Power Deliv.*, vol. 33, no. 2, pp. 992–1001, Apr. 2018, doi: 10.1109/TPWRD.2017.2747518.

[3] H. Rahman and B. H. Khan, "Power Upgrading of Transmission Line by Combining AC–DC Transmission," *IEEE Trans. Power Syst.*, vol. 22, no. 1, pp. 459–466, Feb. 2007, doi: 10.1109/TPWRS.2006.887895.

[4] M. Kizilcay, A. Agdemir, and M. Losing, "Interaction of a HVDC System with 400-kV AC Systems on the Same Tower," in *International Conference on Power System Transient in Kyoto, Japan June*, 2009, pp. 3–6.

[5] D. A. Halamay, K. M. Saxby, J. L. Bala, and R. Spacek, "Feasibility study of a high-voltage DC & AC multi-circuit hybrid transmission line," in *Proceedings of the 37th Annual North American Power Symposium, 2005.*, 2005, pp. 310–316.

[6] A. Mehdi, C.-H. Kim, A. Hussain, J.-S. Kim, and S. J. U. Hassan, "A comprehensive review of auto-reclosing schemes in AC, DC, and hybrid (AC/DC) transmission lines," *IEEE Access*, vol. 9, pp. 74325–74342, 2021.

[7] B. Sander, J. Lundquist, I. Gutman, C. Neumann, B. Rusek, and K. H. Weck, "Conversion of AC multi-circuit lines to AC-DC hybrid lines with respect to the environmental impact," *Cigre Sess. Paris*, vol. 2, no. 105, 2014.

[8] M. P. Bahrman and B. K. Johnson, "The ABCs of HVDC transmission technologies," *IEEE Power Energy Mag.*, vol. 5, no. 2, pp. 32–44, Mar. 2007, doi: 10.1109/MPAE.2007.329194.

[9] A. Mehdi, A. Hussain, S. J. U. Hassan, and C.-H. Kim, "An Intelligent protection scheme for classification of hybrid (AC/DC) Transmission line Faults," *KIEE Proc.*, pp. 864–865, 2021.

[10] D. Lu, Y. Liu, W. Huang, and X. Xi, "Accurate fault location in AC/DC hybrid line corridors based on eigenvalue decomposition," in *2020 IEEE Power & Energy Society General Meeting (PESGM)*, 2020, pp. 1–5.

[11] W. Zhao, S. Shi, Z. Wang, and X. Dong, "AC transmission line fault current analysis in 220kV AC/DC hybrid system," in *2015 5th International Conference on Electric Utility Deregulation and Restructuring and Power Technologies (DRPT)*, 2015, pp. 1105–1109.

[12] G. Ebner, D. Döring, F. Schettler, K. Würflinger, and M. Zeller, "Fault handling at hybrid high-voltage AC/DC transmission lines with VSC converters," *IEEE Trans. Power Deliv.*, vol. 33, no. 2, pp. 901–908, 2017.

[13] J. Peralta, H. Saad, S. Dennetiere, J. Mahseredjian, and S. Nguefeu, "Detailed and Averaged Models for a 401-Level MMC–HVDC System," *IEEE Trans. Power Deliv.*, vol. 27, no. 3, pp. 1501–1508, Jul. 2012, doi: 10.1109/TPWRD.2012.2188911.

[14] M. U. Usman, J. Ospina, and M. O. Faruque, "Fault classification and location identification in a smart DN using ANN and AMI with real-time data," *J. Eng.*, vol. 2020, no. 1, pp. 19–28, 2020.

[15] A. Mehdi, A. Hussain, W. Haider, S. J. Hassan, M. Saad, and C.-H. Kim, "Classification of Power System Faults Using Random Forests," *KIEE Proc.*, pp. 957–958, 2020.

[16] A. Hooshyar, E. F. El-Saadany, and M. Sanaye-Pasand, "Fault Type Classification in Microgrids Including Photovoltaic DGs," *IEEE Trans. Smart Grid*, vol. 7, no. 5, pp. 2218–2229, Sep. 2016, doi: 10.1109/TSG.2015.2451675.

[17] Q. Yang, J. Li, S. Le Blond, and C. Wang, "Artificial neural network based fault detection and fault location in the DC microgrid," *Energy Procedia*, vol. 103, pp. 129–134, 2016.

[18] S. Naik and E. Koley, "Fault detection and classification scheme using KNN for AC/HVDC transmission lines," in *2019 International Conference on Communication and Electronics Systems (ICCES)*, 2019, pp. 1131–1135.

[19] A. K. Tamrakar and E. Koley, "A SVM based fault detection and section identification scheme for a hybrid AC/HVDC transmission line with wind farm integration," in *2020 IEEE First International Conference on Smart Technologies for Power, Energy and Control (STPEC)*, 2020, pp. 1–5.

[20] S. Heo and J. H. Lee, "Fault detection and classification using artificial neural networks," *IFAC-Pap.*, vol. 51, no. 18, pp. 470–475, 2018.

[21] A. Hussain, C.-H. Kim, and A. Mehdi, "A Comprehensive Review of Intelligent Islanding Schemes and Feature Selection Techniques for Distributed Generation System," *IEEE Access*, 2021.

[22] U. Khayam and A. Zaeni, "Application of squaring—Low pass filtering—Square rooting method for enveloping partial discharge waveform," in *2017 4th International Conference on Electric Vehicular Technology (ICEVT)*, 2017, pp. 71–75.

[23] S. Baloch *et al.*, "Microgrid protection strategy based on the autocorrelation of current envelopes using the squaring and low-pass filtering method," *Energies*, vol. 13, no. 9, p. 2350, 2020.

[24] "Passive islanding detection scheme based on autocorrelation function of modal current envelope for photovoltaic units - Haider - 2018 - IET Generation, Transmission & Distribution - Wiley Online Library." https://ietresearch.onlinelibrary.wiley.com/doi/full/10.1049/iet-gtd.2017.0823 (accessed Nov. 11, 2022).