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Fast and Accurate Fault Detection and Classification in Transmission Lines using Extreme Learning Machine

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A R T I C L E I N F O

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A B S T R A C T

To provide stability and a continuous supply of power, the detection and classification of faults in the transmission lines (TLs) are crucial in this modern age. It is required to remove a faulty section from a healthy section to provide safety and to minimize power loss due to the fault. In the contemporary world, machine learning (ML) is extensively used in every aspect of life. In this study, a spontaneous fault detection (FD) and fault classification (FC) system based on ML has been proposed. MATLAB Simulink was employed to simulate two different TLs and to generate normal and fault data (Per unit voltage and current) of ten different types. TL-1 consisted of a single generator and a single load whereas TL-2 consisted of two generators and three loads. Upon normalizing the data, an extreme learning machine (ELM) algorithm was used as the classifier. Two different ELM models were developed for FD and FC purposes through training. The method achieved fault classification accuracies of 99.18% and 99.09% for the TL-1 and TL-2 respectively. On the other hand, fault detection accuracies of 99.53% and 99.60% were achieved for the TL-1 and TL-2. The proposed ELM model compared to a traditional artificial neural network (ANN) model demonstrated relatively a shorter processing time and reduced computational complexity. In addition, the proposed method outperformed the existing state-of-the-art methods.

1. Introduction

In the current era of Industry 4.0, the electrical power demand is increasing continuously. To fulfill the demand, the number of power generation units is also increasing. All these units are connected through a complex power system network (PSN) [1], which has basically three major components: power generation, transmission, and distribution [2]. Power is transferred from one place to another place through the transmission lines. Reliable and stable operation of the power system is essential to minimize its impacts on industry, business, transportation and domestic sectors. Any fault in the power system can cause major disruption causing significant financial loss. Hence, uninterrupted and secured power transmission is absolutely vital to ensure a country's economic activities [3]

Power outages occur due to different reasons such as transmission line insulation breaks, thunderstorms, equipment failure, human intervention, animal interference, fallen trees and so on [4,5]. Transmission lines are short-circuited due to these reasons and make the power system unstable. A huge amount of power is lost during a short-circuit fault [6]. To provide stability, it is compelled to instantaneously detect the fault type and its physical location accurately. Afterwards, the faulty section must be removed from the healthy section to guarantee a smooth flow of power.

In real-life scenarios, a relay and circuit breaker perform this operation. However, actuating the relay is time-consuming and this operation can be made faster using machine learning (ML). ML is widely used in every aspect of life because of the availability of relevant data. Using available fault data such as fault voltage and current a ML model can be

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trained to identify and classify new cases. In the area of power systems, researchers have focused on detecting and classifying faults using different Deep Learning (DL) and ML algorithms.

For fault detection and classification, numerous neural network-inspired algorithms, including a convolutional neural network (CNN) and artificial neural network (ANN), have been widely used. Tong et al. [7] proposed a CNN model for the detection and classification of transient faults in the power transmission lines. They have considered a total of five types of faults and achieved an average classification accuracy of 98.24% and an area under the curve (AUC) of 0.9994. Again Guo et al. [8] used CNN for the classification of faults in the power distribution system where small currents are grounded. The authors utilized the Hilbert-Huang transform (HHT) filter for creating time-frequency energy and achieved an average accuracy of 99.92% with ten types of faults. Lee et al. [9] proposed CNN for the detection and classification of faulty battery sensors and communication data. Using CNN, they were able to detect four different types of faults and attain an accuracy of 98.00%. Tawfik and Morcos [10] used an ANN model for the identification of fault locations using the Prony method to fit the time signal. Their ANN model consisted of two hidden layers, and the maximum error of the ANN model was limited to 2%. Abdullah [11] extracted the high-frequency components using discrete wavelet transform (DWT) and used ANN to detect the faults in the TLs that achieved an accuracy of 98%.

Fahim et al. [12] developed an unsupervised framework to detect and classify faults in the TLs using a sparse filter (SF) to the capsule network (CN) named CNSF. The authors have used eleven types of faults and four TLs and achieved an average accuracy of 99.72%. Vyas et al. [13] identified a new fault zone using an undecimated DWT and a Chebyshev neural network (NN) using 52,200 numeric data and achieved an accuracy of 98.69% while identifying ten types of faults. Saini et al. [14] suggested a hybrid technique that combines two hidden layers of a back-propagation NN with a DWT to accurately identify and classify faults in parallel TLs. Mukherjee et al. [15] extracted the features of the fault using probabilistic NN from the three-phase intensity index and achieved an accuracy of 99.33%. Xuebin et al. [16] proposed a deep belief network for the detection of cable faults in the underground distribution system. Their network consisted of three hidden layers. Furthermore, they employed sixteen cables and considered nine faults and achieved an accuracy of 97.8%.

In parallel with the neural network inspired algorithm, several ML algorithms have also been used for fault detection and classification, which include ELM, support vector machine (SVM), decision tree (DT), and k-nearest neighbors (K-NN). Chen et al. [17] presented fault classification using summation wavelet transmission with ELM (SW-ELM) and summation gaussian transmission with ELM (SG-ELM). Their method was not dependent on ad-hoc feature extraction. However, it is less accurate. Zhang et al. [18] used two ML algorithms: long short-term memory networks (LSTM) and SVM for the prediction of transmission line faults. Dropout and batch normalization were proposed to handle the overfitting problem and obtained an accuracy of 97.7%. Ray et al. [19] developed a hybrid machine learning approach for feature extraction by using the wavelet packet model. Furthermore, they classified the fault using SVM. Majd et al. [20] identified and classified the faults using KNN while considering ten types of faults and achieved an accuracy of 98.6% but the proposed system delay was 15 ms. Dasgupta et al. [21] proposed cross-correlation and kNN models for the detection and classification of the TL faults after considering ten types of faults and achieved a classification accuracy of 99.67%. Jamehbozorg and Shahrtash [22] proposed a DT algorithm for the classification of faults in the TLs. Godse et al. [23] proposed a mathematical morphology-based approach for detecting and classifying transmission line faults. Utilizing a morphological median filter, unique and efficient features were identified. Finally, these features were used for classification by using DT. Musa et al. [24] suggested a regression model that used a simple threshold value of zero to detect faults in three-phase current signals. System failure happened when the model showed a value larger than 0, and normal operation was achieved when the model showed a value of 0.

The existing works have used ANN, CNN, DWT, LSTM-SVM, etc., for the FD and FC purposes. All of them were complex in terms of architecture, time, and computational effort. Especially in the case of ANN and CNN algorithms having many parameters, it takes a huge amount of time to train this type of model. Again, some of these methods show poor accuracy, particularly in the case of FC. Furthermore, some studies have not performed FC in detail. Considering this gap in the literature, it is worth developing an alternative model with faster processing time, less complexity and better accuracy in order to facilitate uninterrupted power supply by detecting and classifying the faults in the TL lines.

This study proposes a self-activating fault detection and classification system using the extreme learning machine (ELM) algorithm. Fault data was simulated using MATLAB Simulink. Most of the existing methods used simulation as like this study. No real-time applications dataset is publicly available. The key contributions of this study are:

- The novel ELM has been used to make a fast and accurate system for automatic fault detection and classification on transmission lines with a small number of parameters and without any computationally complex data transformation technique, which has not been addressed by the previous studies.
- The adaptability of the proposed method has been tested on two different fault datasets obtained from two TL configurations designed.
- The performance of the proposed method has been compared to that of an artificial neural network (ANN) and other state-of-the-art (SOTA) methods.

The rest of this article is structured in the following manner. Section II depicts the proposed framework while Section III presents the classification outcomes of the proposed method. Section IV is dedicated to showing the superiority of the proposed ELM model over the state-of-the-art models. Finally, Section V presents key conclusions from this study.

2. Proposed framework of fault detection and classification

In this study, a novel fault detection and fault classification framework has been proposed as graphically illustrated in Fig. 1. Two different typical power TLs were simulated using MATLAB Simulink and voltage-current data representing various types of faults (10 types) were generated. Faulty data were collected at the time of the fault. On the other hand, not faulty data were collected at random in normal condition. Subsequently, the data were split into training and testing sets. Following that, min-max data normalization was carried out. Finally, two different novel ELM models were trained for the fault detection (binary) and classification (multiclass). The proposed method was compared with the SOTA models in terms of model classification performance, dataset size, and model complexity. Each stage has been discussed elaborately in the later subsections.

2.1. Model simulation and data generation

Figs. 2 and 3 depict the graphical views of the simulation models of two TLs designed and specifications of various components within the TLs. These two models are analogous to a long-distance transmission line, in which energy is generated in one region and transmitted to a distant area. In a real-life scenario, the loads are the combinations of R, L, and C, but the number of loads is greater than that have been considered here. Total loads can be represented by an equivalent single load. To perform the study, two of these typical models were considered. The TL-1 configuration consisted of a single generation unit and a single RLC load, whereas the TL-2 configuration consisted of two generation

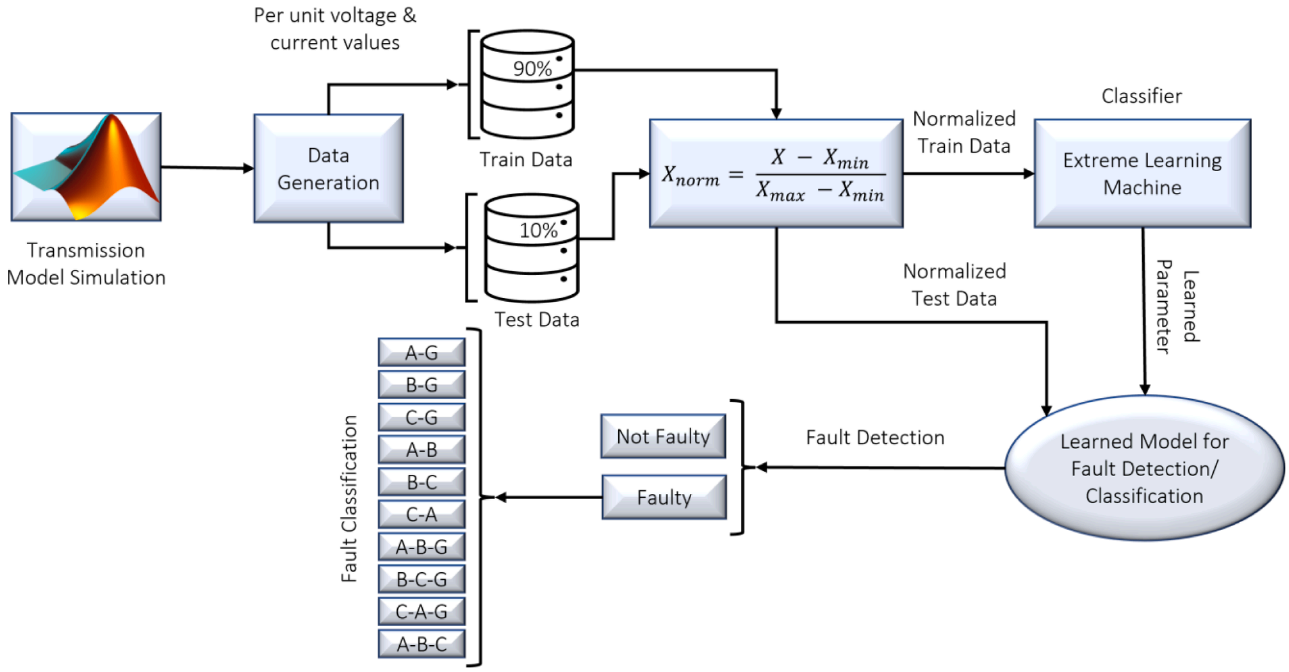

Fig. 1. Proposed framework for fault detection and fault classification.

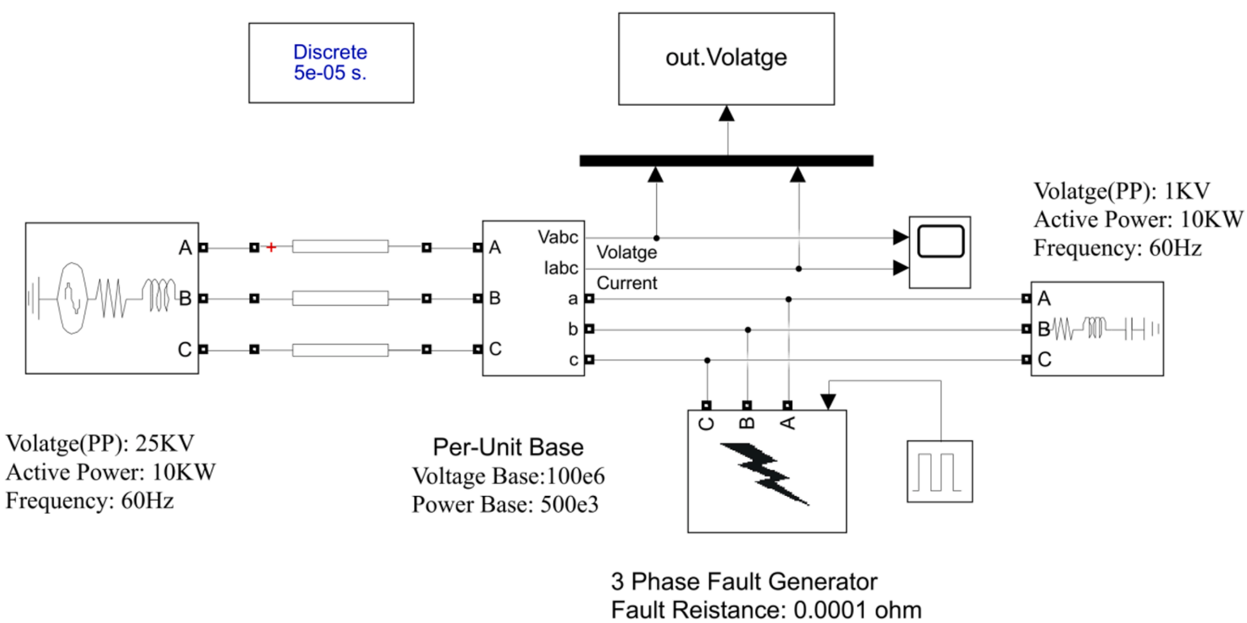

Fig. 2. MATLAB Simulink simulation model for 1st transmission line (TL1).

units and three RLC loads. The length of the transmission line is 100 km. All forms of faults were triggered based on a set program using a fault generating block, and the per-unit fault voltage and current were saved. All the parameters are in actual values, as it is easy to understand in actual values. The voltage and power base values for each simulation model were provided. Any abnormal situation in TL due to which regular flow of voltage and current are disrupted can be termed as the TL fault.

Table 1 depicts the classification of TL faults. All the short-circuit faults can be broadly classified into symmetrical and unsymmetrical faults. A three-phase short-circuit fault is called a symmetrical fault as the fault current is identical for all the phases. In the case of unsymmetrical, only one or two phases are involved. Fig. 4 depicts the voltage and current waveforms during the ABG fault. The voltages of phases A and B go to zero when the fault occurs, as shown in the Fig. 4(a) by a dotted red rectangle. The current, on the other hand, increases in comparison to the usual state with some abruption marked by dotted red rectangle in Fig. 4(b).

For the FC purposes, a total of 11 classes (10 faulty and 1 not faulty) were considered. 1001 data samples for each category were generated and each sample contained 6 features (3 phase per-unit values of voltage and current). Hence, a total of 11,011 instances were considered and the dataset was fully balanced. For training and testing purposes, the collected samples were divided into a ratio of 90:20.

For the FD purpose, two classes: faulty and no-fault were considered. There was 4000 faulty samples (400 samples from each type of fault)

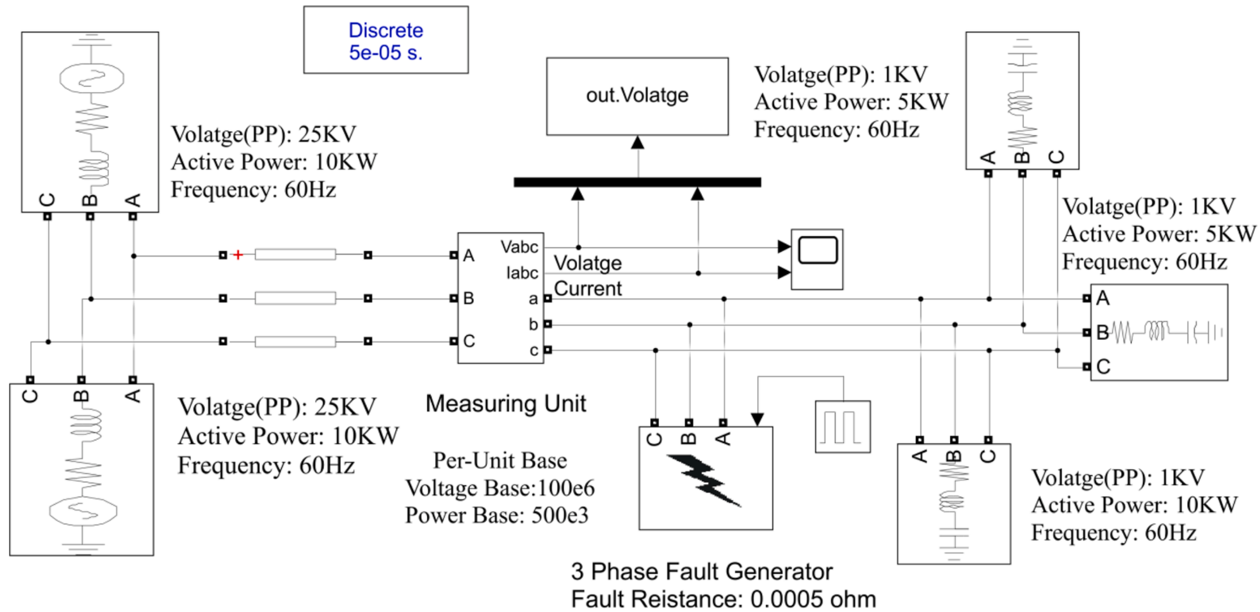

Fig. 3. MATLAB Simulink simulation model for 2nd transmission line (TL2).

TABLE 1
Different types of faults in transmission line.

Level - 4	Level - 3	Level - 2	Level - 1
AG	Single Line to Ground Fault	Unsymmetrical Fault	Short CKT Fault
BG			
CG			
ABG	Double Line to Ground Fault		
ACG			
BCG			
AB	Line to Line Fault		
BC			
AC			
ABC	3 Phase Short CKT Fault	Symmetrical Fault	
ABCG	3 Phase to Ground Fault		

and 1001 samples from not faulty were considered. Each sample consists of 6 features making a total of 5001 samples for the FD. Only 20% has been used for training the proposed FD model.

2.2. Normalization

Normalization converts the values of different features/attributes into the same range without losing the information and relation between the elements. Normalization converts the values of different features or attributes into the same range without losing the information and relations between the elements. It is always not necessary to convert the range. If normalization is not performed, then the loss function oscillates too much [25]. In this study, min-max normalization was used, and the mathematical expression can be represented by Eq. (1) where X represents original values of all the samples.

$$Normalized\ Data = \frac{X - MIN(X)}{MAX(X) - MIN(X)} \tag{1}$$

2.3. ELM

ELM is a recent invention proposed by Huang [26] to reduce the model learning dilemmas. Architecturally, it consists of a single hidden layer where the hidden layer weight metric is generated at random. The output weight metric is developed by implementing the matrix pseudoinverse process. Model parameters were set up in a single step make its learning process faster in contrast to the classical approach [27]. ELM is very useful for its simple structure, no parameter adaptation, shorter processing time and lower computational complexity. It is structured to minimize the least square error. Because of these reasons, ELM has gained popularity over the ANN. Fig. 5 illustrates a visual representation of the ELM architecture. The hidden layer of the proposed ELM model contained 700 nodes. For FD, one node was accommodated in the output layer while for the FC, there were 11 nodes. Each node includes a function for activating it. The nodes were activated using the ReLU function. The operational sequence of ELM is given in Algorithm 1 [28]:

Here, $\{X_{(n,m)}, T_{(n,t)}\}$be the training samples, **n** be the number of samples, **m** be the number of features in each sample, **t** be the number of targets, **G** represents the ReLu activation function and †represents the pseudoinverse.

2.4. Assessment criteria

Several well-known statistical concepts were employed to assess the models such as accuracy, precision, recall, and F1-score. The mathematical expression of these assessment criteria such as accuracy is given by Eq. (2).

$$Acc = \frac{(TP + TN)}{(TP + TN + FP + FN)} \times 100\% \tag{2}$$

Where TP, TN, FP, and FN indicate actually faulty, actually not faulty, not faulty but predicted as faulty, and faulty but predicted as not faulty, respectively.

The ratio of TP to all positive forms is the precision (P) as defined by Eq. (3) [29]. It is the proportion of correctly anticipated faulty data relative to all faulty data.

$$P = \frac{TP}{(TP + FP)} \tag{3}$$

The recall (R) is the ratio of the number of exact predictions made by the model to the total number of actual instances [29].

$$R = \frac{TP}{(TP + FN)} \tag{4}$$

The harmonic mean of precision and recall should be used to calculate the F1-score [30].

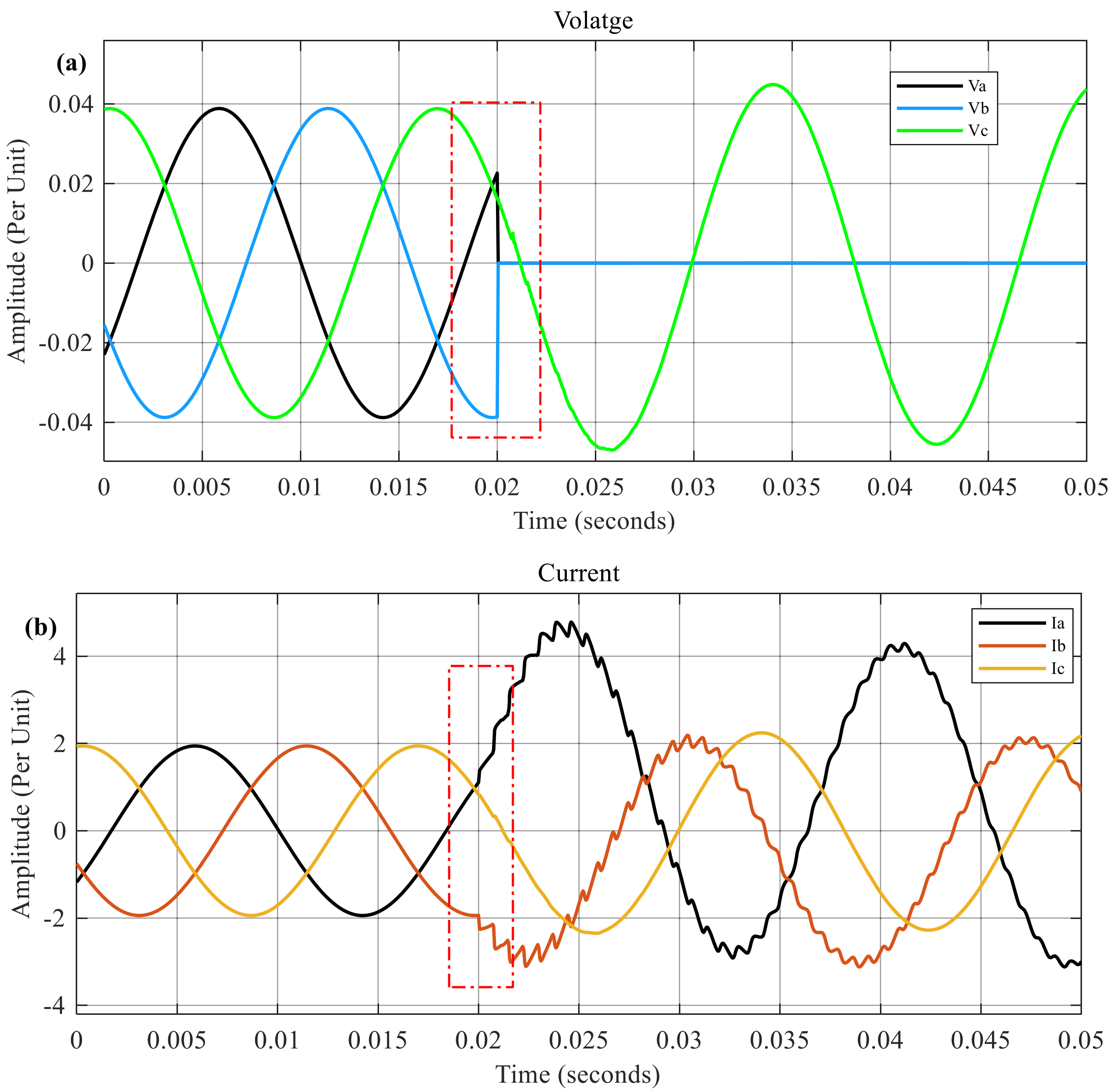

Fig. 4. (a) Voltage and (b) current wave shape during the fault (ABG).

$$F1-score=\frac{2*(Precision*Recall)}{(Precision+Recall)} \tag{5}$$

Other parameters such as training and testing times, number of layers and nodes, and number of epochs were determined for comparative analysis between the proposed ELM and traditional ANN algorithm.

3. Results and analysis

3.1. Fault classification

The proposed model was analyzed based on the TL fault data, which were generated from two different simulated TLs. Figs. 6 and 7 represent corresponding confusion matrixes (CMs) for the TL-1 and TL-2. Scores of different performance criteria using CM is presented in Table 2 for both the TL cases.

The results clearly indicated that the developed models performed well for all kinds of TL faults considered here as accuracies of 99.18% and 99.09% were attained for the TL-1 and TL-2 respectively. The proposed ELM model shows an impressive result for both cases. Hence, it can be said that the proposed model performance is independent of the transmission line configuration.

Figs. 8 and 9 represent the receiver operating characteristics (ROC) curves for the TL-1 and TL-2. An area under the curve (AUC) of 100% was obtained for all types of faults in both the cases except for ABG in TL1. The proposed ELM model was tested on other fault data provided by Jamil et al. [31] which is publicly available at Kaggle [32] and 100% accuracy was achieved as shown by the confusion matrix in Fig. 10.

3.2. Fault detection

Fault detection was performed with the TL-1 and TL-2 as shown by CMs in Figs. 11 and 12 respectively. Based on these two CMs, it is possible to conclude that the predicted model can detect faults accurately because there are no false positives.

Table 3 presents performance scores of the proposed ELM method for the fault detection for both the simulated power TLs. With the moderate size of training data (20%), the models obtained 99.53% and 99.60% accuracy in the two situations. It demonstrates that the proposed method can learn from a minimal quantity of data and is a powerful classifier.

Figs. 13 and 14 present the corresponding ROC curves for the TL-1 and TL-2. Again, AUC scores of almost 100% were attained for both the cases. By observing the outcome of the proposed model for both the TL configurations in terms of FD and FC, it can be concluded that

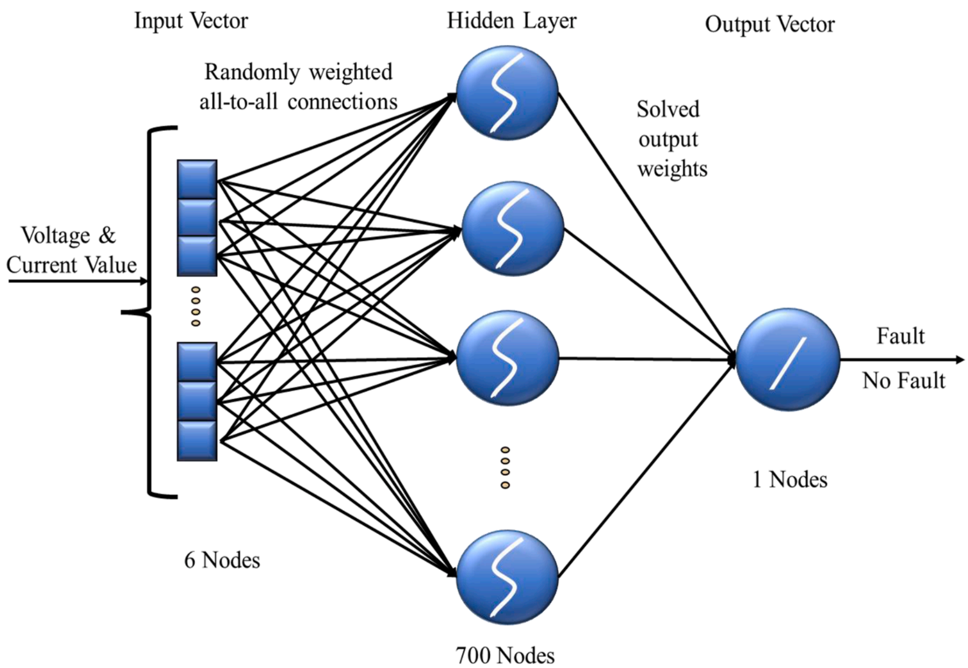

Fig. 5. Structure of ELM classifier employed.

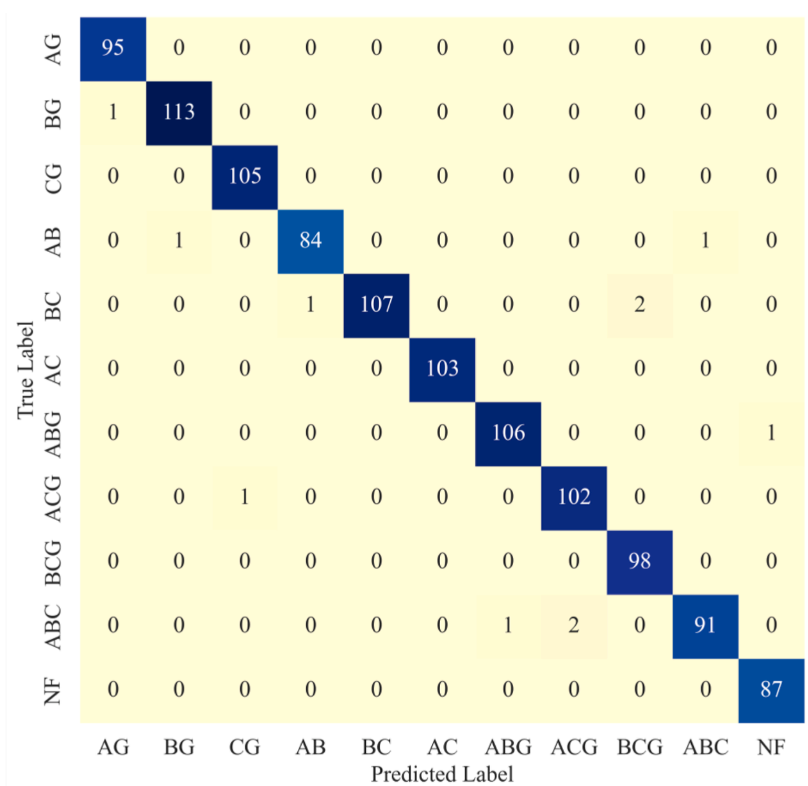

Fig. 6. TL-1: Confusion matrix for fault classification.

performance of the novel ELM can be adaptable to different TL configurations.

3.3. *Time and computational complexity analysis*

Processing time and computational complexity of the developed models were compared with traditional ANN, which is most used for solving different problems. Table 4 presents the contrastive analysis between the ELM and ANN models based on different complexity analysis parameters for the FC. It was observed that to achieve the same performance, the ANN needed larger training and prediction times compared to the ELM as the ANN employed an error back-propagation process to optimize the model parameters.

In contrast, in the ELM model, the parameters were set through a single step. Again, the ANN needed additional hidden layers with a small number of total nodes implying more individual weight matrices to

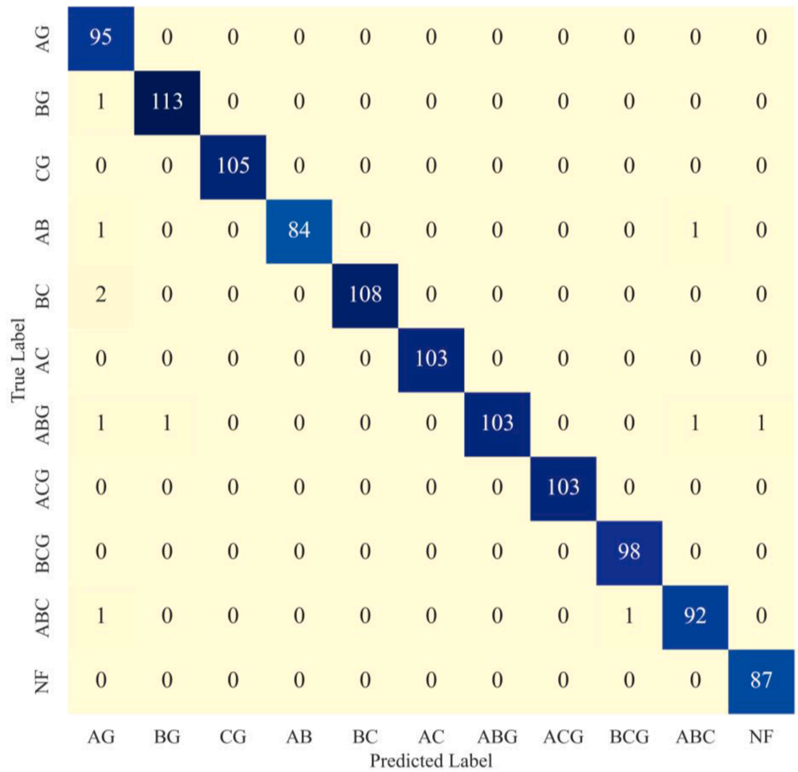

Fig. 7. TL-2: Confusion matrix for fault classification.

Table 2
Proposed model outcomes on different evaluation standard for FC.

Fault Type	Precision	Recall	F1-score	Count	Accuracy
TL 1					
AG	96.94	100	98.45	95	–
BG	100	100	100	114	–
CG	99.06	100	99.53	105	–
AB	98.81	96.51	97.65	86	–
BC	100	99.09	99.54	110	–
AC	99.04	100	99.52	103	–
ABG	100	99.07	99.53	107	–
ACG	99.03	99.03	99.03	103	–
BCG	98.99	100	99.49	98	–
ABC	100	96.81	98.38	94	–
No Fault	98.86	100	99.43	87	–
Average	99.16	99.14	99.14	1102	99.18
TL 2					
AG	94.06	100	96.94	95	–
BG	99.12	99.12	99.12	114	–
CG	100	100	100	105	–
AB	100	97.67	98.82	86	–
BC	100	98.18	99.08	110	–
AC	100	100	100	103	–
ABG	100	96.26	98.1	107	–
ACG	100	100	100	103	–
BCG	98.99	100	99.49	98	–
ABC	97.87	97.87	97.87	94	–
No Fault	98.86	100	99.43	87	–
Average	98.99	99.01	98.99	1102	99.09

multiply, which led to more computational effort to predict the output. However, the ELM needed more nodes in total but fewer hidden layers, which also speeded up the prediction process by the ELM. The novel ELM is 7.6 times faster than ANN to make a prediction. Therefore, it could be concluded that the proposed ELM models showed superior performance compared to the ANN models.

3.4. Comparison with state-of-the-art models

To demonstrate the superiority of the proposed ELM method, existing state-of-the-art methods for FD and FC were also compared as shown in Table 5. For the FD purpose, Zhang et al. [18] used LSTM with SVM, and Amiruddin [33] used ANN. Zhang and his co-workers used real-life data that was collected from a substation under southern power grid of China. LSTM was used to excerpt important features from data that was used to train SVM. They used 5120 data samples for this study. The LSTM-SVM achieved 97.7% accuracy. Amiruddin achieved 78% accuracy using only 272 samples in the conducted study using ANN. Neural networks such as ANN, CNN, LSTM etc. have complex architecture and required high computation power [34]. In comparison to the proposed ELM, both models have lesser accuracies and complicated architecture.

Furthermore, ANN was mostly used for the FC [35–37]. Chen et al. [17] used SW-ELM with 11 classes of faults and still the accuracy was lower than the ELM. In [36], they reduced the number of classes by considering the fault as two phases short circuit fault, two-phase to ground fault, and a single line to ground fault. Their system consisted of 3 RLC loads and a source. Their dataset was too small consisted of only 1000 data points. Considering these, the classification accuracy is 97.9% that is lower by 2.5% from the proposed ELM model. Similarly, another study [37] considered a 14-bus system to generate a smaller dataset that consisted of 1000 data points. They also reduced the total number of faults with 4 classes. However, the classification accuracy is only 70% which is very low. Again, Chen [17] used ELM for classification that was trained on excerpted feature using SW. SW-ELM can classify fault 98.67% accurately.

Guo et al. [8] showed higher accuracy than the proposed method (11 types) considering lesser number of fault (10 types) types. They used CNN for classification which has a complex architecture and large number of parameters compared to the proposed ELM architecture. Again, Dasgupta et al. [21] and Mukherjee et al. [15] found higher accuracies with a very low number of samples. A smaller dataset has a high probability that it cannot hold all types of distribution [40]. Dasgupta

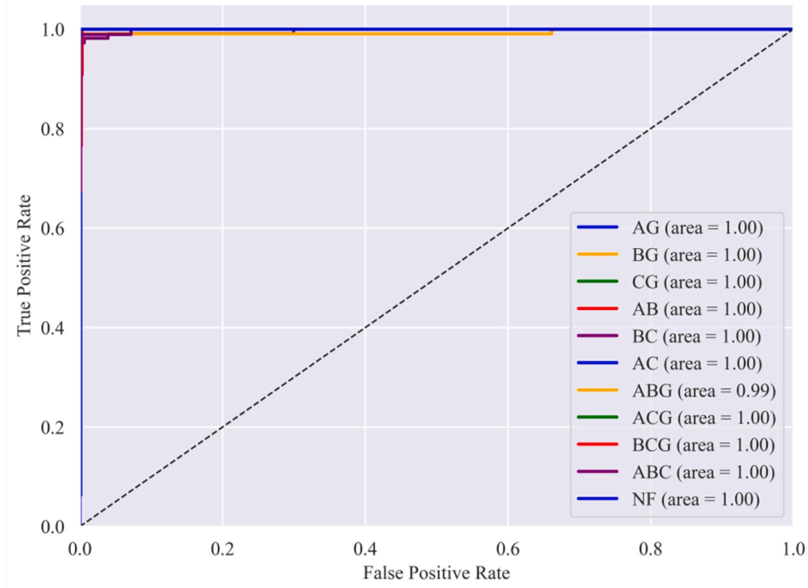

Fig. 8. TL-1: Receiver operating characteristics curves for fault classification.

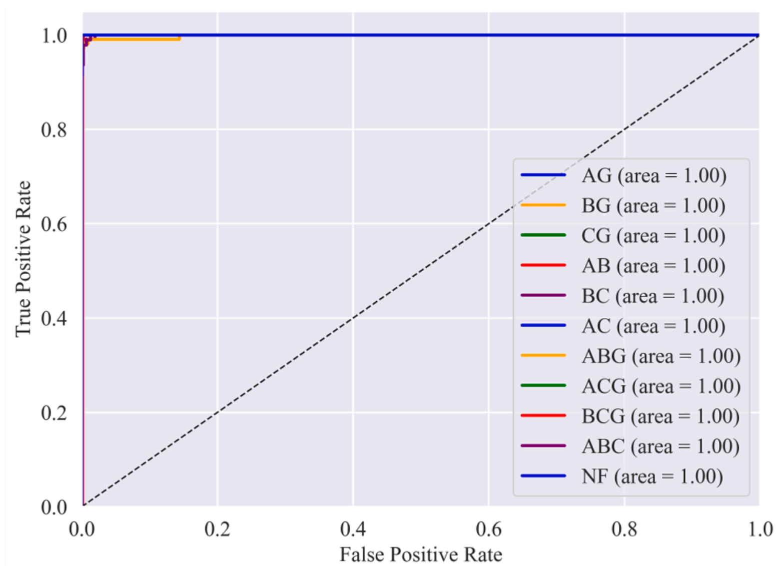

Fig. 9. TL-2: Receiver operating characteristics curve for fault classification.

et al. used only 800 samples to train their proposed KNN model where it does not have any pattern learning mechanism. KNN stores the whole training samples and prediction on new samples is conducted by calculating the distance between training samples which is time consuming [41]. It is very sensitive to outliers [42]. As well, Mukherjee et al. used only 250 samples to train their proposed PNN model that poses a complex architecture and large number of parameters. Lastly, Fahim et al. [12] achieved around 0.5% higher accuracy than the proposed method. Their dataset is large enough to get a stable result. However, their proposed model has a large number of parameters.

The actual numerical values of training-testing time and number of model parameters are not available in most of the literatures. Normally, deep learning architectures have a large number of parameters [43] and more the number of layers more the number of parameters. Table 5 shows the number of layers of the SOTA models.

Again, some methods proposed in the literature [11,13,14,17,19] have additional computational burden for data transformation for example wavelet transform. In contrast, the proposed novel ELM did not apply any data transformation still achieved very high accuracy.

Anyway, most methods showed lower accuracy and uses a smaller amount of data to conduct their studies. Again, most of the studies used CNN, CN, PNN and ANN, which contained larger number of parameters [34] and needed relatively much higher training time. Therefore, the results presented in Tables 4 and 5 clearly demonstrated that the proposed ELM not only detected and classified fault accurately but also needed fewer parameters and shorter computational time. The proposed method achieved a competitive accuracy with lesser number of parameters.

Though, some above mentioned complex models showed optimistic results but none of them were concerned about processing time. However, in this study, time and computational complexity were contemplated by using simpler models. The performance of the proposed method on real-life data is out of the scope of this study.

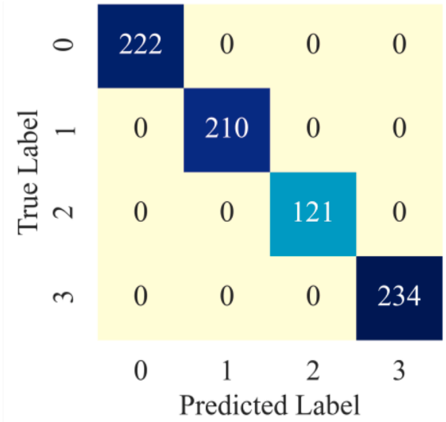

Fig. 10. Confusion matrix for fault classification on fault data from a previous study.

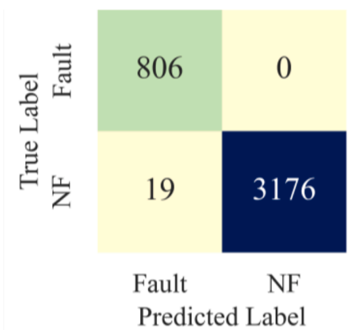

Fig. 11. TL-1: confusion matrix for fault classification.

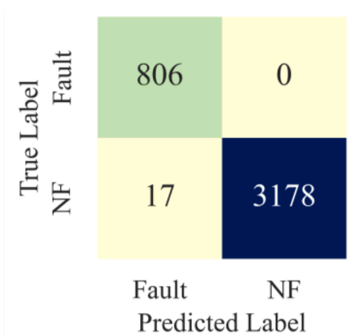

Fig. 12. TL-2: confusion matrix for fault classification.

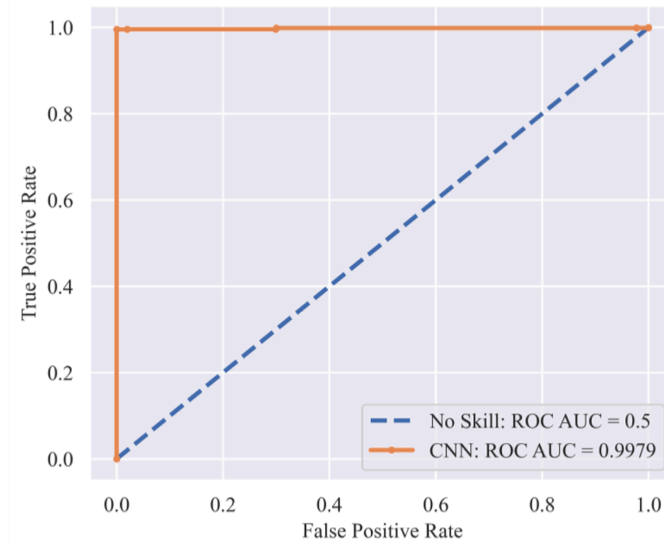

Fig. 13. TL-1: Receiver operating characteristics curve for fault detection.

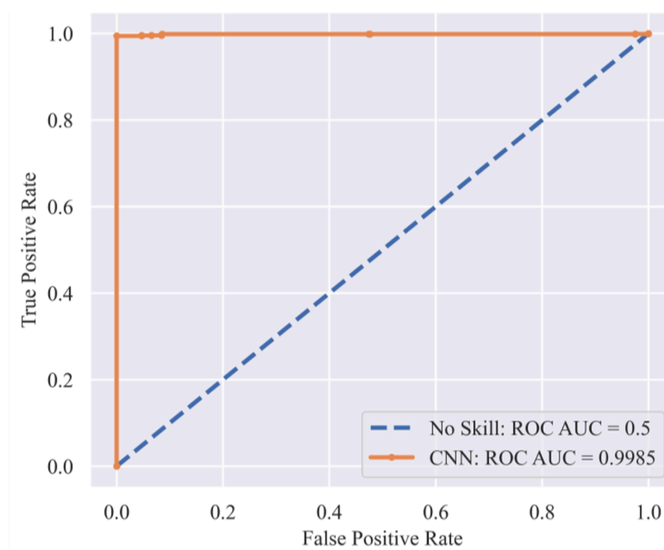

Fig. 14. TL-2: Receiver operating characteristics curve for fault detection.

Table 3
Proposed model outcomes on different evaluation standard for FD.

Presence of fault	Precision	Recall	F1-score	Count	Accuracy
TL-1					
No Fault	97.7	100	98.84	806	–
Fault	100	99.41	99.7	3195	–
Average	98.85	99.7	99.27	4001	99.53
TL-2					
No Fault	97.11	100	98.53	806	–
Fault	100	99.25	99.62	3195	–
Average	98.55	99.62	99.08	4001	99.60

Table 4
Comparison of ELM with ANN in terms of different model parameters for Fault Classification.

Parameters	ANN	ELM
Epoch	70	1
Training time (*sec*)	20.73	3.39
Prediction time (*sec*)	0.38	0.05
No. of total nodes	291	700
No. of intermediate layers	4	1
No. of weight multiplications	5	2

table 5
Comparison of ELM with other State-of-the-art models.

Reference	Algorithm	Data (Training & Testing)	No. of Class Considered	No. of Layers	Accuracy (%)
Fault Detection (Binary)					
Zhang et al. (2018) [18]	LSTM Network with SVM	4100 & 1010	2	5	97.70
Amiruddin et al. (2018) [33]	ANN	190 & 41	2	2	78.00
Proposed TL1	ELM	1000 & 4001	2	2	99.53
Proposed TL2	ELM	1000 & 4001	2	2	99.60
Fault Classification (Multiclass)					
Fahim et al. (2019) [35]	ANN	208 & 44	3	3	84.40
Padhy (2018) [36]	ANN	800 & 150	4	3	97.90
Guo et al. (2019) [8]	HTT-CNN	1672 & 1752	10	6	99.92
Abdullah (2017) [11]	WT-ANN	54,336 & 8066	10	40	98
Fahim et al. (2021) [12]	WT-CN	26,680 & 11,435	11	9	99.72
Dasgupta (2015) [21]	Cross-correlation KNN	800 & 1820	11	–	99.67
Mukherjee (2021) [15]	PNN	250 & 450	11	3	99.33
Chen et al. (2017) [17]	SW-ELM	–	11	2	98.67
Leh et al. (2020) [37]	ANN	–	11	3	70.00
Rajesh (2022) [38]	TSVD-HUARPNN	–	11	–	98.31
Moradzadeh (2022) [39]	CNN-LSTM	–	11	9	98.60
Proposed TL1	ELM	9909 & 1102	11	2	99.18
Proposed TL2	ELM	9909 & 1102	11	2	99.09

Algorithm 1
Sequence of operations in ELM

1:	Randomly generates the input weight $W_{(m,N)}$ and bias $B_{(1,N)}$ matrix.
2:	Determine the output $H_{(n,N)}$ of the hidden layer. $H_{(n,N)} = G(X_{(n,m)} \cdot W_{(m,N)} + B_{(1,N)})$
3:	Determine the output weight matrix $\beta_{(N,t)}$ $\beta_{(N,t)} = H^{\dagger}_{(N,n)} \cdot T_{(n,t)}$
4:	Make prediction using $\beta_{(N,t)}$ $P_{(n,t)} = H_{(n,N)} \beta_{(N,t)}$

4. Conclusion

In this study, to ensure the safety and reliability of the power system, an automatic fault detection and classification system using the novel ELM has been proposed for two different transmission line (TL) configurations with 10 types of faults. The proposed method achieved an optimistic result for the fault detection (FD) and fault classification (FC) cases due to its excellent generalization capability. FD models achieved promising accuracies (99.53% for TL 1 and 99.60% for TL 2) with a smaller volume of training data (20%) for both the cases. On the other hand, accuracies of 99.18% and 99.09% were achieved for the TL1 and TL2 respectively in the case of FC. Moreover, the models took shorter processing time and showed less computational complexity compared to the regular ANN model. The proposed novel ELM model showed the superior performance mainly due to the absence of gradual hyperparameter tuning and having fewer hidden layers, hence less weight multiplication. It also does not include any complicated data transformation methods. It is 7.6 times faster than an ANN with similar performance. Combining the novel ELM with a circuit breaker can detect and isolate the faulty section. In future, the determination of fault location can also be studied. The performance of this novel method can be analyzed further within a real-word scenario.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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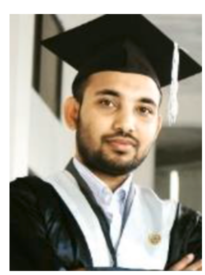

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