Classification and direction discrimination of faults in transmission lines using 1D convolutional neural networks

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ABSTRACT

This paper presents a fast and accurate fault detection, classification and direction discrimination algorithm of transmission lines using one-dimensional convolutional neural networks (1D-CNNs) that have ingrained adaptive model to avoid the feature extraction difficulties and fault classification into one learning algorithm. A proposed algorithm is directly usable with raw data and this deletes the need of a discrete feature extraction method resulting in more effective protective system. The proposed approach based on the three-phase voltages and currents signals of one end at the relay location in the transmission line system are taken as input to the proposed 1D-CNN algorithm. A 132kV power transmission line is simulated by Matlab simulink to prepare the training and testing data for the proposed 1D-CNN algorithm. The testing accuracy of the proposed algorithm is compared with other two conventional methods which are neural network and fuzzy neural network. The results of test explain that the new proposed detection system is efficient and fast for classifying and direction discrimination of fault in transmission line with high accuracy as compared with other conventional methods under various conditions of faults.

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1. INTRODUCTION

The one of the basic components in power systems is Transmission Lines. The possibility of faults occurs in transmission lines are higher than that in other power components in power system because transmission lines are exposed to different conditions of the environment. If a fault happens in transmission line, the power system is exposed to a damage, therefore, it is needed to reliable and rapid effective method to classify and detect the faults to improve the power system transient stability, transmission line transfer power has been increased and to reserve the healthy operation of power system. Different methods have been used for faults detecting, classifying and discrimination in transmission line, which are conventional methods and artificial intelligent methods. The artificial neural networks (ANNs) based direction fault discriminator was proposed by [1]. The proposed method using the samples of instantaneous values of voltages and currents of faults occurs at different locations on a transmission line to feed the proposed ANN. ANNs was used for fault location in extra high voltage transmission line [2]. Elman recurrent neural network has been used by Ekici *et al.* [3] to locate the faults in the transmission line. Application of ANN for detection of phase to ground fault, classifier and direction estimation was introduced for transmission line with a double end fed using terminal data [4]. Implementation and development of ANN-based algorithm was presented by Santos and Senger suitable for transmission line protection was developed to avoid the limitation existing in ANN [5]. Artificial neural networks were presented for fault location and direction estimation in double end fed transmission line using one terminal data only [6]. The method employs the three-phase voltage and currents measured at only one end. A method for detection and fault type identification in transmission line based on back propagation neural networks is studied and implemented using voltages and currents signals of the line to implement protective method in [7]. Syahputra [8] has been use fuzzy method to compare the output of fuzzy model with the measurements of real process. A protective scheme for fault direction comparison in transmission line has been introduced by Hashemi *et al.* [9] based on average values of superimposed components of voltages and currents at relay point to detect the fault and discriminate its direction. A method of ANN for recognition of fault location in power system transmission has been introduced in [10] was analyzed with different fault impedances. A review study was introduced by Yadav and Dash [11] for reviewing approximately the important techniques of ANN based protection of transmission line and this review has been decrease the new researcher's difficulties for evaluating different ANN-based algorithms. Back propagation feed forward neural network has been used to distinguish whether is a fault present or not also locates fault zone in [12]. A proposed model using Matlab software to detect the fault on transmission line using neural networks presented by Kesharwani and Singh [13]. A protective relay using ANN for transmission lines has been used to recognize the impedance patterns to produce a trip if fault is present and no trip otherwise [14]. A new ANN algorithm is proposed for fast fault detection and classification in which voltages and currents at one end are taken as input for the proposed algorithm in [15]. A directional comparison method of transient energy has been used for transmission lines protection in [16]. It is based on the transient power polarity variation and calculation of window of data to improve sensitivity. An efficient protective scheme using ANN was introduced to improve the setting of first zone reach and fault detection with time of half cycle in [17]. A hybrid ANN module was used for detecting, locating and classifying faults on transmission lines by use a large amount of data for training process of the proposed method in [18]. A hybrid protection of transmission line scheme has been introduced for detection and classification of fault in [19]. This scheme proposes multi-layer feed forward neural network to diagnosis, classify and locate faults in transmission line consists from underground cable and overhead line. A review of ANN technique has been used to protect transmission line is presented by Upadhyay *et al.* [20] for fault detection and location using intelligent methods. A new method based on single ANN system for fault detection and classification using multilayer perceptron feed forward ANN is proposed for reliable and efficient detection model in [21]. A review of different methods used for detection of fault, location and classification into power transmission lines has been introduced also presents a comparison between various algorithms used for fault classification and detection in [22].

Due to the difficulties in feature extraction of fault signals in all types of fault detection techniques and in order to overcome this problem a deep-learning algorithms such as convolutional neural network (CNN) is used recently. CNNs are feed-forward neural networks whose different layers for alternating convolutional and sub sampling. The final layers are fully connected after the convolutional layers which are multilayer perceptrons [23], [24]. Recently, CNNs have been commonly used in deep-learning problems, such as object recognition and fault detection. Guo [25] proposed a fault detection method based on continues wavelet transform and convolutional neural network in power distribution system. The proposed method can solve the problem of feature selection and classification of fault signals. Convolutional Neural Network (CNN) based algorithm is proposed for detecting and classifying the faults in transmiddion lines without using feature extraction in [26]. In this algorithm the optimal model of output is determine with high accuracy. The adaptive CNNs have been used successfully over one dimensional 1D signal. A 1D-CNNs are simple to train with a few numbers of epochs of back-propagation and can perform a faster classification process with 1D convolution of only few hundred [24]. During the training process the CNNs convolution layers are optimized for extracting the features with highly discrimination using 1D filter kernels with a large data set. Consequently, a 1D CNNs if properly trained for a given data set can optimize feature extraction and classification problems. In this paper, a novel method is proposed for fault classification and direction discriminator in transmission line based on 1D CNNs algorithm to solve the problems of difficulties in feature extraction selection and classifier. The proposed approach used the samples of voltages and currents signals obtain from one end of the relay site for the proposed transmission line model as an input to train and test the proposed algorithm in which the feature extraction of fault current and classification method are merge into a one machine learner. The rest of paper is organized as follows: transmission line model is presented in section 2. Convolution neural networks overview and algorithm of 1D CNN are discussed in section 3. Section 4 introduced the proposed protective scheme. The proposed structure of 1D CNN is given in section 5. The discussion and evaluation of the tests results is given in section 6. Finally, the conclusions are presented in section 7.

2. TRANSMISSION LINE PROPOSED MODEL

A 132kV power system composed of 180km overhead line between bus bars A and B, 120km line between bus bars B and C which are connected between equivalent sources through power transformers and 100km line between buses B and load bus D. Figure 1 show the single line diagram of the power system model. The relay voltages and currents measurements are located at bus A. This power system is used to prepare the training and testing data for the proposed protective algorithm.

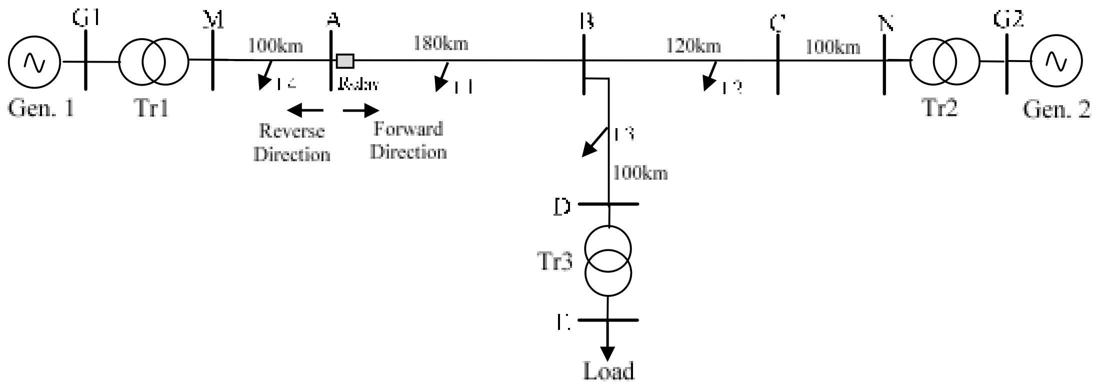

Figure 1. Transmission line model

The forward fault direction is the current outward from the bus bar in which the relay located, as shown from Figure 1 the current flow from bus A to other buses B, C, and D which are represented by faults points F1, F2, and F3. While, the reverse fault direction is the current flow in opposite direction to forward fault from bus A to bus M such as fault point F4 in Figure 1. The patterns for training and testing the proposed method are obtained by different conditions and parameters of power system. Normal operation with light load and full load operation, under faults conditions with different faults location, faults resistance, faults inception time and different faults types for forward and reverse faults direction. Table 1 summaries the parameters values of power system model and different conditions values for generating patterns.

Table 1. Power system parameters and conditions setting for patterns generating

Parameters	Values
Gen. 1, Gen. 2	3-phase, 20kV, 50Hz, 500 MVA, Y-grounded
Tr1, Tr2, Tr3	3-phase, D/Y, 20kV/132kV, 50Hz, 500 MVA
Transmission lines	Z_+=0.01273+j0.293(Ω/km), Zo=0.01273+j1.296 (Ω/km)
Angle of fault inception, deg.	0, 30, 60, 90
Fault resistance, Ω	0.01, 1, 2, 5, 10
Fault location, km	1, 5, 10, 30, 50, 80, 100
Fault types	Line to ground, Double line, Double line to ground, 3-phase fault

3. CONVOLUTION NEURAL NETWORKS OVERVIEW

Convolution Neural Networks CNNs are feed forward ANNs are biologically inspired and have convolutional layers [23]. Between each convolution layer there are sub sampling layers for decimating the feature maps in the neurons of previous layers. By forward propagation for certain number of sub-sampling the last sub-sampling layer reaches to scalar 1D neurons. Following CNNs layers there are a fully connected layers and feed forward networks have the same structure of the multilayer perceptron MLP which has the output layer for classification decision. The topology of CNN, are number of CNN layers, sub-sampling factors in each layer, and number of neurons in each MLP hidden layers all of these parameters must be set for a typical CNNs in order to achieve decimation to reach 1D vector at the output layer. A 2D-CNN model is shown in Figure 2 with input layer consist of pixel images with 28x28. After the input layer each layer of convolution are follows with layers of sub-sampling in which decimated of 2D maps propagated from the previous layer neurons. CNNs are training using the back-propagation (BP) algorithm. However, the two major parameters in CNN are the size of kernel and under-sampling factor which are seting to 5 and 2 for structure shown in Figure 2, a passive layer represent the input layer which only receive input image and gives of channels of color as three neurons for feature maping. With forward propagation for a certain down-sampling layers number, which are decimated for (1-D) scalar vector in a last down-sampling layer of output. Following layers are fully-connected layers identical to MLP and feed-forward networks that have an output layer determining a classification of output vector [24]. The configuration of CNN should be arranged according to the dimensions of input vector in order that the CNN output layer reaches to a 1x1 feature map. For addressing these drawbacks, a certain modification is performed on CNN topology to train an adaptive CNN by back propagation algorithm of 1D-CNN which is works by 1D vector.

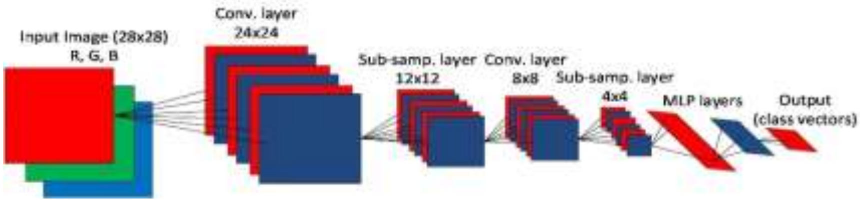

Figure 2. 2D-CNN sample overview [24]

3.1. Adaptive 1D CNNs

The adaptive 1D-CNNs are used for extraction of feature and classification the 1D data of each signal [23]. The topology of the adaptive 1D CNN will provide the possibility for working with any dimension in input layer [24]. CNN is the active type in deep learning and is widely used in different fields such as speech recognition, computer vision, and fault diagnosis. CNN reduces the parameters of the network as compared with a typical neural network by local connection and sharing in weights using convolutional layers [27]. In compact 1D CNNs there are two kinds of layers, the CNN layers for 1D convolution and sub-sampling layers and fully connected layers which are the same layers in the traditional multilayer perceptron MLP [28]. The structure of 1D-CNN is modeled with different parameters as, a hidden CNN number and multilayer perceptron layer/neurons, size of filters (kernel) into each CNN layer, factor of sub-sampling (pooling) in each layer, and choosing the pooling and activation function. The construction of 1D CNN is shown in Figure 3. In this model, the size of filters of 1D is 4 and the under-sampling factor is 3 where the j^{th} neuron of hidden CNN layer, l, firstly execute convolutions sequence, then a convolutions sum is passed by the activation function, and then a sub-sampling operation is performed. Basically, this is representing the main different of 1D CNN and 2D CNN, where the arrays of 1D replace the matrices into 2D in both filter kernel and feature maps. Consequently, the 1D raw data are processing in the CNN layers and learn to extrac given features which could be used in a process of classification which are performed in the multilayer perceptron layers. Consequently, operations of feature extraction and classification are both merge into single process that may be optimize for maximizing the classification performance. This is representing a 1D CNNs main advantages also which can provide a lower complexity of computation since the only costly process is the sequence of convolutions of 1D arrays wich are linear weighted sums of 1D two arrays. Like this linear process through both propagation in forward and backward can be performed efficiently in parallel [24], [28].

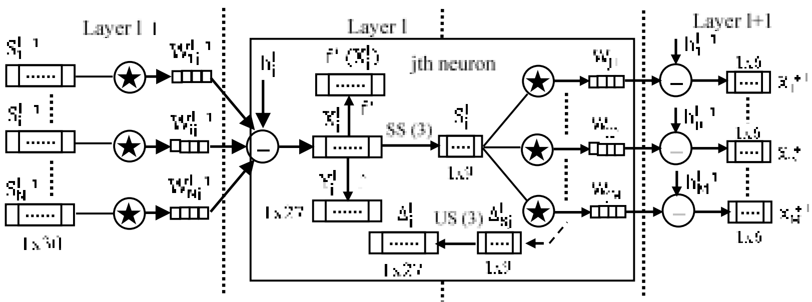

Figure 3. The structure of hidden CNN layers in 1D CNN

3.1.1. Forward and backward propagation in 1D CNN

The forward propagation in each CNN-layer is expresses as [23], [24], [28]:

$$X_j^l = b_j^l + \sum_{i=1}^{N} \mathrm{conv1D}(w_{ij}^{l-1}, S_i^{l-1}) \tag{1}$$

where X_j^l is input, b_j^l is bias of the j^{th} neuron in layer l, S_i^{l-1} is neuron output in layer l-1, w_{ij}^{l-1} is filter kernel from i^{th} neuron of layer (l-1) to j^{th} neuronof layer l, and conv1D (….) is used for performing 1D convolution operation without zero-padding. The dimension of X_j^l, input array is less than from dimension of output arrays, S_i^{l-1}.

The output, Y_j^l, in layer l may be expressed by passing input X_j^l with activation function f(.), as:

$$Y_j^l = f(X_j^l) \tag{2}$$

$$S_j^l = Y_j^l \downarrow ss \tag{3}$$

where S_j^l represent output of j^{th} neuron in layer of l and ↓ ss stand for operation of under-sampling with factor, ss.

In back-propagation algorithm propagating an error from output of MLP-layer. Let l=1 of input layer and l=L of output layer. Assume Q_L is number of classes in output, for a given input vector, let the target be [t_1 …, t_{Q_L}], and output vectors, [y_1^L ..., $y_{Q_L}^L$]. The mean-square error (MSE), E, in output layeris expressed as:

$$E = \sum_{i=1}^{QL} (y_i^L - t_i)^2 \tag{4}$$

A delta error, $\Delta_j^l = \frac{\partial E}{\partial X_j^l}$ must be computed to calculate the derivative of E with respect to each parameter in the network. For updating all weights of neurons and bias of that neuron in preceding layer the chain-rule of derivative is used as:

$$\frac{\partial E}{\partial w_{ij}^{l-1}} = \Delta_j^l\, y_i^{l-1} \tag{5}$$

$$\frac{\partial E}{\partial b_j^l} = \Delta_j^l \tag{6}$$

Therefore, the regular back propagation from first MLP layer to last CNN layer is performed as:

$$\frac{\partial E}{\partial S_j^l} = \Delta S_j^l = \sum_{i=1}^{M} \frac{\partial E}{\partial X_i^{l+1}} \frac{\partial X_i^{l+1}}{\partial S_j^l} = \sum_{i=1}^{M} \Delta_i^{l+1} w_{ji}^l \tag{7}$$

After performing the first operation of back-propagation from layer (l+1) to present layer l, then the back propagation may carry for input delta in CNN layer l, Δ_j^l . Assume zero order up-sampled can be us_j^l =up (s_j^l), then delta error may be expressed as:

$$\Delta_j^l = \frac{\partial E}{\partial y_j^l} \frac{\partial y_j^l}{\partial X_j^l} = \frac{\partial E}{\partial u S_j^l} \frac{\partial u S_j^l}{\partial y_j^l} f'(X_j^l) = \mathrm{up}(\Delta S_j^l)\, \beta\, f'(X_j^l) \tag{8}$$

where $\beta = (ss)^{-1}$.

Back propagation of delta error ($\Delta S_j^l \xleftarrow{\Sigma} \Delta_i^{l+1}$) is expressed as:

$$\Delta S_j^l = \sum_{i=1}^{M} \mathrm{conv1Dz}(\Delta_i^{l+1}, \mathrm{rev}(w_{ji}^l)) \tag{9}$$

Where is rev (.) used to array reversing and conv1Dz (…) is used to full 1D convolution performing with zero-padding.

The derivative of error with respect to weight and bias may be expressed as:

$$\frac{\partial E}{\partial w_{ij}^{l}} = \mathrm{conv1D}(S_j^l, \Delta_i^{l+1}) \tag{10}$$

$$\frac{\partial E}{\partial b_j^{l}} = \sum_n \Delta_j^l(n) \tag{11}$$

The weights and biases can be updating with learning rate $\propto$ using the following equations:

$$w_{ij}^{l-1}(t+1) = w_{ij}^{l-1}(t) - \propto \frac{\partial E}{\partial w_{ij}^{l-1}} \tag{12}$$

$$b_j^{l}(t+1) = b_j^{l}(t) - \propto \frac{\partial E}{\partial b_j^{l}} \tag{13}$$

The more details of the back propagation algorithm of 1D-CNN are presented in [23].

4. PROPOSED PROTECTIVE SCHEME

The transmission power system model shown previously in Figure 1 is simulated by Matlab Simulink to generate data at different fault conditions for training and testing the proposed protective algorithm of 1D CNN. The three-phase voltages and currents signal in transmission line at the relay position firstly are recording and then sampling with a 2 kHz sampling frequency to reach 40 samples per each cycle for each voltage and current signals. The recording data are scaling between -1 and +1 to be feed to proposed configuration of 1D CNN algorithm to classify the fault and discriminate its direction. The overall proposed protective method is shown in Figure 4.

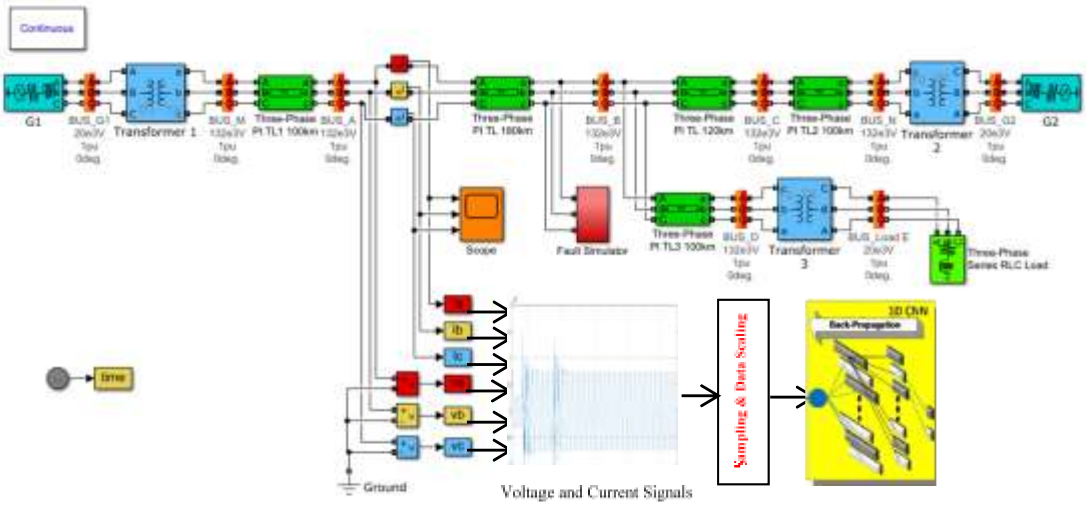

Figure 4. Proposed protective method

5. STRUCTURE OF PROPOSED 1D CNN

The structure model of the proposed 1D-CNN consists of input layer which receives a 1D data signal, a three convolution layers CNN1, CNN2, and CCN3 with sub-sampling pooling layers P1, P2, and P3 there exist after each convolution layer, respectively. Also consists of two full connection MLP layers FC1, FC2, and output layer has neurons number is equal to the classes number. The input pattern contains six signals which are the three-phase voltages and currents and each signal has 40 sample per cycle to form 240 sample in each input pattern. The size of filter kernels of 5 is used for each CNNs layer with step size of 1 and the three convolution layers contains 12, 24, 36 convolution kernels, respectively. The rectifier linear RLU activation function is used in each CNN layer. Maximum pooling is used after the output of each CNN layer with sub-sampling factor of 4 in P1, in P2 is 5 and in P3 it is set to its input array size, since the last CNN has size is 1x7, so the sub-sampling factor of P3 is 7. This possible adaptation in CNN structure due to the last CNN layer output dimension is automatically down-sampling to 1- scalar values regardless of sub-sampling factor which was used in other CNN layers. The two full connection layers FC1 and FC2 have 36 neurons and number of neurons in output layer is 4 for fault classification. In output layer, neuron node number one to indicate the fault in phase A which has a value of 1 if fault occurs in forward direction of protective relay and has value of -1 if fault occurs in reverse direction or has 0 value for no fault detected in this phase. Similarly, neurons node number two and three to indicate faults in phase B and phase C, respectively. The fourth neuron node is to indicate the ground fault if exist for all types of faults and has value of 1 if there is a certain fault to ground and has 0 value if ground does not exist with a given type of fault. The overall configuration of proposed 1D-CNN is shown in Figure 5. The network is training by Back-Propagation algorithm explained previously in learning algorithm in section 3.1.1.

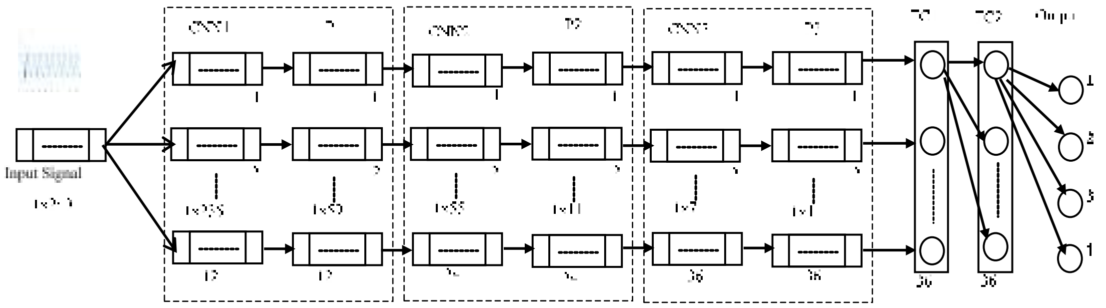

Figure 5. Configuration of 1D CNN

6. RESULTS AND DISCUSSIONS

The total recording data pattern sets obtained from proposed protection model are 88 patterns and each pattern contain six signals of 40 samples, so the number of samples for each pattern set is 240. The pattern sets are randomly divided into 60 set for training and 28 set for testing with equal classification category. The sum of mean square error MSE of all training sets during the learning is 0.001 and convergence after 2550 epochs with learning rate $\propto$=0.13. To examine the accuracy and effectiveness of the proposed 1D-CNN protective algorithm a two other conventional methods of faults classification are used for comparisons which are neural networks NN and fuzzy neural networks FNN, the structure of these methods is shown in Table 2. The accuracy of testing results is computed for the proposed method and for the two other methods. The test results are used to check the accuracy by Measuring F1 score which is the harmonic mean between precision and recall [29]. From Table 2 it seen that the accuracy of proposed method has high identification accuracy from other two methods and with the same total MSE of 0.001 the proposed method is convergence with less than number of epochs of 2550 as compared with convergence number of epochs of NN and FNN. This proves that the performances of proposed 1D CNN algorithm is effective and perform higher classification accuracy. The learning of total MSE with number of epochs for proposed 1D CNN algorithm and other two methods is shown in Figure 6.

The efficiency and test validation accuracy of the proposed 1D-CNN algorithm is ensured by comparing the results accuracy of test validation with transmission lines faults classification models has been proposed by Fuada *et al.* [26]. In this reference has been introduced four types of machine learning classifier model which are includes artificial neural network based desecrate wavelet transform (ANN-DWT), CNN-DWT, CNN with raw dataset, and CNN with normalization data for classifiynig of faults in transmission lines. Table 3 show the comparison of results accuracy in test validation it seen that the proposed 1D-CNN algorithm has higer accuracy of 100% and has the least parameters. The comparison explain that the proposed 1D-CNN model is operative and has high accuracy to classify the faults and discriminate its direction in transmission lines under all conditions of operation.

Table 2. Comparison of results accuracy

Method	Dimensions	Training/testing sets	Testing accuracy 100%	No. of epoch	Total MSE
Proposed 1D-CNN	Figure 5	60/28	98.16 %	2550	0.001
NN	30-50-42-4	60/28	88 %	26416	0.001
FNN	30-45-4	60/28	92.3 %	14651	0.001

The proposed protective model of transmission power system shown previously in Figure 4 is used for testing the proposed 1D-CNN algorithm. Test results of proposed algorithm which is implemented for normal operation and under different faults conditions, such as fault direction location, fault resistance and voltage inception angle of transmission lines model. Table 4 explain the results for testing the normal operation and line to ground faults. Table 5 presents the results of testing of double line, and three-phase faults. The obtained results shows that the new algorithm of 1D-CNN achieves high performance and high accuracy for fault classification and the fault direction determine after the fault inception is performed correctly with simulated fault data. The results show that the algorithm detects and classify the faults correctly for all faults cases.

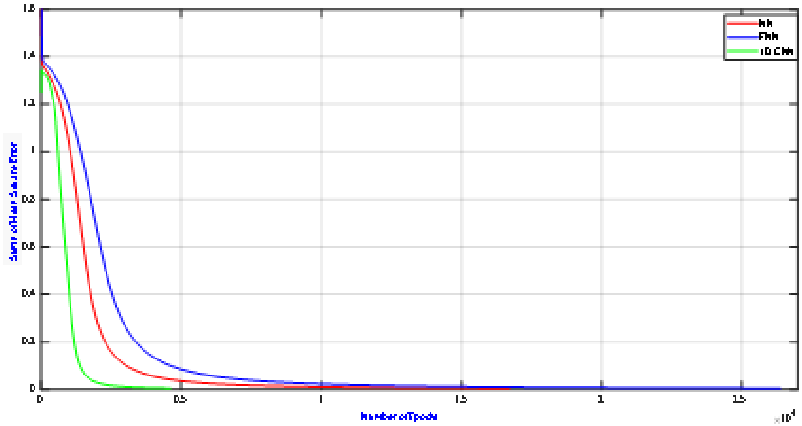

Figure 6. Mean square error with number of epochs

Table 3. Comparison of test validation accuracy

Method name	Filters number in CNN	Neuron number in fully-conection layer	Total parameter	Accuracy of test validation 100%
Proposed 1D-CNN	12-24-36	36	1660	100%
CNN-DWT [26]	16	144	34,203	96.11%
CNN-raw data [26]	17-32	32	87.752	99.99%
CNN-normalization data [26]	17-32	32	87.752	100%
ANN-DWT [26]	-	12-24-12	839	80.764%

Table 4. Line to ground faults test results

Fault type	Direction	Fault position/location	Inception angle	Fault resistance	Output target	Actual output A	Actual output B	Actual output C	Actual output G
Normal half load	-	-	-	-	0000	0.0095	0.0044	0	0
Normal full load	-	-	-	-	0000	0.0108	0.0112	0	0
A-G	Forward	Bus A, 1km	30°	0.01 Ω	1001	0.9827	0.0064	0.0007	0.9952
A-G	Forward	Bus A, 10km	0°	0.01 Ω	1001	1	0.007	0	0.9898
A-G	Forward	Bus A, 50km	60°	5 Ω	1001	1	0.0154	0	1
A-G	Forward	Bus B-D, 20km	0°	2 Ω	1001	0.9989	0.0003	0.0021	1
A-G	Reverse	Bus A, 1km	0°	0.01 Ω	-1001	-1	0.0005	0.0012	0.9897
A-G	Reverse	Bus A, 10km	30°	0.01 Ω	-1001	-1	0.0008	0	0.9997
A-G	Reverse	Bus A, 30km	60°	2 Ω	-1001	-0.989	0.0186	0	1
A-G	Reverse	Bus A, 100km	90°	5 Ω	-1001	-0.998	0.011	0.0001	0.9998
B-G	Forward	Bus A, 90km	0°	0.01 Ω	0101	0	1	0.0006	0.986
B-G	Forward	Bus B-C, 100km	30°	0.01 Ω	0101	0.0418	0.9986	0.0021	0.9815
B-G	Reverse	Bus A, 1km	0°	0.01 Ω	0-101	0.0143	-1	0.0003	0.9979
B-G	Reverse	Bus A, 50km	90°	10 Ω	0-101	0.0019	-0.9998	0.0032	0.9999
C-G	Forward	Bus A, 180km	0°	0.01 Ω	0011	0	0.002	1	1
C-G	Forward	Bus B-C, 120km	30°	2 Ω	0011	0.0016	0.0066	0.9945	1
C-G	Reverse	Bus A, 5km	0°	0.01 Ω	00-11	0	0	-1	1
C-G	Reverse	Bus A, 100km	90°	5 Ω	00-11	0	0	-0.9989	1

Table 5. Test results of double- line and three-phase faults

Fault type	Direction	Fault position/location	Inception angle	Fault resistance	Output target	Actual output A	Actual output B	Actual output C	Actual output G
A-B	Forward	Bus B-C, 30km	0^o	0.01 Ω	1100	0.9972	0.9982	0	0.0104
A-B	Reverse	Bus A, 5km	60^o	10 Ω	-1-100	-1	-0.9999	0	0
B-C	Forward	Bus B-D, 20km	30^o	2 Ω	0110	0.0314	1	0.9984	0.008
B-C	Reverse	Bus A, 30km	90^o	5 Ω	0-1-10	0	-0.9998	-1	0.0032
A-C	Forward	Bus A, 180km	0^o	0.01 Ω	1010	1	0.002	0.9977	0.0003
A-B-G	Forward	Bus B-C, 100km	0^o	2 Ω	1101	0.9819	1	0.0025	0.9933
A-B-G	Reverse	Bus A, 50km	60^o	10 Ω	-1-101	-0.9979	-1	0.0005	0.9987
B-C-G	Forward	Bus B-D, 40km	0^o	0.01 Ω	0111	0.004	1	1	0.9833
B-C-G	Reverse	Bus A, 10km	30^o	5 Ω	0-1-11	0.003	-1	-0.9968	0.9805
A-C-G	Forward	Bus A, 90km	0^o	0.01 Ω	1011	0.9988	0	1	0.9988
A-B-C	Forward	Bus A, 50km	0^o	10 Ω	1110	1	1	0.9998	0
A-B-C-G	Forward	Bus B-C, 120km	60^o	2 Ω	1111	0.9978	1	0.9968	1
A-B-C-G	Forward	Bus B-D, 100km	90^o	5 Ω	1111	0.9898	0.998	0.9948	1
A-B-C	Reverse	Bus A, 5km	0^o	0.01 Ω	-1-1-10	-0.9877	-1	-0.9799	0.0012
A-B-C-G	Reverse	Bus A, 50km	30^o	2 Ω	-1-1-11	-1	-1	-0.9686	0.9969
A-B-C-G	Reverse	Bus A, 100km	90^o	10 Ω	-1-1-11	-0.9988	-1	-0.9398	0.9999

In order to evaluate the speed of fault detection and the accuracy of fault direction discrimination of the proposed 1D-CNN method, different faults cases are studied to show the performance of the proposed protective method are presented here. Figure 7 illustrates the three-phase voltages and currents waveforms at relay position under healthy operation of power system. Figure 8 show a three-phase voltages and currents waveforms at relay position under phase a line to ground fault occurs at 70km in forward direction starting at time of 0.15 sec and clear at 0.57 sec. Figure 9 show the outputs of proposed algorithm under healthy operation of power system it is clear that all the outputs are zero and show that the stability of the algorithm outputs under normal operation conditions of power transmission system. A line to ground fault occur on phase b at 10km in forward direction of Bus A at time of 0.05 sec with fault resistance of 0.01 Ω as explain in Figure 10, it is see that the output B and ground output are both gives value of one at the instant of fault and the two other outputs of healthy phases gives zero output because no fault occurs on the healthy phases a and c. Three-phase to ground fault occur at 110km in forward direction of Bus A at 0.42 sec incident time with fault resistance of 2 Ω is given in Figure 11. It is clear that from this Figure the proposed algorithm correctly classifies and discriminate the direction of fault. Figure 12 show phase a with line to ground fault occur at 5km in the reverse direction of Bus A at 0.17 sec time with fault resistance of 10 Ω. The Figure show that the output A of proposed method gives value of -1 since the fault occur in reverse direction of relay position on Bus A and ground output give value of 1 to indicate the ground fault while the other outputs mention zero values due to it is healthy phases. Line to line to ground occur on Phases b and c at 50km in reverse direction of Bus A at time of 0.62 with fault resistance of 5 Ω as shown in Figure 13. In Figure 14 a line-to-line fault at phases a and c occur at 100km in reverse direction of Bus A start at time of 0.2 sec and clear at time of 0.61sec with fault resistance of 0.01 Ω. It is seen from this Figure that a proposed model correctly detects direction of fault at fault starting time and restore its normal state at the time of fault clear. From all these studied faults cases it is clear that the proposed protective method has fast outputs variable convergence to the expected values of faults conditions and the detection and direction discriminator of fault it is not affected by type, location, inception time and fault resistancet. This is clearly confirming the effectiveness and accuracy of the proposed algorithm.

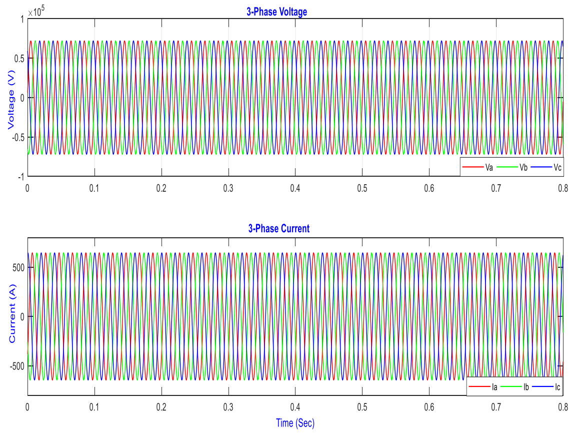

Figure 7. Three-phase voltages and currents at relay site under healthy operation

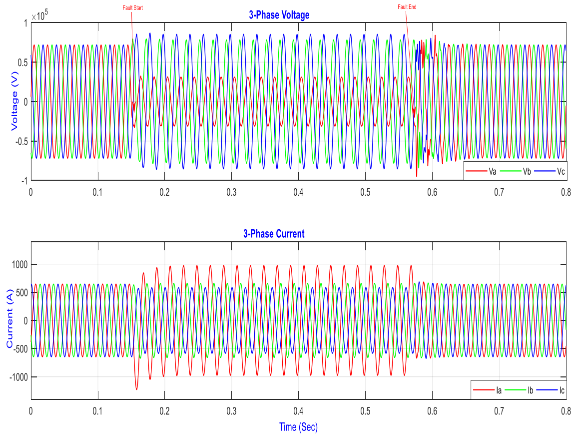

Figure 8. Three-phase voltages and currents at relay site under phase a line to ground fault at 70km in forward direction

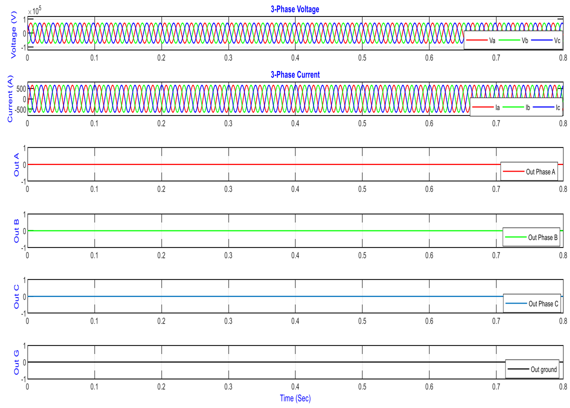

Figure 9. Outputs of proposed algorithm under healthy operation

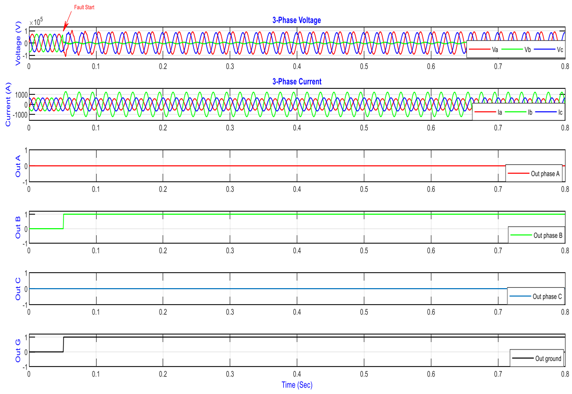

Figure 10. Phase b line to ground fault at 10km in forward direction

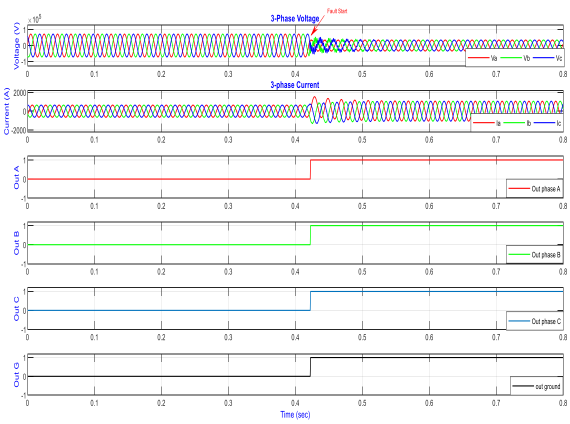

Figure 11. Three-phase to ground fault at 110km in forward direction

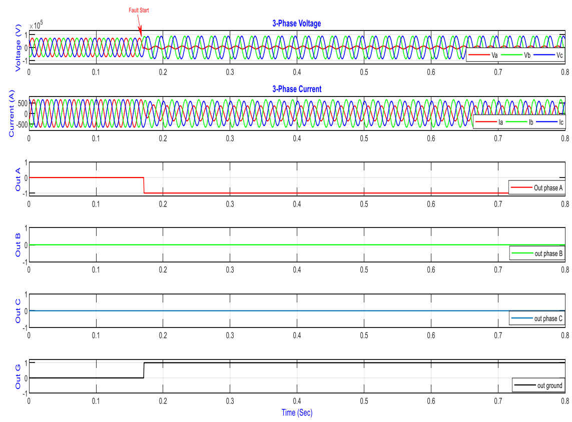

Figure 12. Phase a line to ground fault at 5km in reverse direction

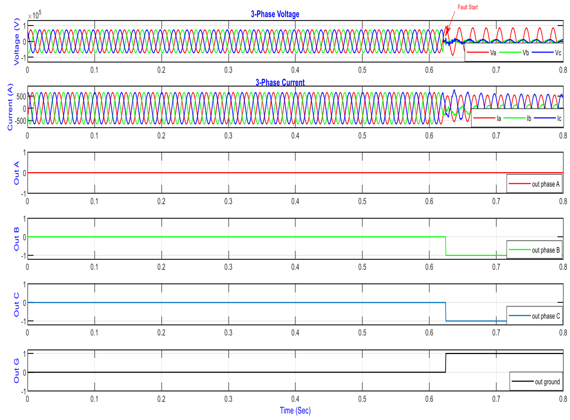

Figure 13. Phases b and c line to line to ground fault at 50km in reverse direction

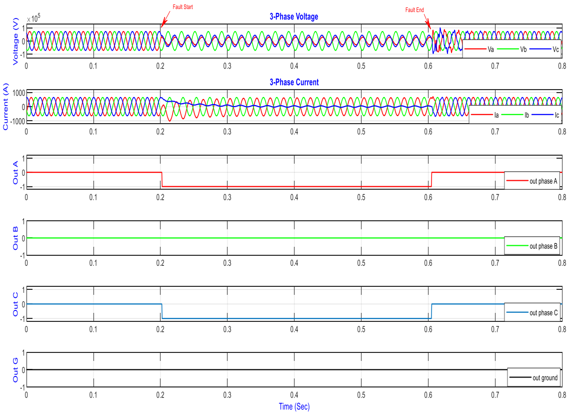

Figure 14. Phases a and c line to line fault at 100km in reverse direction

7. CONCLUSION

A new algorithm of fault classification and direction discriminator in transmission lines based on deep learning 1D CNNs is presents to solve the problems of difficulties in feature extraction selection and classifier. The proposed diagnosis algorithm used the samples for voltages and currents signal into the relay site to train and test a proposed 1D CNN algorithm. This algorithm is tested extensively using simulated recorded data from proposed power system model which is simulate by Matlab simulink. The results of test proved that the proposed protective model is robust and reliable under wide different faults conditions such as fault location, fault type, fault resistance and fault incidence time. The proposed 1D CNN method is correctly detect the fault at any location from the relay position in forward and reverse direction of the power system model and has better performance and accuracy in fault diagnosis, classification and direction discrimination than the traditional methods of machine learning and the comparison of accuracy in test validation shows that the proposed 1D-CNN detection algorithm has higher accuracy for fault classification and has less parameters as compared with other CNN models.

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