Combination of MW and Deep Neural Network based Fault location Identification for Multi-Terminal Transmission Systems

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***Abstract* - It is essential to identify the fault location in multi terminal transmission systems with respect to end terminals of the transmission lines, to provide basic information to design protective components in power system network. In this paper post fault currents are carried out at different terminals of IEEE-9 Bus system using MATLAB simulation tool. These currents have been processed through Morphological Wavelet (MW) filters to discriminate the different faults at various inception angles and fault resistances. Opening, closing, Morphological Closing and Opening Average RMS Value (COAVR) are selected as filters for morphological operations. The COAVR outputs are applied as inputs for Deep Neural Network (DNN) to identify the faulty line, type of fault and exact fault location with respect to one end of the transmission line.**

Keywords* - *Morphological Wavelet, fault classification, Fault identification, inter connected transmission network, Deep Neural Network.

I. INTRODUCTION

Now a days it is really a challenging task for protection engineers to identify the faults in transmission lines to maintain uninterrupted power supply for end consumers, Indirectly which reduces time consumption for maintenance work consequently increases the reliability of power system network by designing suitable power system protective equipment. Especially identification of fault location in multi-terminal transmission network is essential to complete the repair work at exact faulty point. Detection of faulty lines in interconnected network is very complicated task, where it is really mandatory to compare and analyze measured currents at various terminals to determine the faulty line, type and exact location. Such that exact isolation can be predicted accurately, and only few end consumers are outage due to unhealthy portion in the transmission lines [1].

There are several methods have been implemented for fault classifications and identification of location in two terminal networks. Most of the classifiers are neural networks, fuzzy classifiers and SVM tools [12] and other machine learning methods. The inputs for all classifiers have been trained and tested by the feature extraction form classical methods like travelling wave technique, wavelet packet decomposition[13], Discrete wavelet transforms[2] and s-transforms and wavelet lifting schemes[8]

This paper analyses the fault location and classification[16] using wavelet morphology combined with deep neural networks, which improves the accuracy for feature extraction[15] from current signals and over all training and testing accuracy has been improved with the help of deep machine learning algorithm. Here the inputs for deep NN are given from morphological filter outputs. Current signals are recorded at various buses for IEEE-9bus system at different faults, Inception angles and at various fault resistances. All simulations are carried out using MATLAB (simulink). The same current signals are process through morphological filters for generation of features.

The extracted features are formed like patterns at different fault inception angles, fault resistances. These patterns are given as inputs for the deep NN classifier to identify the fault and location exactly with respect to end terminals in the multi terminal network.

The paper has been organized as follows. The detailed analysis of Morphlogical Wavelet, MW, transform is explained in section-II. In section-III, the proposed algorithm has been described. The proposed methodology is explained in brief with pictorial representation in section-IV. Section-V simulation results have been shown for various faults on transmission lines at different locations in Fig1-7 using MATLAB-Simulink Tool, And Patterns are trained and tested using machine learning algorithm and different case studies are explained in Table 1-2. The conclusions are discussed in Section-VI.

II. MATHEMATICAL MORPHOLOGY (MM)

In the domain of signal processing, MM analyzes signal waveforms directly rather than integral transforms like FT and Wavelet Transforms [2], [14]. MM basically emphasize any kind of non periodic signal using structuring element[3], and which is known as basis function for morphological filtering of a transient signals. MM analyses any signal in time domain rather than frequency domain [4]. The morphological operators highly faster than integral transforms, because these are simply included small additions and subtractions for a signal using sliding window (SE) [5]. Basically these mathematical operations are done by dilation and erosion techniques. Which are extracted from the set theory and integral geometry [6]. These operators are analogous to the Union and Intersection operations of set theory in binary level. But same operators can be implemented as Minkowski Algebraic addition [7] and subtraction in greyscale level in signal processing. The other transformations like Morphological opening and closing can be derived based on these two basic operators. MM can analyse a disturbed signal accurately and which can extract boundary features of a signal without causing any distortion. Most of the electrical signals in power systems are two dimensional nature, which can be process through MM operators to analyse the transient signals under fault condition. Modern days the digital relays are mainly designed by microprocessors or other signal processors, MM can give accurate input features for the digital relays consequently the operating time of digital relays at fault location decreases. The Morphological operators are defined as follows [5, 7].

Let and be the main signal and the structuring element respectively, the consequent domains [9] are mapped as,

Let $S(n)$ and $g(m)$ be the main signal and the structuring element respectively, the consequent domains [9] are mapped as:

$$D_s = \{x_0, x_1, x_2, ...x_n\} \text{ and}$$
$$D_g = \{y_0, y_1, y_2, ...y_m\} = \{y_0, y_1, y_2, ...y_m\}$$

respectively [3, 4], with $n>m$.

Where n and m are integers.

Then the dilation of $S(n)$ by $g(m)$, denoted by $(S \oplus g)$ is defined as:

$$y_d(n) = (S \oplus g)(n) = \max\{S(n-m)+g(m)\}, 0 \le (n-m) \le n, m \ge 0 \quad (1)$$

Similarly, Erosion of *S(n)* by *g(m),* denoted by $(S\Theta g)$ is defined as:

$$y_e(n) = (S\Theta g)(n) = \min\{S(n+m) - g(m)\}, \\ 0 \le (n+m) \le n, m \ge 0 \quad (2)$$

Based on above basic operations explained in Eqn. (1) and Eqn. (2), two derivative processes called opening and closing are defined [10]. The opening of *S(n)* by *g(m),* denoted by (Sog) is defined as dilation of eroded signal $(S\Theta g)$ by g:

$$y_o(n) = (Sog)(n) = ((S\Theta g) \oplus g)(n) \quad (3)$$

Similarly, Closing of *S(n)* by g(m), denoted by $(S \bullet g)$ is defined as erosion of the dilated signal $(S \oplus g)$ by g:

$$y_c(n) = (S \bullet g)(n) = ((S \oplus g)\Theta g)(n) \quad (4)$$

Morphological filters [11] are non-signal transforms that modifies geometrical features of signals. The above definitions are utilized in real time applications. Opening generally smooths the sharp edges on a contour, whereas closing fills narrow valleys and gaps in a contour, based on the equations given from Eqn. (1) to Eqn. (4) other composite filters are defined. These transformations perform only addition and subtraction of structuring data with disturbed signal, and which reduces computational burden over other methods. Structuring element is selected based on size and shape of the nonlinear disturbed signal. Feature extraction of any non-stationary signal completely depends on the spectrum of structuring element and sampling rate of original signal. Such that features can be extracted in an optimal level. Eqn. (5) defines an average of closing and opening operation. This is highly innovative parameter which is used for the discrimination of faults in during abnormal conditions. In this paper the fault classification in transmission lines are uses COAV operation for identification type of fault in multi terminal system. The sampling rate has been selected as high rate which is taken as 24 kHz (400 samples per cycle) consequently computational complexity reduces to minimum:

$$yCOAV(n) = (y_c(n) + y_o(n))/2 = (((S \bullet g)(n) + (Sog)(n))/2) \quad (5)$$

III. PROPOSED METHODOLOGY

The Main objective of this paper is to identify the occurrence of fault, locating the fault and classifying the fault [17] using Morphological filters and DNN. To meet these specific objectives a standard IEEE-9 bus system is selected as test system as shown in Fig 1. In which the currents are recorded, sampled and processed through morphological Filter (COAVR) for various faults at different inception angles. Here the sampled currents are grasped at starting and ending terminals of the transmission lines at different fault resistances. These patterns are generated by involving all shunt faults by varying location at different inception periods on each transmission line. Finally the classification and location can be identified accurately by training and testing the neural network with morphological COAVR outputs. The procedural steps have been explained in flow chart in Fig 2.

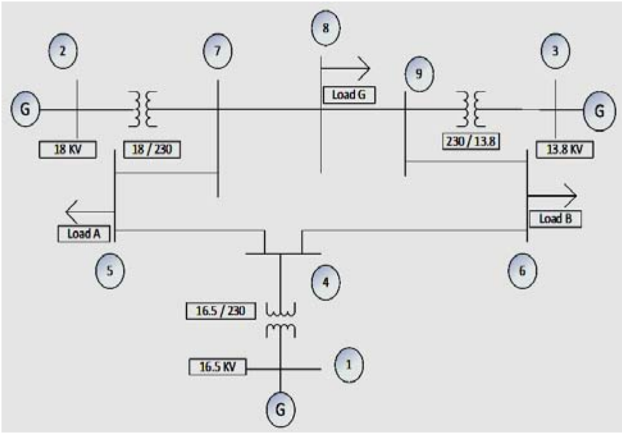

Fig 1. Standard IEEE-9 Bus system

IV. DEEP NEURAL NETWORK (DNN):

DNNs are the neural network with deep learning idea. The main difference between the back propagation neural network and deep learning network is, DNN has more number of layers between input and outputs. The procedural steps are as shown in flow chart in Fig 2.

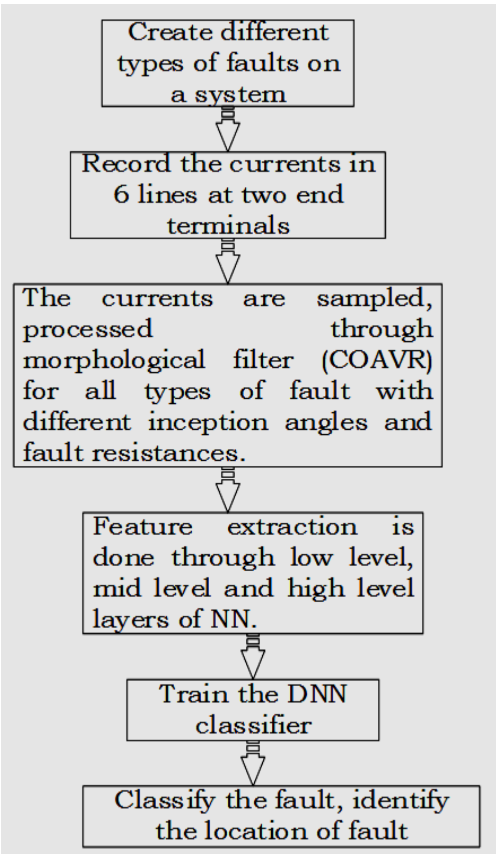

Fig 2. Step by step procedure of methodology

These enable the accurate feature extraction and pre-processing of input data similar to human brain. In DNN the higher layers expresses the combination of features that are educated from the lower level layers. The DNN works on the un-labelled data layer by layer. The architecture of DNN is shown in Fig 3. It has one input and one output layer with three hidden layers.

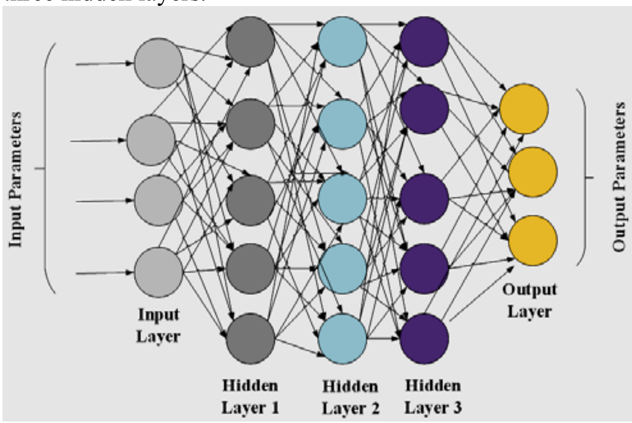

Fig. 3. Structure of Deep learning NN

The learning hierarchical representation is shown in Fig 4. In the first step, in the low level the features are extracted using low level layers of network [19]. Similarly with the help of mid-level and high level layers complete features are extracted and given to classifier with which the output can be obtained. DNNs are found their applications in the areas of speech recognition, image processing, computer vision and artificial intelligence (AI).

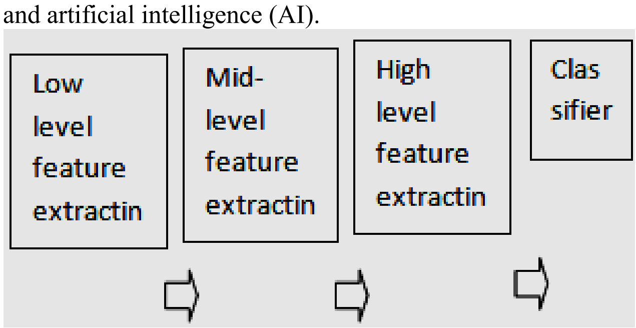

Fig 4. Hierarchical representation of DNN

The activation function used is Rectified Linear Unit (ReLU) to avoid the problem posing by gradient approach. In the present work the DNN is used to identify the occurrence of fault, type of fault and its location on a line.

V. SIMULATION & RESULTS

The proposed methodology has been tested on standard IEEE 9 bus system. It contains three generators at buses 1, 2 and 3. Buses 5, 6 and 8 are selected as load buses with 6 transmission lines as shown in Figure 3. Base kV at all the load buses are taken as 230 kV and frequency of the system is 60Hz. The transmission line sequence parameters are R0

= 0.224825 Ohms/km; L0 = 3.22e-3 H/km; C0 = 4.74e-9 F/km; R1 = 0.08993 Ohms/km; L1 = 1.29e-3 H/km; C1 = 7.922e-9 F/km. From the computations, the current signal of each phase has been measured with a sampling time of 40 μ.sec at generators [22], transformers, transmission lines and loads. These developed time domain current signals are processed through morphological dilation and erosion operators using structuring element (SE) [20] described in Eqn. (1) and Eqn. (2).

Later the dilated signal is eroded by the same structuring element (db8) [18] to recover the loss of information in the process of erosion, which is known Morphological opening. Simultaneously the same eroded signals[6, 7] are dilated by the same structuring element to extract more information from the boundaries of faulted signal using Morphological closing transformation explained in Eqn.(3) and Eqn. (4) . The variations in COAVR Magnitudes are measured at all terminals when different faults incurred at different locations of the transmission lines [20].

Eqn. (5) describes the COAVR which is really a highly powerful tool to synthesize the power system disturbances [4]. COAVR analyses the 400 samples of one cycle from each phase is around the duration of 4.16 ms, for fault inception angles of 00, 180, 360 & 540. Simulations has been carried out at different fault resistances (FR), FR = 1, 10 and 15 ohms. The variations in COAVR Outputs can be acted like features to process the signal in optimal level, the features of closing and opening Average Output RMS Value (COAVR) evaluated from COAV outputs. COAVR is demonstrated in Eqn. (6):

$$COAVR_x = \sqrt{\left(\frac{1}{N} * \left(\sum_{i=1}^{N} COAV_i\right)\right)^2} = a, b, c \text{ Phases} \tag{6}$$

Where N = Total number of samples per a cycle.

COAVR analyses the Ground Fault Index Values (GFI) to discriminate the faults like LL faults and LL-G faults. The expression GFI has been discussed in the following equation (7):

$$GFI = \frac{1}{3}\sum COAV_A + COAV_B COAV_C \tag{7}$$

Different types of faults [21] generally considered as Line to ground, Double line, Double Line to ground and symmetrical faults [15, 16]. Simulations have been carried out at different locations of transmission line and each line contributes 100km. Different types of faults are simulated using MATLAB Simulation Tool box which are measured using workspace block at both ends of the transmission line irrespective of fault location. In the present work DNN has been used to identify the faulty line, fault type and its location. The data which is used for training and testing of DNN must be pre-processed. In the considered interconnected system with 6 transmission lines, 9 fault locations are taken for each line at an interval of 10 km. Simulations are done at an inception angles of 00, 180, 360 and 540 and also the three fault resistances are incorporated for all the 11 possible types of faults [24]. Thus, a total of 6× (9×3) ×11×4 = 7,128 patterns are developed. The total 7,128 patterns contributed to 164 different classes. It has been observed that the data for line 1 and line 2 are identical, at the same time for line 3 and line 4 and line 5 and line 6 also. The identical data was processed by considering their average. After considering the average values the input parameters are reduced from 36 to 24 attributes. Consequently after processing the redundant data of target parameters they are classified in to 164 classes. After obtaining the data, 70 % samples were used to train the DNN and 30% was used for testing purpose. The training accuracy is shown in Table I in terms of fault locating for different types of fault inception angles with fault resistance 10 ohms [25].

TABLE I. FAULT LOCATION IDENTIFICATION WITH DIFFERENT INCEPTION ANGLES AND DIFFERENT FAULT RESISTANCES

Type of fault	Fault location											
	10				40				100			
	0°	18°	36°	54°	0°	18°	36°	54°	0°	18°	36°	54°
AG	10.001	10.02	9.894	10.04	39.87	39.78	40.14	40.07	99.89	100.02	100.17	99.8
BG	10.125	9.9654	10.040	10.14	40.01	39.8	40.01	39.99	100.01	100.14	100.17	99.96
CG	10.087	10.074	10.524	9.896	39.78	39.90	40.20	39.97	99.98	100.07	99.901	100.02
AB	10.18	10.078	9.97	9.720	39.69	39.91	39.93	40.05	100.1	99.91	99.96	100.08
BC	10.257	9.120	9.872	10.07	40.01	40.09	39.98	39.89	100.1	100.01	100.00	99.9
AC	9.971	9.546	10.075	9.971	39.86	40.10	40.37	39.9	100.01	99.97	99.89	100.03
ABG	10.240	9.875	10.081	10.17	40.03	40.02	40.05	40.02	99.95	100.17	100.05	100.01
BCG	10.068	10.141	10.167	9.998	40.10	39.93	39.98	39.99	99.86	99.96	100.18	99.87
ACG	9.741	10.179	9.970	10.00	39.96	40.08	39.87	40.00	99.48	99.9	99.96	100.1
ABC	10.148	9.901	9.931	10.04	40.00	39.93	40.00	39.69	100.10	100.01	100.11	99.90
ABCG	9.976	10.24	10.193	10.10	40.10	39.98	40.07	40.06	99.69	100.05	100.01	100.09

It has been observed that using the proposed approach the fault location is identified accurately with different fault inception angles. The accuracy of the proposed approach is also validated with the methods already reported in the literature as shown in Table II.

TABLE II. COMPARISON OF METHODS

Serial No	Method	Error %
1	Ref (25)	5.40 E-02
2	Ref (26)	8.90 E-01
3	Ref (27)	5.10 E-01
4	Ref (28)	1.00 E-3
5	Ref (29)	1.10 E-03
6	Ref (30)	2.10 E-03
7	Present Proposed approach	2.7484 E-04

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From the Table II, it has been observed that the present proposed methodology yields to the exact solution in identifying, classifying and locating the fault. The relative error obtained is 2.7484E-04, which is very less compared to the remaining methods listed in Table II. The proposed scheme uses a data window of a complete cycle during the post fault condition.

VI. CONCLUSION

In this paper, the fault classification was carried out using a Morphological COAV Outputs. Morphological filters are process through structuring element (Db-8) for the transformation of three phase currents of transmission lines at the line terminals. The COAVR outputs of fault currents are taken as input to discriminate the different fault types with reference to one end of the transmission line. For classifying the fault DNN approach has been used. The proposed methodology was tested on a standard IEEE 9 bus system and the results were compared at various inception angles. The results show that Morphological Wavelet transformation with DNN proves to have outstanding performance in fault classification compared to Discrete Wavelet Transform approach.

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