Approach for High voltage transmission line protection by using line trap network & ANN over SVM

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***Abstract*—This paper presents a new approach to classify fault types and predict the fault location in the high-voltage power transmission lines, by using ANN over Support Vector Machines (SVM) and Wavelet Transform (WT) of the measured one-terminal voltage and current transient signals. Wavelet entropy criterion is applied to wavelet detail coefficients to reduce the size of feature vector before classification and prediction stages. The experiments performed for different kinds of faults occurred on the transmission line have proved very good accuracy of the proposed fault location algorithm. The fault classification error is below 1% for all tested fault conditions. Efficiency of this method is 89% as compared with Support vector machine technique having 73% efficiency and the maximum error did not exceed 0.95 km.**

***Index Terms*— Line trap, support vector machine (svm), transients-based protection, Matlab.**

I. INTRODUCTION

The accurate fault location is a very challenging task for power transmission line protection, since a more accurate location results in the minimization of the amount of time spent by the repair crews in searching for the fault. There are several methods such as radial basis function neural networks, back propagation neural networks, fuzzy neural networks, WT based on measuring faulty current and voltage signals and a lot of study has been continued with advance in computer technology [1,2]. The above mentioned approaches require large training sets and training time. These methods are also sensitive to system frequency changes [3].The methods based on artificial neural network (ANN) combining with WT are very encouraging for line protection applications. In recent years, a widely used method in the classification and regression problems is SVM. In SVM technique, the original input space is mapped into a high dimensional dot product space called feature space in which the optimal hyperplane is determined to maximize the generalization ability of the classifier [3]. The optimal hyperplane is found by using optimization theory and the Statistical Learning Theory. In recent years, SVM has been widely used in many research areas, such as face recognition, signal and image processing and fault diagnosis. SVM based classifiers have better generalization properties than ANN based classifiers. The efficiency of SVM based classifier does not depend on the number of features. This property is very useful in fault diagnostics because the number of features to be chosen is not limited, which make it possible to compute directly using original data without preprocessing them to extract their features. These advantages make SVM an excellent choice for the fault detection and localization applications.

Unlike conventional statistical and neural network methods, the SVM approach does not attempt to control model complexity by keeping the number of features small. "In comparison with traditional multilayer perceptron neural networks that suffer from the existence of multiple local minima solutions, convexity is an important and interesting property of nonlinear SVM classifiers SVMs have been developed in the reverse order to the development of neural networks (NNs). SVMs evolved from the sound theory to the implementation and experiments, while the NNs followed more heuristic path, from applications and extensive experimentation to the theory."ANNs are very efficient tools for pattern recognition and they can be successfully used in dermatological applications

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II. SIGNAL PROCESSING TOOLS

A. Wavelet Transform

The wavelet transform is a mathematical tool that decomposes the input signal into different frequency bands. It provides the time- and frequency-domain localization which makes it an appropriate mathematical tool to process non stationary transient signals [17].

$$Wf(s,b) = |s|^{-1/2} \int^{\infty} f(t)\, \overline{\psi(\frac{t-b}{s})}\, dt$$

Ψ(t) is the complex conjugate of the wavelet function, is the time shifting factor, and S is the scaling factor. The wavelet Ψ(t) is a limited duration function with an average value of 0. The wavelet function depends on the shifting factor and the scaling factor S. The wavelet transform is, in fact, a comparison analysis which determines the amount of similarity of a given signal to a shifted and scaled version of a predefined basis function. The data window length of the wavelet transform can vary through variation of the scale factor. This way, transient behavior and discontinuities of the signal can be well investigated using short-length windows for high-frequency components and long-length windows for low-frequency components [10].

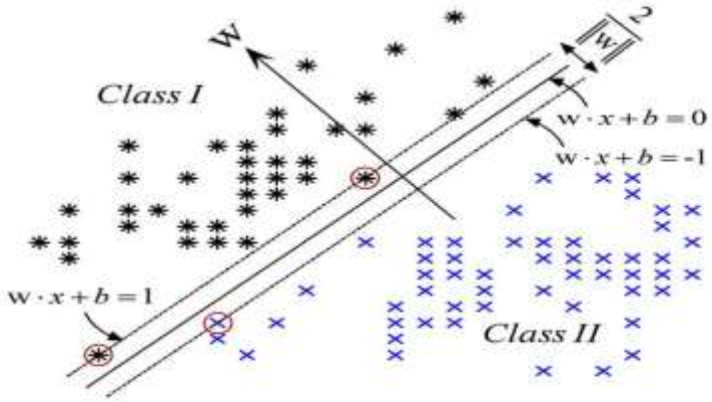

Fig.1. Maximum margin separating hyperplane using SVM

B. SVM

SVM fits a hyperplane/function between 2 different classes given a maximum margin parameter. This hyperplane attempts to separate the classes so that each falls on either side of the plane, and by a specified margin. There is a specific cost function for this kind of model which adjusts the plane until error is minimized.

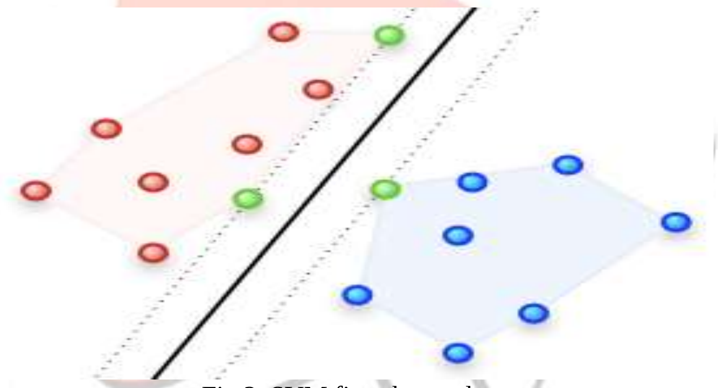

Fig.2. SVM fits a hyperplane

The SVM is a machine-learning technique used for statistical classification and regression analysis. An SVM constructs a hyperplane or a set of hyperplanes in a high-dimensional space to separate the data points which belong to different classes. The separating hyperplanes are obtained so that the maximum separating margin between the classes is achieved [18], [19]. Fig.1depicts a linear hyperplane separating a set of two-class data points. It is, in fact, a simple example in which the data points are linearly separable. Let the training data set be composed of p-dimensional data points as well as their corresponding classes as follows

$$D = \{(x_i, c_i) | x_i \in R^p,\ c_i \in \{-1, 1\}\}_{i=1}^{N}$$

where Ci is either 1 or -1, indicating the class to which the data point xi belongs xi, is a p -dimensional real vector, and is the number of samples. Any hyperplane which successfully separates the data points can be given by

$$f(x) = \mathrm{w} \cdot x + b = 0$$

Multiclass SVM aims to assign labels to instances by using support vector machines, where the labels are drawn from a finite set of several elements. The dominant approach for doing so is to reduce the single multiclass problem into multiple binary classification problems. Common methods for such reduction include: Building binary classifiers which distinguish (i) between one of the labels and the rest (one-versus-all) or (ii) between every pair of classes (one-versus-one). Classification of new instances for the one-versus-all case is done by a winner-takes-all strategy, in which the classifier with the highest output function assigns the class (it is important that the output functions be calibrated to produce comparable scores). For the one-versus-one approach, classification is done by a max-wins voting strategy, in which every classifier assigns the instance to one of the two classes, then the vote for the assigned class is increased by one vote, and finally the class with the most votes determines the instance classification. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall. When data are not labeled, supervised learning is not possible, and an unsupervised learning approach is required, which attempts to find natural clustering of the data to groups, and then map new data to these formed groups. The clustering algorithm which provides an improvement to the support vector machines is called support vector clustering[2] and is often[citation needed] used in industrial applications either when data are not labeled or when only some data are labeled as a preprocessing for a classification pass.

As can be seen, the maximum fault classification accuracy is 93.5%, which is obtained by the polynomial classifier. Table II presents some of the fault casesfor which the designed SVM is not able to correctly classify the fault. In this table, the fault location is given from bus A. Most of the misclassified faults are those which occur very close to the remote buses B or C. Indeed, it is difficult to distinguish between faults occurring close to the remote buses on the TL under protection or on the next TLs [15]. The other misclassified fault cases are those occurring at very small inception angles. Since such faults do not generate a considerable amount of HF transients, training the SVM classifier using faults occurring at very small inception angles reduces the separating margin of the classifier and may lead to misclassification in some boundary cases. To increase the separating margin of the trained SVMs in discrimination between the two classes of internal and external faults, in this paper, the training data set is modified so that it does not contain fault cases occurring near the remote buses onthe three-terminal TL under protection. In other words, to increase the reliability of the proposed fault classification scheme, the protected zone was selected to protect 95% of the TL length. In addition, the minimum fault inception angle was considered as 10 . This approach guarantees the relay security which is of great importance for a protection scheme.

table 1:Some of the obtained results for the case of change in the power system parameters.

Case number	Fault type	Location (km)	Inception angle (degree)	Fault resistance (ohms)	Classifi-cation
1	AG	50 (AB)	90	10	1
2	ABC	50 (AB)	90	0.01	1
3	BG	65 (AB)	10	0.01	1
4	BG	65 (TC)	10	0.01	1
5	ABG	125 (AB)	90	5	1
6	ABG	70 (TC)	90	5	1
7	ABG	131 (BE)	90	0.01	-1
8	AG	140 (BE)	90	5	-1
9	BG	170 (BE)	10	0.01	-1
10	ABC	180 (BE)	90	0.01	-1

C. Design of the Line Trap

Line traps are connected in series with HV transmission lines to prevent dissipation of the power-line carrier (PLC) signal in the substation or in other transmission lines. The main function of the line trap is to present high impedance at the carrier frequency band while presenting negligible impedance at the power system frequency. The high impedance is required to reduce the carrier signal attenuation due to the division among the several transmission lines terminated at the same bus. A line trap consists of three major components in parallel (i.e. mail coil, tuning device, and surge arrester). The main coil carries the rated current of the transmission line and is designed to withstand the maximum short-circuit current. The tuning device is connected across the main coil and provides high impedance over a specified PLC frequency band. The surge arrester limits the lightning and switching over voltages applied to the line trap. Depending on the type of tuning (i.e., single-frequency, double frequency, and wideband), the tuning device consists of capacitors, inductors, and resistors, all having relatively low-power ratings compared to the main coil [20]. When line traps are installed at the TL ends, most of the fault-induced HF components are confined to the faulty transmission line regardless of configuration of the primary system switchgear. As a result, a protective algorithm based on the spectral energy of the fault-induced transients can well discriminate between internal and external faults. In other words, the line trap provides the required high impedance at the high frequencies so that the reflection and refraction coefficients of the TL termination points are not affected considerably by variation of the substation parameters. It should be considered that, in practice, there are some limitations in selection of the values of the line trap parameters. Since the main coil carries the TL current, a high inductance main coil could develop into a physically very large dimension. Moreover, the undesired voltage drop across the line trap at the fundamental frequency increases with an increase of the main coil inductance. According to theIEC 60353 standard, the value of the main coil inductance should not be more than 2 mH [21]. For this value, the voltage drop across the line trap is negligible. For high-frequency studies, the stray capacitance of the main coil should also be modeled.

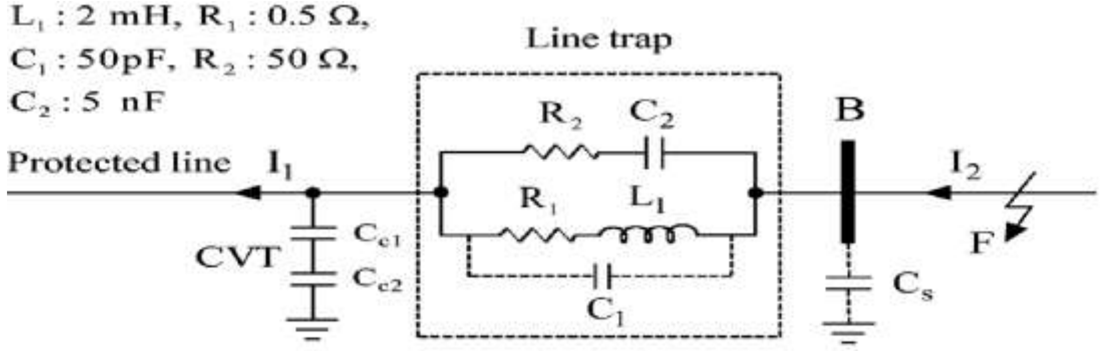

Fig.3. Circuit diagram and parameters of the designed line trap.

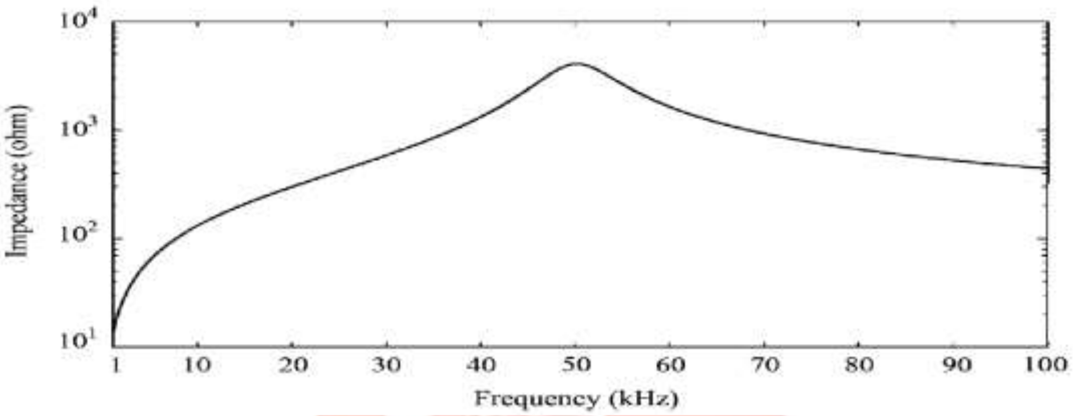

Fig.4. Equivalent impedance of the designed line trap at different frequencies.

Fig.3 depicts the designed line trap installed at the protected TL ends. In thisfigureL1,R1,C1,and denote the inductance, resistance, and the equivalent stray capacitance of the main coil, and R2 and C2 denote the resistor and tuning capacitor, respectively. The frequency response of the designed line trap is shown in Fig. 4. Considering the frequency band of the fault-induced HF transients, which is mostly in the range of 10–100 kHz, the resonance frequency of the line trap is tuned at 50 kHz. It should be noted that, in practice, CVTs are also installed at the TL ends to measure the phase voltages. CVTs are installed after the line trap at the TL side. Thus, in this paper, CVTs are appropriately modeled to consider their influence on the frequency characteristics of the line trap.

D. Neural Network

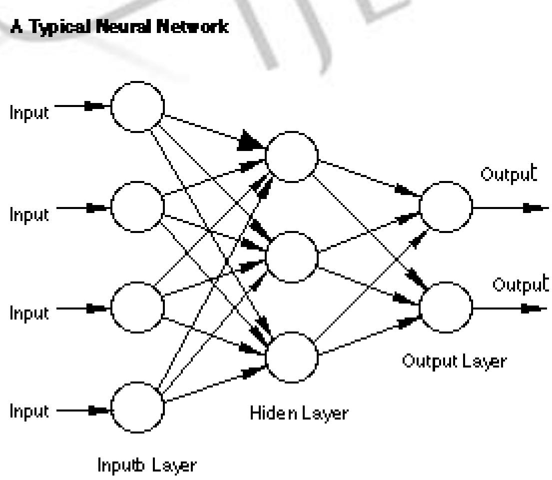

Fig.5. Typical Neural network layer

A neural network has several input, hidden, and output nodes. Each node applies a function some data (could be softmax, linear, logistic), and returns an output. Every node in the proceeding layer takes a weighted average of the outputs of the previous layer, until an output is reached. The reasoning is that multiple nodes can collectively gain insight about solving a problem (like classification) that an individual node cannot. The cost function differs for this type of model the weights between nodes adjust to minimize error. . The objective of the training process is to adjust all ANN weights and biases to obtain minimal deviations between the target and calculated ANN outputs in relation to the mean value of all input samples. Once the training process is completed the results of training must be checked, first using the samples used in training and then new samples not used in training. To implement a neural network, the following steps must be taken, selection of a suitable network architecture; selection of the learning rule best suited to the network established; training of the neural network; checking of network behaviour.3. Fault location approach using ANN The basic points of the procedure used to implement neural network in the fault location process in single, two-terminal transmission lines.

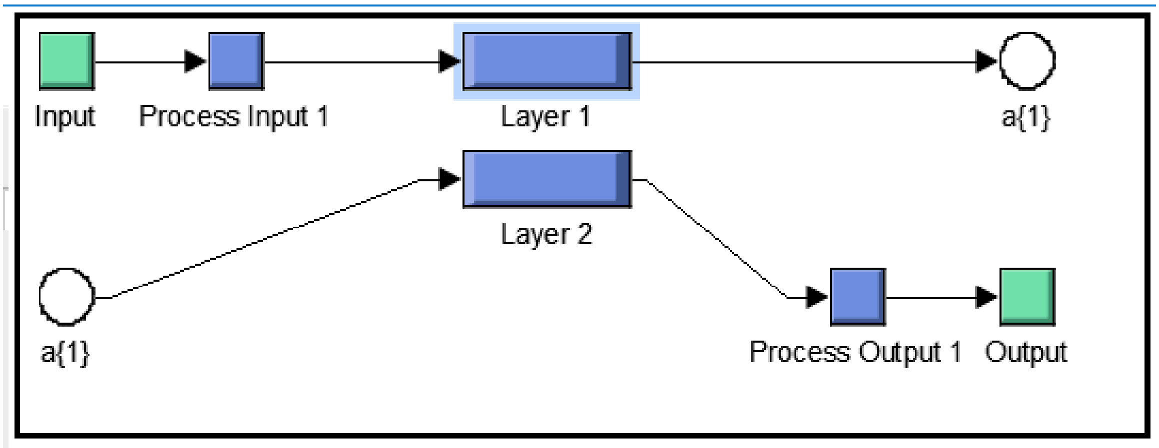

Fig.6. ANN architecture for fault type classification**.**

Figure5. shows the internal configuration of layer 1 of ANN2 in which total 15 number of neurons with weights and bias value shown. The weight value updated based on input training data set for generation of target value which also decided by designer. All 15 neurons consist of activation function or transfer function which coupled using multiplexer for generation of single decision based on training data set. Where layer 2 is output layer consist of 3 neurons layer which decide fault zone location likewise zone1, zone2 and zone3 fault on transmission line shown in fig.6

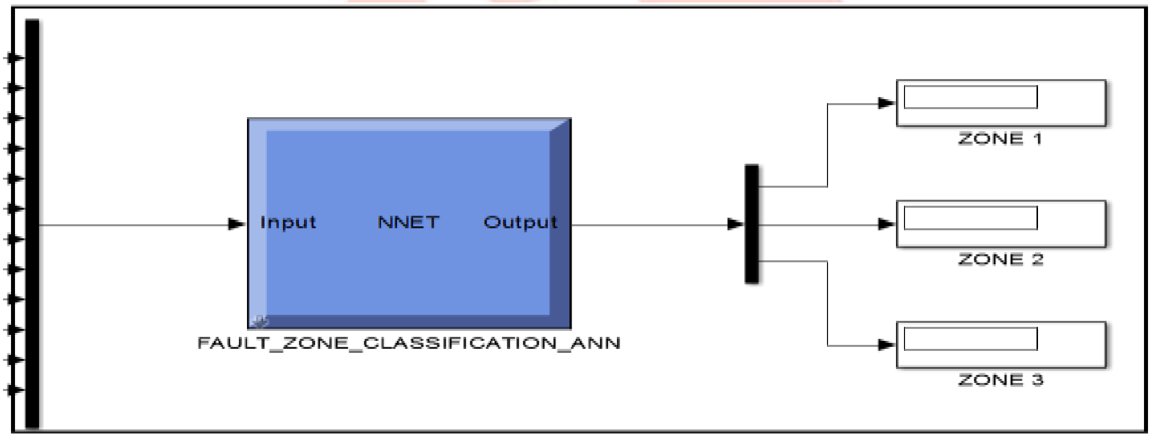

Fig.7. ANN2 model for fault zone identification.

Figure 6shows the neural network structure, in which layer 1 is input layer while layer 2 is output layer of ANN2 for transmission line fault zone identification. Figure

III.PROPOSED APPROACH

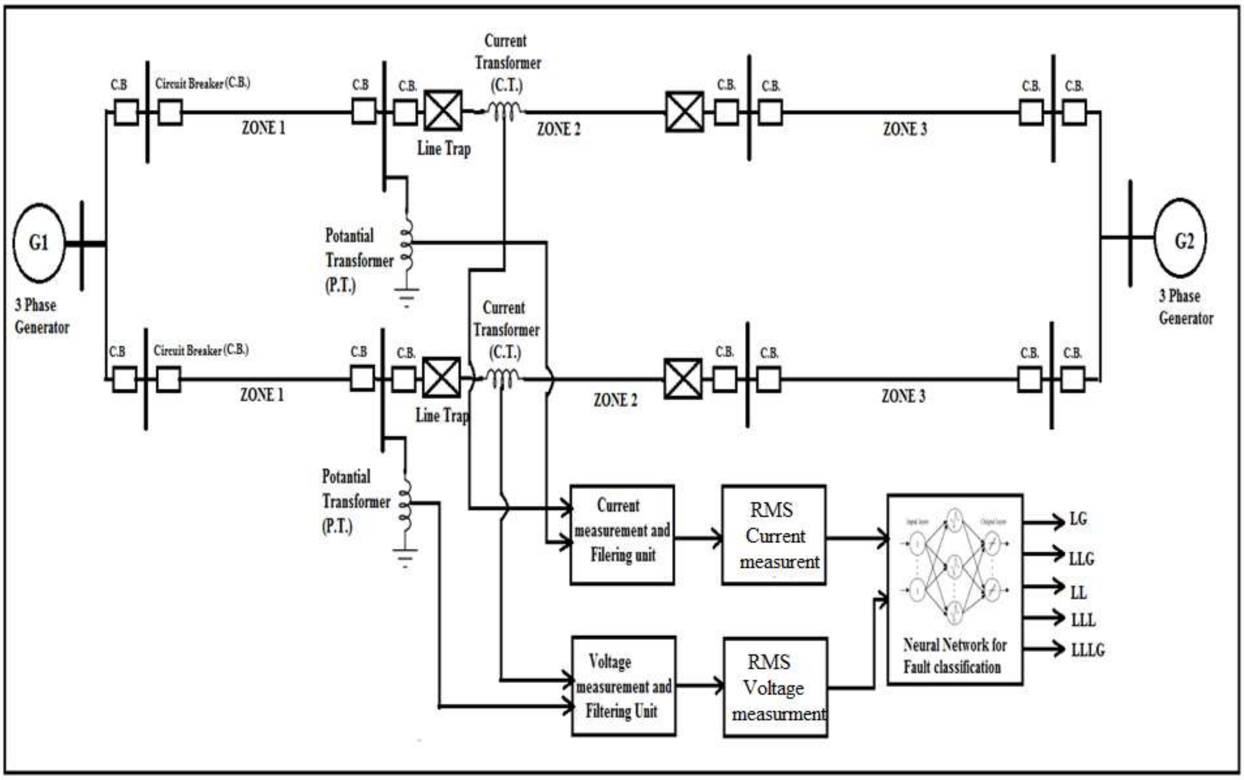

Fig.8. PROPOSED APPROACH

This method presents a protection technique based on the high-frequency transients generated by the fault to cover almost the total length of double circuit transmission lines. For this purpose, appropriately designed line traps are installed at terminals of the protected transmission line, and the Artificial Neural Network with suitable number of Neurons is used to classify the different types of faults based on the frequency spectrum of the current and voltage signals decomposed by the wavelet transform. Extensive simulation studies indicate that the proposed approach is well capable of discriminating between the internal and external faults and provides a very fast, secure, and reliable protection technique. The simulation model done in MATLAB Simulink for system analysis.

A. Current transformer (C.T.)

The transformer used for measurement of current is called as current transformer. The current transformer is used with its primary winding connected in series with line carrying the current to be measured and, therefore, the primary current is dependent upon load connected to system and is not determine by the load (burden) connected on the secondary winding of the current transformer. The primary winding consists of very few turn and, therefore, there is no appreciable voltage drop across it. The secondary of current transformer has larger number of turns, the exact number being determined by the turns ratio. The ammeter or wattmeter current coil, are connected directly across secondary winding terminals. Thus a current transformer operates its secondary winding nearly under short circuit condition. One of the terminals of the secondary winding is earthed so as to protect equipment and personnel in the vicinity in the event of insulation breakdown in current transformer.

B. Capacitance voltage transformer (C.V.T.) or Potential transformer (P.T.)

The transformer used for measurement of voltage is called as current transformer. Potential transformers are used to operate voltmeters, the potential coils of wattmeter and relays from high voltage lines. The primary winding of transformer is connected across the line carrying the voltage to be measured and the voltage circuit is connected across the secondary winding.
The design of potential transformer is quite similar to that of a power transformer but the loading of potential transformer is always small, sometimes only a few volt-ampere. The secondary winding is design so that a voltage of 100 to 120V is delivered to the instrument load. The normal secondary voltage rating is 110V.

C. Training of ANN

Figure.9. Training matrixes

Figure. shows that 93% data are perfectly classify the fault and remaining fault case data not classify using neural network 1. It means that for remaining 7% data set neural network was in confusion state for classify the fault.

D. Training of ANN2 for fault zone identification

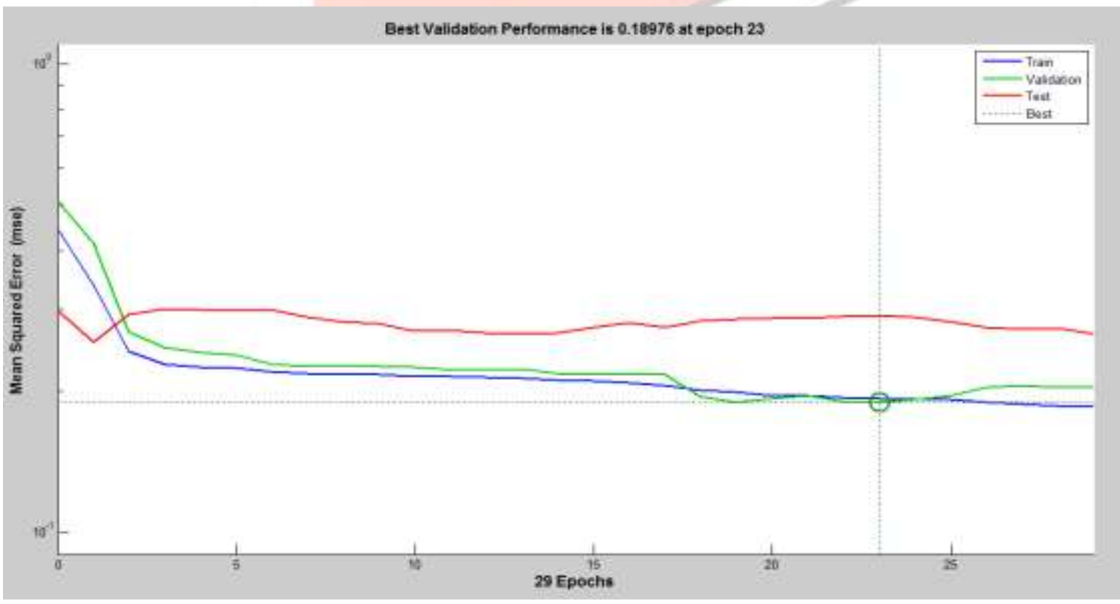

Fig.10. Training performance of ANN2 for transmission line fault zone identification

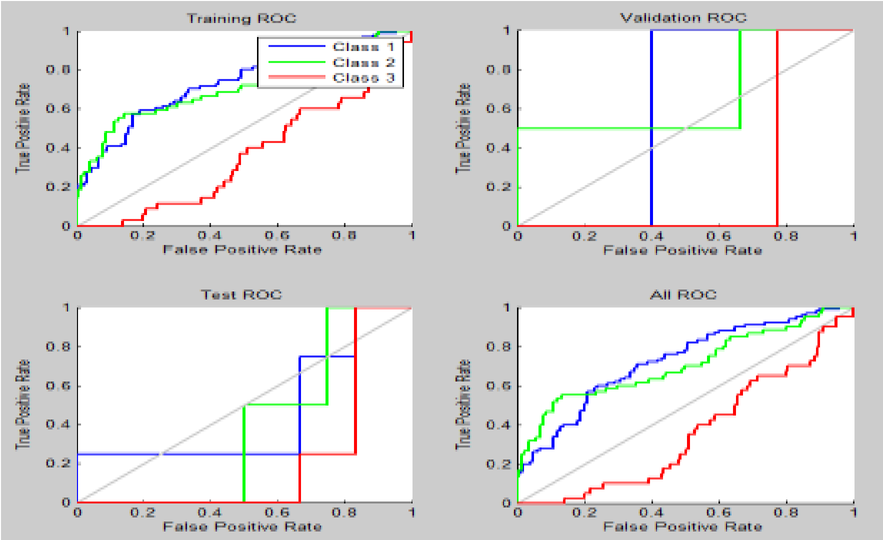

Fig.11. ROC after successful training of ANN2 for transmission line fault zone identification

The receiver operating characteristic (ROC) is a metric used to check the quality of classifiers. For each class of a classifier, roc applies threshold values across the interval [0,1] to outputs. For each threshold, two values are calculated, the True Positive Ratio (the number of outputs greater or equal to the threshold, divided by the number of one targets), and the False Positive Ratio (the number of outputs less than the threshold, divided by the number of zero targets).

E. ANN training data set

Table 7.4: ANN training data set for fault classification and fault zone identification of first three phase of transmission line.

S.N.	ZONE	Location	TYPE OF FAULT	VA B21	VB B21	VC B21	IA B21	IB B21	IC B21
1	Zone 1	100km (BUS 1&2)	AG	2.42E+04	2.42E+04	2.73E+04	3.17	3.84	3.74
2	Zone 1	100km (BUS 1&2)	BG	2.43E+04	2.42E+04	2.73E+04	4.29	3.6	4.299
3	Zone 1	100km (BUS 1&2)	CG	2.43E+04	2.42E+04	2.73E+04	3.79	3.905	3.222
4	Zone 1	100km (BUS 1&2)	AB	2.43E+04	2.42E+04	2.73E+04	0.3997	0.4535	0.4052
5	Zone 1	100km (BUS 1&2)	BC	2.43E+04	2.42E+04	2.73E+04	0.3997	0.4534	0.4052
6	Zone 1	100km (BUS 1&2)	AC	2.43E+04	2.42E+04	2.73E+04	0.3997	0.4535	0.4052
7	Zone 1	100km (BUS 1&2)	ABG	2.43E+04	2.42E+04	2.73E+04	2.696	2.576	3.217
8	Zone 1	100km (BUS 1&2)	BCG	2.43E+04	2.42E+04	2.73E+04	3.166	2.54	2.641
9	Zone 1	100km (BUS 1&2)	ACG	2.43E+04	2.42E+04	2.73E+04	2.936	3.596	2.932
10	Zone 1	100km (BUS 1&2)	ABCG	2.43E+04	2.42E+04	2.73E+04	0.3997	0.4534	0.4052
11	Zone 1	100km (BUS 1&2)	A'G	1.89E+04	2.42E+04	2.15E+04	88.48	5.695	5.534
12	Zone 1	100km (BUS 1&2)	B'G	1.97E+04	1.98E+04	2.73E+04	6.271	96.41	6.32
13	Zone 1	100km (BUS 1&2)	C'G	2.43E+04	1.87E+04	2.17E+04	5.539	5.595	83.79
14	Zone 1	100km (BUS 1&2)	A'B'	9466	2.26E+04	2.38E+04	123.3	123.5	0.4051
15	Zone 1	100km (BUS 1&2)	B'C'	2.25E+04	9486	2.40E+04	0.3999	117.7	117.7
16	Zone 1	100km (BUS 1&2)	A'C'	2.08E+04	2.06E+04	1.07E+04	106.9	0.4535	106.8
17	Zone 1	100km (BUS 1&2)	A'B'G	9466	2.02E+04	2.14E+04	124	130.1	4.554
18	Zone 1	100km (BUS 1&2)	B'C'G	2.01E+04	9486	2.15E+04	4.581	127.1	116.8
19	Zone 1	100km (BUS 1&2)	A'C'G	1.86E+04	1.85E+04	1.07E+04	114.3	5.148	110.5
20	Zone 1	100km (BUS 1&2)	A'B'C'G	9466	9486	1.07E+04	132.4	144.2	125.3

CONCLUSION

This proposed approach needs more time for generating the training data set required for training neural network hence it is time consuming method during training but after successful training both neural network classify the fault class and fault zone. For improving the performance of ANN, it needs proper selection of transfer function or activation function and number of neurons as well as neuron layers for ANN architecture design this will required proper analysis and more time. Efficiency of this method is 89% as compared with Support vector machine technique having 73% efficiency.

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