A Simple Approach to Identify Power System Transmission Line Faults using PNN

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***Abstract* -** Large interconnected overhead transmission lines are very often subjected to various types of faults leading to mal-operation or even discontinuity of good quality power flow. Hence, accurate and prompt identification and classification of different power systemfaultshave become one of the major areas of research these days to ensure reliability, protection and system stability.This paper presents a Probabilistic Neural Network (PNN) based simple and novelapproachto distinguish and classify different types of power system faults. Electromagnetic Transient Program (EMTP) simulation software has been used to simulate a frequency dependent model and extract the receiving end voltage data only for various faults carried out at different distances. Only two sets of simulated data corresponding to two different locations are fed directly to the PNN algorithm so designed for training, instead of preprocessing the data by filtering tools like Wavelet Transform, component analysis etc. which is done most commonly, thus requiring lesser computation burden, thus saving time. Experimental verification has been carried out to validate the proposed algorithm.

***Index Terms*—**Probabilistic Neural Network (PNN), Electromagnetic Transient Program (EMTP),

I. INTRODUCTION

Electrical power transmissionsystem is one of the most widespread and largest engineering networks meant for energy transfer. The lion's share of this power transmission is done by overhead transmission lines which remain directly in contact with the atmosphere, and hence, quite often are subjected to several atmospheric hazards leading to minor to severe power system faults. Sometimes these faults are temporary in nature, and sometimes, sustain for a long time. The relays connected to the transmission lines and the Current Transformer (CT) and Potential Transformer (PT) sense the line currents and voltages and send the actual signals to the controller unit which senses the fault, if any, and sends an actuating (or tripping) signal to the respective circuit breakers which operate accordingly to interrupt the fault current at the exact location or bus specified. The situation complicates further when it is a three phase system, since the fault could occur in any one or two or may be among all the three lines, may be involving ground in some cases. Isolation of only the faulty phase is the most essential in order to ensure a reliable and continuous power supply, even at a reduced power flow through the healthy phases. Therefore, quickidentification and classification of faults is of most importance to ensure power system stability and reliability. The proposedresearch work is intended to serve the same purpose, i.e. to detect power system fault, if any, and categorize the fault in different fault types for a 400 kV, three phase, single circuit, 150 km long overhead transmission line.

The primary objective of power system fault analysis is to extract some key features from the fault waveforms using the different identifier techniques and provide these data to the detection mechanism to find the true cause of the fault and restore the normal operation in least possible time.Techniques normally used to develop such power system protection algorithm are Wavelet Transformation based Artificial Neural Network (ANN) analysis, Fuzzy Inference system, Principal Component Analysis (PCA), support vector analysis etc.and differenthybrid models of these individual techniques.The tripping circuit of the circuit breakers and other protective relaying mechanisms are given proper signals at the correct instants during any mal-operation, to interrupt the power flow immediately.Hence, fast and accurate detection of fault along with precise fault location have been practiced by researchers to ensure safety.Researchers have devoted much time for the purpose of fault identification and classification and developed different mathematical and computational tools for the detection, classification and localization of electrical power system faults to activate the tripping elements at proper time and proper locations[8].

Artificial Neural Network (ANN) along with Neuro Fuzzy System and Wavelet based fault pattern recognition techniques have been extensively used these days [1]-[6]. But the ANN implementation requires a large number of training data as well as training cycles, thus requiring heavier amount of data and computational burden [7]-[11].Other techniques include wavelet transform with other methods such as Probabilistic Neural Network (PNN), adaptive resonance theory, adaptive neural fuzzy inference system, and support vector machines [3], [12]-[14]. Fuzzy logic has also been combined with discrete Fourier transform, adaptive resonance theory, principles of estimation and independent component analysis to enhance performance [15],16].

II. SYSTEM DESIGN

The proposed algorithm has been designed based on the pattern recognition capability of the Artificial Neural Network (ANN). The design has been carried out to identify faults and find out the particular fault type if any. The phase voltages of the three phases have been given as inputs to the proposed neural network. The power system network has been taken to be a 150 km long transmission line which is segmented into 15 blocks each of 10 km line. The simulation has been carried out in EMTP-ATP simulation software and the data have been taken therefrom.The simulation model is of frequency independent type so that we get a more realistic approach to the real time situation.The entire simulation schematic has been shown in fig. 1.

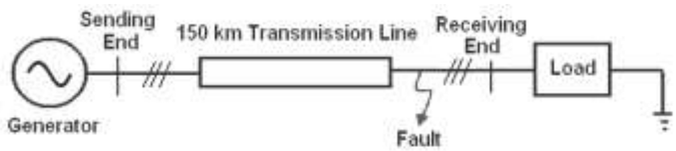

Fig. 1. Single line diagram of power system network.

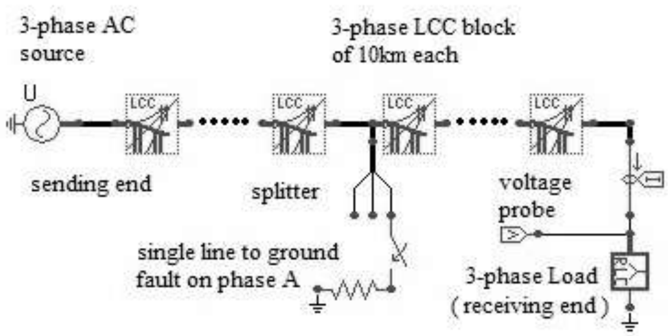

Fig. 4.EMTP simulated radial power system network

A simple technique for fault type classification in a radial system has been developed here. EMTP-ATP simulation software has been used to simulate the transmission line model. The faults were considered as a part of the transmission line which has been simulated at every 10 km in a 400 kV-150 km long three phase single circuit transmission line. The simulation was followed by analysis of the three phase voltage waveform for classification of fault types using Artificial Neural Network in the MATLAB environment. The proposed protection scheme is tested under different fault types and varying fault locations. The entire test results of the automatic recognition achieved by the ANN, show that the exact fault types have been detected and classified within half cycle after the occurrence of the fault.

A. Radial Power System Network

To obtain the necessary information about the fault types of a radial power system network, a 400kV 150 km long three phase transmission line model is experimented. The one line EMTP simulation diagram of the studied system is shown in fig 1. The circuit is mainly designed to detect the types of faults in the transmission line. The voltage waveforms are monitored from the receiving end. Since we have used a single side fed power system model, the transmission system consists of only one three phase AC voltage source having a rating of 400 kV 50 Hz.Fifteen LCC three phase blocks of 10 km are taken for simulating the 150 km long overhead transmission line. The frequency dependent 'JMarti' model is taken here as the basic building block of the power system network. The line resistance is taken as 20 Ohm/km and the fault resistance being 10 Ohm. For the various types of faults occurred at different locations, the faulty voltage signals only are collected and analyzed in ATP analyzer. The sampling frequency is taken to be 2000 samples/cycle, yielding better accuracy.

III. NEURAL NETWORK CLASSIFIER

An Artificial Neural Network (ANN) can be defined as a modern data processing system. The ANN architecture is basically a mathematical model intended for computation of especially a very large number of simplesby, usually a large number of highly interconnected processing elements called artificial neurons. These neurons can compute values from inputs by feeding information through the network. This ANN technique is highly useful for pattern recognition as it can be programmed or designed to identify the identical types of data from a very large number of information, i.e. pattern recognition is its one of the most useful applications. Now-a-days, this particular feature of these neural networks is used extensively in power system analysis for fault classification process. Usually, the voltage or current waveforms of the system of the corresponding fault are collected and matched with the prototypes using suitable algorithm to obtain the correct pattern matching.

A. Probabilistic Neural Network

Probabilistic neural network (PNN) is a special category of ANN structure differing from the conventional ANN architecture in only a few areas.It is a kind of radial basis network suitable especially for classification problems. The architecture is feed forward in nature which is similar to back propagation algorithm adopted for ANN, but differs in the learning process, i.e. how the training is performed before testing. Fig. 2 describes a prototype PNN model which has been adopted in this work. Similar to the ANN architecture, PNN also hasan input layer, an exemplar layer, a summation layer or class layer and an output layer or decision node.Probability Density Functions (PDFs) are statistically estimated based on training waveform patterns and are used as the activation function of a neuron to train the network.The input layer represents the input pattern and takes the feature vector as an input. Although in our experiment, we have simply given the original sampled data regarding the three phase voltage waveform taken at the receiving end without any modification or feature extraction. Next layer is called exemplar or more commonly referred to as hidden layer. This layer consists of several nodes, usually much higher in number compared to the input layer and it is highly interconnected with all the nodes or inputs of the input layer. Thus, each point of this particular layer receives the information regarding all the inputs. This layer contains the example vectors (the training set for the PNN), thus the actual example vector serves as the weights as applied to the input layer. Finally, there is an output layer consisting of several decision-making nodes, thus representing each of the possible cases for which the input data can be classified. In the proposed work, the total number of possible cases is eleven, i.e. one healthy condition and ten different types of faults.However, the hidden layer is not fully interconnected to the output layer. The example nodes for a given class connect only to that class's output node and none other.Thus, it is evident that PNN is a supervised learning algorithm but includes no weights in its hidden layer. Instead each hidden node here represents an example vector, which acts as the weights to that hidden node.

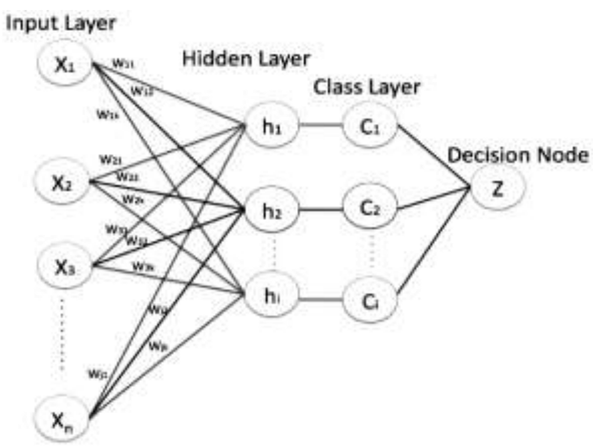

Fig. 2.PNN Architecture showing different layers

B. Back Propagation Algorithm

Among the several algorithms used in neural networks, Back Propagation has been adopted in the proposed work. Sigmoid function, similar to the step function,is used in the proposed work to train the neurons in between the nodes in the hidden layer, the transfer function and characteristic curve of which is given by σ(x) and fig. 3 as follows:

$$\sigma(x) = \frac{1}{1+e^{-x}};$$

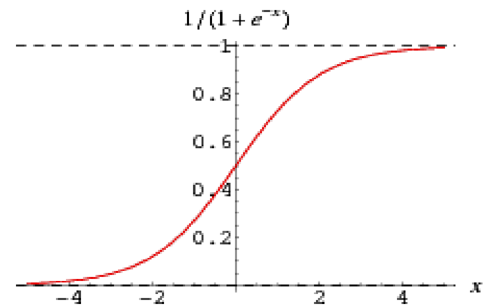

Fig. 3. Characteristic curve of Sigmoid Function used for PNN

Hence,

$$\frac{d\sigma(x)}{dx} = \sigma(x)[1-\sigma(x)]$$

If input to the neuron isξ, say and the corresponding weight issay ω, then output ***O*** is given by,

$$O = \sigma(\xi\omega)$$

And considering a threshold or bias term, say θ, the output becomes as,

$$O = \sigma(\xi\omega + \theta)$$

Minimizing the Mean Square Error (MSE) is the primary objective of the given method. Hence, for a given set of target data points $t_j$and layer output O_j, theMSE is given as,

$$E = \frac{1}{2}\sum_{k\epsilon K}(O_k - t_k)^2$$

The summation is taken over all the nodes in the output layer (K). This method calculates the rate of change of MSE with respect to the connective weights of each respective path, i.e. $\frac{\partial E}{\partial \omega_{jk}^{l}}$and updates the weights in consecutive iterations in a direction of convergence of MSE towards zero.

For the output layer, this rate of change of MSE is given by:

$$\frac{\partial E}{\partial \omega_{ij}^{l}} = O_j\delta_k$$

Where,$\delta_k = (O_k - t_k)\, O_k(1-O_k)$, and ω_{ij}^{l} is the weight from node "*i*" of (l-1)th layer to node "*j*" of the layer l and for the hidden layer node the weight is to be calculated from input layer to hidden layer, and rate of change of mean square error is given can be formulated as,

$$\frac{\partial E}{\partial \omega_{jk}^{l}} = O_j \delta_j$$

Where , $\delta_j = O_j(1 - O_j)\sum_{k\epsilon K}(\delta_k \omega_{jk})$

Even incorporating of the bias term θ, it can be observed that,

$$\frac{\partial O}{\partial \theta} = 1$$

Hence, the bias term is looked upon as output from a node which is always equal to 1 and it holds for every layer.

Hence, it can be said that,

$$\frac{\partial E}{\partial \theta} = \delta_l.$$

A prototype Neural Network classifier is used here for different types of faults recognition and classification. A total of thirteen sets of data are taken at thirteen different locations, each separated by 10 km of the 150 km long transmission line, excepting for the generating station andthe load point. Each set of data contains quarter cycle pre-fault and half cycle of post-fault sampled voltage data corresponding to the receiving end for the three phases.Each set consists ofone pure and ten different types of faulty signals for the training as well as testing purpose of the neural network for the radial power system transmission network. Since we have used 2000 samples/sec as the sampling rate, (1/4) cycle pre-fault and (1/2) cycle post-fault waveform counts for a total of 1500 sample data.

C. Training of PNN

The PNN architecture constructed by connecting the nodes layer by layer has to be trained before testing, i.e. the neural network must be provided with some specific inputs and the corresponding known outputs in order to make the network understand the relationship between the input and the output and modify the weights in each layer accordingly. This is done so that the network becomes adaptable to similar unknown inputs to predict or determine the corresponding output.

In our work, the power system model simulated using the PNN feature is trained in two ways. At first, the model is trained using only one set of data corresponding to a particular location in the network. This location is taken to be at 70 km away from the sending end i.e. almost the midpoint of the transmission line. Thus, a total of eleven sets of signals containing ten types of faults and one healthy signal are taken here for the training. Thus the dimension of the training data matrix becomes 1500 × 11 and the results were taken using the remaining twelve sets of data corresponding to remaining locations and tested whether the designed model could successfully identify the faults or not. We have deliberately taken the fault location at almost the mid-point of the transmission system to make the system more adaptable to identify faults on both sides of the midpoint.

In the second run, the designed PNN model is trained by twenty two sets of signals i.e. eleven sets of data corresponding to two different locations, viz. 70 km and 10 km from the sending end, for achieving better accuracy. In this proposal, one set of data is taken at the midpoint as before and the other training set has been taken almost at the generating end, i.e. at one side of the transmission system. The size of the training input vector for this run becomes 1500 × 22 this time to ensure better accuracy for faults occurring at any point all throughout the entire length. In this case, the training is done more accurately, but at the cost of higher processing time.

D. Target of PNN

Target of PNN is modeled here as numbers like 1, 2, 3, 4, 5, 6, 7, 8, 9, 10 and 11. Each number representany particular type of fault, e.g. 1 represent healthy condition 2, 3, 4 represent pure, single line to ground fault for line A, B and C respectively, 5, 6, 7 represent line to line fault in between lines AB, BC and CA respectively, 8, 9, 10 represent double line to ground fault in between linesAB-G, BC-G and CA-G respectively and 11 represents three phase fault ABC.

E. Testing of PNN

Pure signal along with ten different types of faults are considered in each set to test the simulated PNN based protection algorithm.The three phase receiving end voltage signals for different types of faults at thirteendifferentlocations for the first part of the experiment and corresponding totwelve different locations for the second part of the experiment are used here for testing the radial network to classify the types of faults. The PNN model has been tested successfully as the results have matched the target pattern.

IV. SIMULATION AND RESULT ANALYSIS

After training the neural network based fault detector and classifier, it is tested extensively using independent data sets consisting of fault scenarios not used previously for training the network. The fault type, fault locations are changed to investigate the effects of these factors on the performance of the classifier and validate the proposed scheme.

The proposed classification system uses only the three phase voltage signals. As has been stated before, we have performed the training in two ways, first by taking only one set of training data of the receiving end three phase voltages for a fault located at 70 km from the sending end in the first case and noted the results. In the second case, the training data has been doubled to achieve higher accuracy of the fault type identification. Table I and table II give the classifier performance for each type of fault for the two types of experiments respectively. We have also incorporated table III here which shows the variation of the fault detection and classification accuracy for the thirteen different fault experiment locations, each separated by 10 km. Observation of table III yields the fact that accuracy of the PNN is very poor when considering the distances close to the sending end, especially at 10 km distance the classifier cannot detect any fault at all, and concludes it to be a healthy system. The accuracy level increases as we move towards the receiving end as can be seen from table IV. Hence, in the second case, we have deliberately taken the second fault data corresponding to 10 km from the sending end as our second set of training data.

TABLE – I

PNN RESULTS SHOWING THE FAULT CLASSIFIER PERFORMANCE WITH ONLY ONE SET OF TRAINING DATA TAKEN AT 70 KM FROM SENDING END

Fault Type	PURE	AG	BG	CG	AB	BC	CA	ABG	BCG	CAG	ABC
PURE	**13**	0	0	0	0	0	0	0	0	0	0
AG	**1**	**12**	0	0	0	0	0	0	0	0	0
BG	**1**	0	**12**	0	0	0	0	0	0	0	0
CG	**1**	0	0	**12**	0	0	0	0	0	0	0
AB	**2**	0	0	0	**11**	0	0	0	0	0	0
BC	**2**	0	0	0	0	**11**	0	0	0	0	0
CA	**1**	0	0	0	0	0	**12**	0	0	0	0
ABG	**2**	0	0	0	0	0	0	**11**	0	0	0
BCG	**1**	0	0	0	0	0	0	0	**12**	0	0
CAG	**1**	0	0	0	0	0	0	0	0	**12**	0
ABC	**1**	0	0	0	0	0	**1**	0	0	0	**11**
Overall Accuracy: 90.21 %											

TABLE – II

PNN RESULTS SHOWING THE FAULT CLASSIFIER PERFORMANCE WITH TWO SETS OF TRAINING DATA TAKEN AT 70 KM AND 10 KM FROM SENDING END

Fault Type	PURE	AG	BG	CG	AB	BC	CA	ABG	BCG	CAG	ABC
PURE	**12**	0	0	0	0	0	0	0	0	0	0
AG	0	**12**	0	0	0	0	0	0	0	0	0
BG	0	0	**12**	0	0	0	0	0	0	0	0
CG	0	0	0	**12**	0	0	0	0	0	0	0
AB	0	0	0	0	**12**	0	0	0	0	0	0
BC	0	0	0	0	0	**12**	0	0	0	0	0
CA	0	0	0	0	0	0	**12**	0	0	0	0
ABG	0	0	0	0	0	0	0	**12**	0	0	0
BCG	0	0	0	0	0	0	0	0	**12**	0	0
CAG	0	0	0	0	0	0	0	0	0	**12**	0
ABC	0	0	0	0	0	0	0	0	0	0	**12**
Overall Accuracy: 100 %											

TABLE – III

FAULT CLASSIFIER PERFORMANCE WITH VARYING DISTANCES FOR FIRST PHASE OF EXPERIMENT

Location of the Fault (km)	Total Data Taken	Correct Results	Wrong Results	% Accuracy
10	13	0	13	0
20	13	9	4	69.23
30	13	13	0	100
40	13	13	0	100
50	13	13	0	100
60	13	13	0	100
80	13	13	0	100
90	13	13	0	100
100	13	13	0	100
110	13	13	0	100
120	13	13	0	100
130	13	13	0	100
140	13	13	0	100

TABLE – IV

FAULT CLASSIFIER PERFORMANCE WITH VARYING DISTANCES FOR SECOND PHASE OF EXPERIMENT

Location of the Fault (km)	Total Data Taken	Correct Results	Wrong Results	% Accuracy
10	13	13	0	100
20	13	13	0	100
30	13	13	0	100
40	13	13	0	100
50	13	13	0	100
60	13	13	0	100
80	13	13	0	100
90	13	13	0	100
100	13	13	0	100
110	13	13	0	100
120	13	13	0	100
130	13	13	0	100
140	13	13	0	100

V. CONCLUSIONS

- The purpose of this work is to find an effective technique suitable for the fault identification and classification of power system overhead long transmission lines.A simple PNN model has been implemented here to classify the different kinds of faultsalong with affected phases within half cycle after the occurrence of the faults using, at best, only two sets of receiving end voltage data at two different locations, without considering the current waveforms or any other parameters which may reveal the existence of any fault, thus making the training as well as testing convenient.

- Conventional classifier methods normally use entropy or energy based Waveletdecompositionor other filtering techniques to extract some key features from the waveforms and then use the PNN model to recognize the different fault patterns, where as in the proposed work, the sampled voltage data is fed directly to the PNN classifier model without any modification of the original data, thus reducing computational burden arising from the conventional filtering processes and minimizing analysis time.Hence the operation of this classifier is very simple and here lies the novelty of the proposed scheme.

- The results presented in this paper show that the classifier accuracy reaches 90.21% while using only one set of training data. In the second phase of the experiment where receiving endvoltage data corresponding to two different locations have been used for training the network,i.e. the training data is doubled using suitable locations, the accuracy improves to as high as 100% which convey the possibility of developing an accurate fault classifier which can be implemented to develop a reliable transient-based power system protection scheme.Further investigations are being carried out to validate the robustness and flexibility of the PNN based proposed classifier performance under varying conditions like changes in the network configurations, different fault inception angles, varying fault resistances etc. The proposed work is also expected to be carried out to detect and classify faults for ring main type system with more than one source, as well as for double circuit long transmission lines.

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