



ANN-BASED ALGORITHM FOR POWER TRANSMISSION LINE FAULT LOCATION

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Abstract

Accurate location of faults on power transmission lines can save both time and money for the electric utility industry. Line search for faults is costly and time consuming. Prompt acquisition of accurate information in a format useful to the system operator is essential for fast fault localization. It would therefore be desirable to use a knowledge-based approach to localize transmission line faults as fast as possible and with a high degree of accuracy. This paper highlights the application of the concept of artificial neural network based algorithm in detecting, classifying and locating different electric transmission lines faults. The fault detection algorithm highlighted in this paper is error back propagation algorithm.

Introduction

According to (Sanaye-Pasand, & Khorashadi-Zadeh, 2003) faults on power transmission lines should be detected, classified and located as fast as possible to ensure that outages due to faults are minimized. Artificial Neural Network (ANN) is a tool used in solving many engineering problems related to detection, classification as well as optimization as opined by (Salman, Yousuf, Saidur, and Parijat, 2011). The neural network is capable of self learning since it is a simplified model of the human brain (Rajveer S., 2012). This self learning capability of the ANN can be applied to faulty transmission lines to

1. detect the presence or absence of fault,
2. classifying the fault into its type
3. and say the distance to fault from a measured substation.

Conventional schemes set thresholds according to the fault currents and voltages (Farhat I., 2013). He further stated that when a fault occurs, the fault currents and voltages develop a transient DC offset component and high-frequency transient component in addition to the power frequency component.

The fault currents and voltages vary with fault type, location, size, and fault inception angle and system condition. These variations cause the space to be nonlinearly separable and an intelligent system like ANN has the capability to handle this nonlinearity.

This process is imperative because fault occurrence on transmission lines cannot be completely avoided owing to some multiple factors. Power transmission line faults should be detected as quickly as possible, in real time if possible, so that appropriate remedial action can be taken before major disruptions to the power supply system take place (Rajveer S., 2012). This paper looks at the possibility of using ANN technology to detect, classify and localize transmission line faults. Accurate fault location can aid in the fast restoration of power in transmission lines.

Concept of ANN

An ANN may be considered a great simplified model of the human brain which can be used to perform a particular task of interest (Wong, Ryan, and Tindle, 1996). An ANN may be connected in different architectural forms and organized in several layers in order to accomplish different tasks of generalization, pattern recognition as well as optimization (Rajveer S., 2012). Neural networks have massively parallel distributed structures which can either be implemented using electronic components or simulated in software (Wong, Ryan and Tindle, 1996).

Artificial neuron model

The neuron model shown in Fig.1 can be described by a function which calculates the output as a function of n number of inputs to it. The idea behind the neuron model as well as the activation function as illustrated below has been adopted from (Introduction to Artificial Neural Networks, 2014).

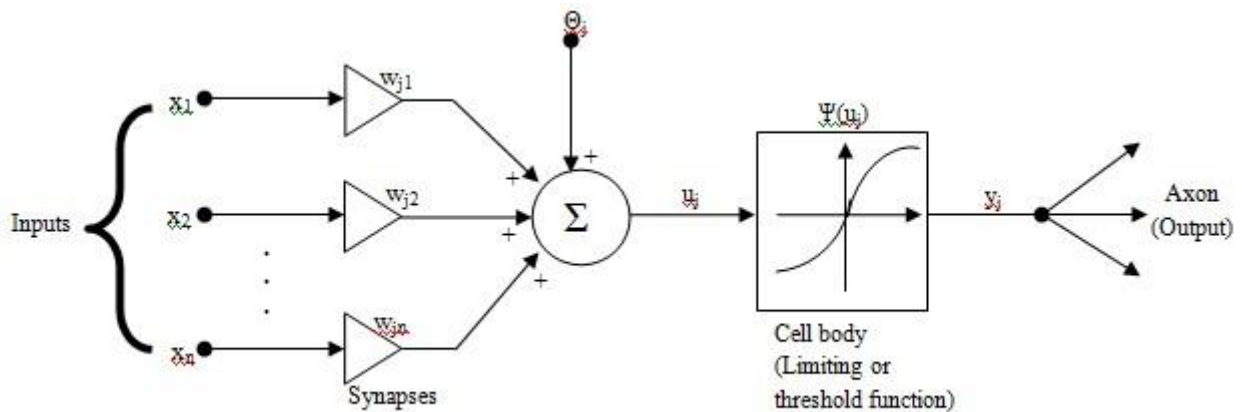


Fig. 1: McCulloch-Pitts Neuron Model

The output of the neuron is given by

$$y_j = \psi \left(\sum_{i=1}^n w_{ji} x_i + \theta_j \right)$$

Where:

- θ_j : external threshold, offset or bias
- w_{ji} : synaptic weights
- x_i : inputs
- y_j : output

Neural networks are known to be universal function approximators as various architectures are available to approximate any nonlinear function (Introduction to Artificial Neural Networks, 2014). Different architectures allow for generation of functions of different complexity and power. There are basically three types of ANN architecture:

1. Feed forward networks
2. Feedback networks and
3. Lateral network

Only one and two will be looked at in this paper.

Feed-forward networks

This network consists of the input layer, one or more hidden layers and an output layer (Wong, Ryan and Tindle, 1996). In the input layer, the number of neurons in this layer corresponds to the number of inputs to the neural network. The function of this input layer is simply to transmit the incoming signal to the next layer. The input nodes are passive because they do not take part in the actual signal modification.

In the hidden layer however, the nodes take part in signal modification, hence, they are said to be active. There exists no magic formula for selecting the optimum number of hidden layer neurons. However, some rule of thumb can be followed in order to calculate the number of hidden layer nodes for optimal performance of the network (Jha, G., n.d.). Geometric pyramid rule can be applied to get a rough approximation for a three layer network with n number of inputs and m number of outputs neurons, the hidden layer would have square root ($n \cdot m$) neutrons.

The number of neurons in the output layer corresponds to the number of the output values of the network. For neural networks with multiple outputs, especially if these outputs are widely spaced, inferior output results are obtained compared to a network with a single output.

Activation function is mathematical formula that determines the output of a processing node. Each mode takes its net input and applies an activation function to it. Examples of nonlinear activation functions are logistic, sigmoid, hyperbolic tangent, etc. The primary purpose is to normalize functions to avoid “saturation” which in turn inhibit training. A feed-forward neural network (FFNN) is capable of modeling complex relationships between variables. A FFNN with just one hidden layer can be used to model the relationship between fault currents and voltages and distance to faults from a measured substation. Examples of FFNN are Figs 4,6, adopted from (Jha G., n.d.).



Feedback network

The output of this neural network is either directly or indirectly fed back to its input via other linked neurons and is used in complex pattern recognition tasks such as speech recognition. A typical example is Jordan Recurrent Network in Fig 2. Feedback networks can have signals traveling in both directions by introducing loops in the network. Feedback networks are dynamic; their ‘state’ is changing continuously until they reach an equilibrium point. They remain at the equilibrium point until the input changes and a new equilibrium needs to be found.

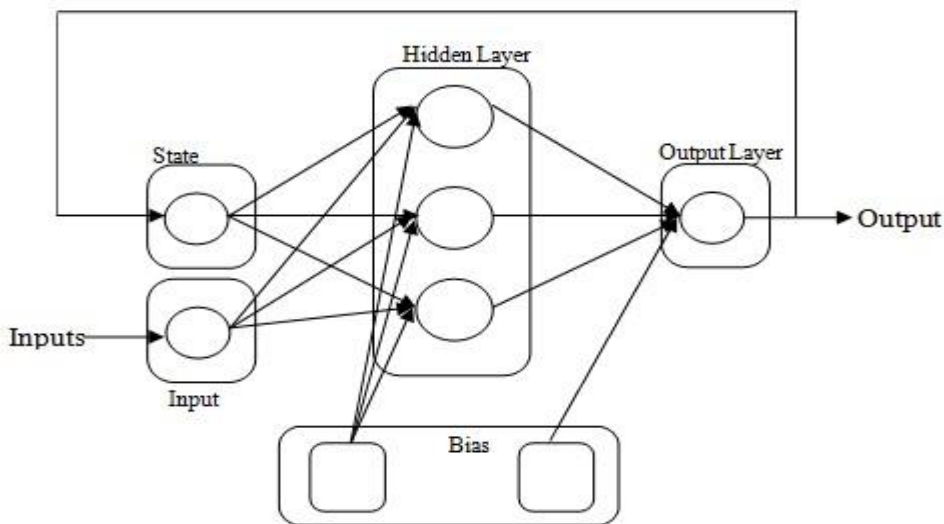


Fig 2: Jordan Recurrent Feedback Network

Learning methods

Artificial neural network works by optimizing network weight values. The method by which the optimized weight values are attained is called learning. There are three types of learning strategies associated with ANN, namely supervised, unsupervised and reinforced learning. In this paper only supervised learning is of interest. In supervised scheme, the network weights are modified iteratively with the prime objective of minimizing the error between a set of inputs and their corresponding target output values (Nwankwo, Inyama, & Azubogu, 2014). The inputs and target output values are to be known prior to the training. The training input-output vectors are obtained either by physical measurement or by performing some kind of simulation. In Fig.3, adopted from (Introduction to Artificial Neural Networks, 2014), the neural network is taught to adjust its weights according to the error “e” between the outputs and the targets. The weights of the neural networks are modified iteratively according to equation (2).

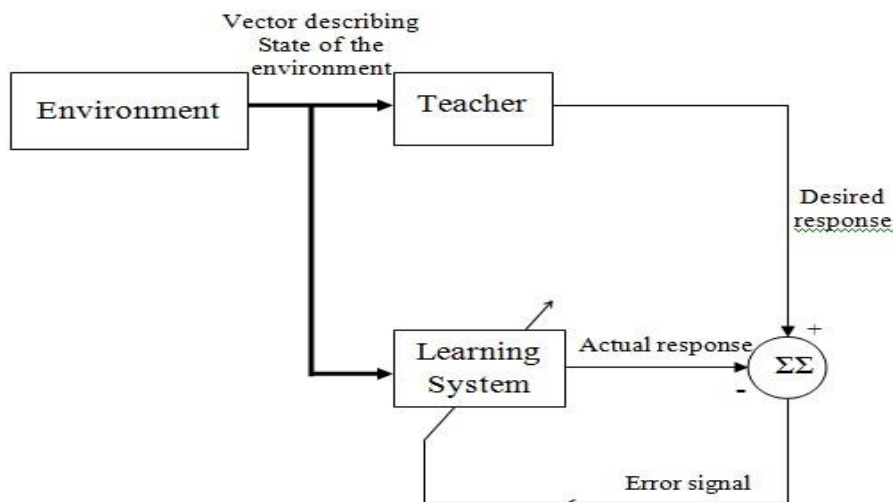


Fig3: Schematic of Supervised Learning



$$f_j = \psi \left(\sum_{i=1}^{n+1} w_{ji} x_i \right); \text{Error} = \sum_{p=1}^p (t_p - f_p)^2$$

Where t_p and f_p are respectively the target and actual outputs for patterns p

The updated weight is given by equation (1),

$$w_i(t + 1) = w_i(t) + \Delta w_i(t) \dots \dots \dots (1)$$

$$\text{with } \Delta w_i(t) = \eta \left(-\frac{\partial E}{\partial w_i} \right)$$

$$\text{and } \frac{\partial E}{\partial w_i} = -2(t_p - f_p) \frac{\partial f}{\partial u_p} x_{i,p}$$

Where η : learning rate

$w_i(t+1)$: new weights

ANN fault detection

The Structure of a feed-forward ANN adopted from (Tahar B, n.d) is shown in Fig. 4. This ANN structure is proposed as a fault detector in this paper. A fully-connected multi layer (input, hidden and output) feed-forward neural network (FFNN) has been used to classify faulty or non faulty condition (Tahar B, n.d). Using supervised learning, ANN can be trained with various input patterns which correspond to different fault types (RG, YG, BG, RYG, YBG, BRG, and RYB, where, R, Y, and B refer to phase values).

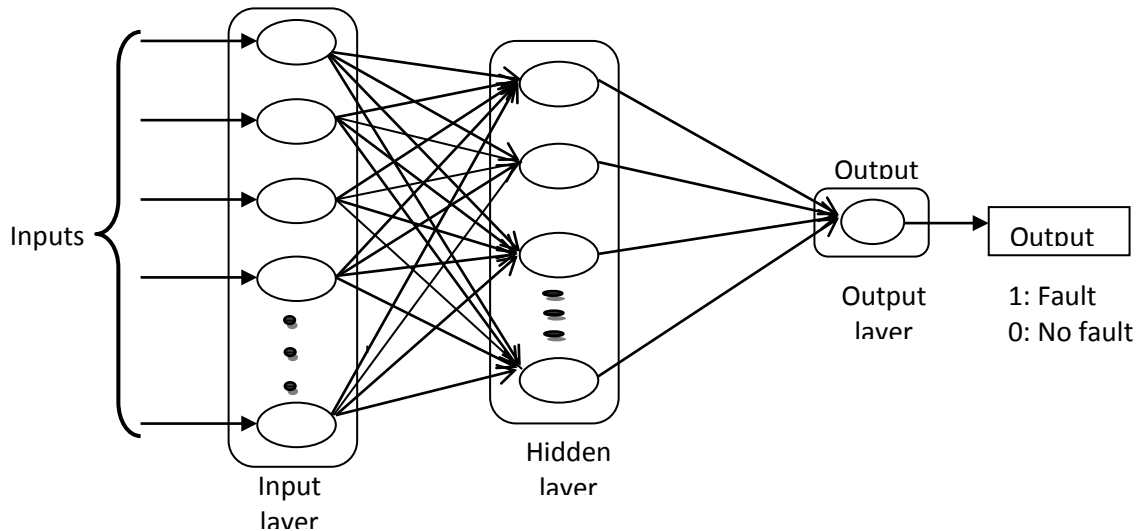


Fig. 4: Structure for ANN fault detector

Fault type classification using ANN

ANNs are characterized by exceptional pattern recognition and learning capabilities. It was stated in (Sanaye-Pasand, & Khorashadi-Zadeh, 2003) that Current based starters get confused when load current is significant compared to fault current and that conventional over current based starter may not be able to detect faults with high amount of fault resistance. It is therefore evident from the above facts that conventional fault detectors might not be able to perform correctly for different fault conditions. It would then be desirable to design a more reliable and fast algorithm to classify different transmission line faults. An ANN-based approach is the focus of this paper as a transmission line fault detector, fault type classifier and fault distance estimator. The ANN structure proposed for their classification is shown in Fig.5. The network has n inputs and three outputs. The number of neurons for the hidden layer is chosen by some heuristics as mentioned earlier. Depending on the type of fault that occurs on the line, the output should be either ‘1’ or ‘0’, which is a normalized value. Table1 shows the neural network desired output for different fault types.



Table 1: Neural network designed outputs

Fault Type	R	Y	B	N
RG	1	0	0	1
YG	0	1	0	1
BG	0	0	1	1
RY	1	1	0	0
YB	0	1	1	0
BR	1	0	1	0
RYG	1	1	1	1
YBG	1	0	1	1
BRG	0	1	1	1
RYB	1	1	1	0

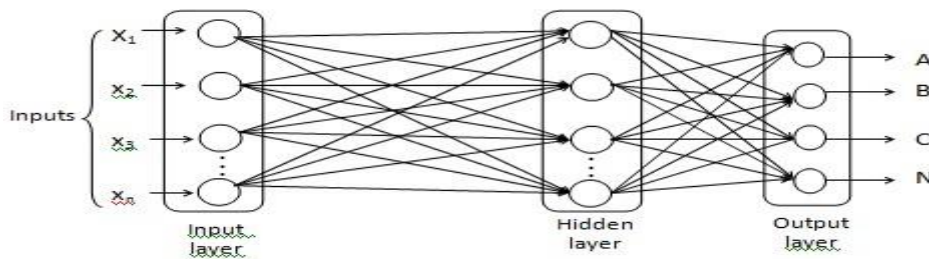


Fig. 5: Schematic diagram of a fault type classifier

ANN fault locator

The ANN based-fault locator is supposed to locate faults on transmission lines. This will use voltage and/ or current magnitudes for each phase that corresponds to the post-fault fundamental frequency as inputs. Normally, the outputs of interest are fault distances (Tahar B, n.d).

When the ANN-based fault locator is fed with the input signals, the ANN locator uses the fed data to estimate the distance to a fault from a given substation. It is worth mentioning again that the ANN system must first be trained under supervised learning mode using any convenient learning algorithm. Gradient Descent, Least Mean Square, Generalized Delta and Error-correction are examples. The training data set are first presented to the locator, in this case, previously recorded post-fault current (or voltage) values and the distances where those faults were located. After this teaching phase, the ANN locator is presented with test data set. The inputs and outputs are checked for satisfactory performance. ANN architecture of the fault locator is shown in Fig. 6, adopted from (Tahar B, n.d).

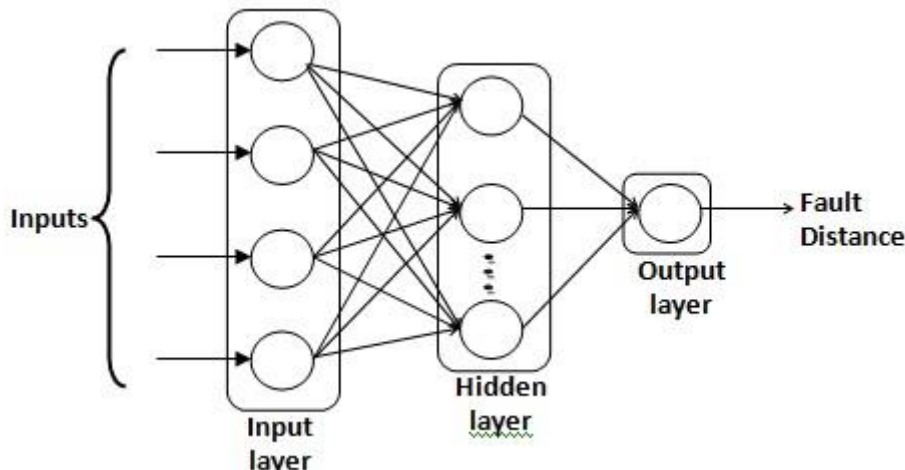


Fig 6: Schematic diagram of ANN fault distance locator



Conclusion

In this paper the application of Artificial Neural Network for more accurate fault detection, classification and localization in transmission lines has been explained. The application of supervised ANN for detection, classification and localization in power transmission lines is the main goal of this paper. Various technologies, methods and strategies have also been looked at so that an interested researcher /designer in ANN-based fault localization system will be able to know which direction to go in further studies.

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