Power system fault prediction using artificial neural networks

Conference or Workshop Item

Power System Fault Prediction Using Artificial Neural Networks

K C P Wong, H M Ryan, J Tindle

School of Engineering and Advanced Technology, University of Sunderland
Edinburgh Building, Chester Road, Sunderland,
SR1 3SD, United Kingdom.
patrick.wong@sunderland.ac.uk, hugh.ryan@sunderland.ac.uk,
john.tindle@sunderland.ac.uk

Abstract -- The medium term goal of the research reported in this paper was the development of a major in-house suite of strategic computer aided network simulation and decision support tools to improve the management of power systems. This paper describes a preliminary research investigation to access the feasibility of using an Artificial Intelligence (AI) method to predict and detect faults at an early stage in power systems. To achieve this goal, an AI based detector has been developed to monitor and predict faults at an early stage on particular sections of power systems. The detector only requires external measurements taken from the input and output nodes of the power system. The AI detection system is capable of rapidly predicting a malfunction within the system . Simulation will normally take place using equivalent circuit representation. Artificial Neural Networks (ANNs) are used to construct a hierarchical feed-forward structure which is the most important component in the fault detector. Simulation of a transmission line (2-port Π circuit) has already been carried out and preliminary results using this system are promising. This approach provided satisfactory results with accuracy of 95% or higher.

1.0 Introduction

Adequate fault detection is vitally important to ensure reliable power system operation. Many system fault studies are concerned mainly with a 'what if' scenario i.e. on considering what would happen after a fault occurred, identifying its location and accessing the nature and degree of damage. To date, few studies have been made concerning early fault detection (EFD) techniques which facilitate the prediction of a major fault before it actually occurs. In a typical power system, the states (voltages and currents) of most bus bar nodes are monitored and gradual changes are analysed. However, because of the complexity of recorded data, faults at an early stage cannot be easily recognised. These faults can be disguised by the complexity of power system operational data [1-6].

The aim of the EFD method is to detect and alert the operator before a catastrophic fault actually occurs. In other words, this is an early warning fault prevention method. ANNs are employed to monitor the states of some important components in power networks, such as switchgear and transformers. The ANN is trained to detect minor changes to the internal parameters modelled as power system equivalent circuits [6]. The small variations of voltages and currents resulting from internal parameters changes, at sending end and receiving ends of the power system can be derived under simulation and then presented to the ANN for training. As some of the internal parameters of the power system do not physically exist, they cannot be measured directly by simple measurement methods. Thus, the application of an intelligent technique, such as an ANN method , is obviously required. The principle of the EFD can be applied to various sections of a power system. A typical extremely simplified example will now be given.

Transmission lines in power systems carry high currents and voltages. Small changes in state, caused by partial faults, on transmission lines are often too insignificant to trigger the conventional protection systems. However, these small scale changes may develop and eventually lead to major faults. For example, in winter, snow may gradually accumulate on transmission lines. The impedance of transmission lines could change accordingly. The circuit breaker would trip when the snow formed a short-circuit and this could "black-out" a large area. With early warning fault monitoring, the interruption of power supply could possibly be prevented. The change of impedance of the transmission line provides vital information which can be analysed by EFD technique to provide an early detection capability. This technique could alert the operator before the main fault actually occurs enabling, in some situations, appropriate action to be taken, e.g. providing power supply from another circuit and switching out the endangered line.

2.0 Artificial Neural Network

An ANN may be considered as a greatly simplified model of the human brain which can be used to perform a particular task or function of interest. The network is usually implemented using electronic components or simulated in software on a digital computer. The massively parallel distributed structure and the ability to learn and generalise makes it possible for ANNs to solve complex problems that otherwise are currently intractable. A brief description of neural network characteristics is given below. For more information, see [9-23].

2.1 Neurons and Synapses

A neuron is an information processing unit that is fundamental to the operation of an ANN. Two basic elements can be identified from a neuron; an adder and an activation function. An adder is used to sum up the input signals, weighted by the respective synapses of the neuron. The activation function limits the amplitude of the output of a neuron. It compresses the permissible amplitude range of the output signal to some finite value. [16]

Synapses are simple connection that can either impose excitation or inhibition on the receptive neuron. Knowledge is acquired by the network through a learning process. The synaptic weights are used to store the knowledge. Through the learning process, the synaptic weights of the network are modified in such a way to map the input patterns to the output patterns. [16]

2.2 Structure of a Artificial Neural Network

Four popular neural network architectures are being widely used [16]. They are the single-layer feedforward network, multi-layer feedforward network, recurrent network, and the lattice structure. The standard multi-layer feedforward network is employed as the network architecture in this project, and is described below. The multi-layer feedforward network is a network of neurons and synapses organised in the form of layers. There are three kinds of layers in an ANN : the input layer, hidden layer and output layer. The function of the input layer is simply to buffer the external inputs to the network. The hidden neurons have no connections to the inputs or outputs. By including hidden layers, the network is empowered to extract higher-order statistics as the network acquires a global perspective despite its local connectivity by virtue of the extra set of synaptic connections and the extra dimension of neural interactions (Churchland and Sejnowski, 1992)[10]. Figure 1 shows the structure of multi-layer feedforward network.

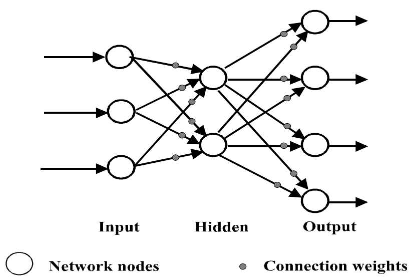


Figure 1. A 3-2-4 multi-layer feedforward network.

As ANNs basically consist of a network of neurons and synapses organised in layers, the source nodes in the input layer of the network supply respective elements of the activation pattern, which constitute the input signals applied to the neurons (computation nodes) in the second layer. The output signals of the second layer are used as inputs to the third layer, and so on, for the rest of the network.

2.3 Learning Algorithm

The procedure used to perform the learning process is called a learning algorithm, the function of which is to modify the synaptic weights of the network in an orderly fashion so as to attain a desired design objective. Many learning methods have been developed in the last few decades. Detailed information of ANN learning algorithms can be obtained from [10],[16],[19].

Two learning algorithms have been used for this project; the standard back-propagation (BP) method and the genetic learning algorithm (GA). BP has already been successfully applied by several workers to solve some difficult and diverse problems by training ANNs in a supervised manner. With regard to the BP method, a training set is applied to the input of the network, signals propagate through the network and emerge as a set of output states. An error term is derived from the difference between the desired and actual output values and synaptic weights are then adjusted in accordance with an error correction rule. As the iteration proceeds, the overall error normally approaches zero.

However, the very slow rate of learning and premature convergence are limitations of the standard BP learning method. An alternative to the BP is the GA which is an evolutionary algorithm based on the concept of natural selection and evolution. Genetic methods seek to imitate the biological phenomenon of evolutionary reproduction, described in [7], [8]. Evolutionary computing techniques are based upon Darwin's theory of evolution where a population of individuals, in this case potential solutions, compete with one another over successive generations, 'survival of the fittest'. After a number of generations, the best solutions survive and the less fit are gradually eliminated from the population [8]. As the GA's can prevent the local solutions when guided by the parallel search strategy, premature convergence can be avoided. The synaptic weights of ANNs are considered to be the chromosomes of a population. Standard crossover and mutation are employed as the reproduction operators. Each new population of weights will be transferred to the ANN for evaluation. After the fitness values are calculated, a new generation of weights will be genetically created. This process is repeated many times until the pre-defined precision is met. Figure 2 shows a representation of the GA training method.

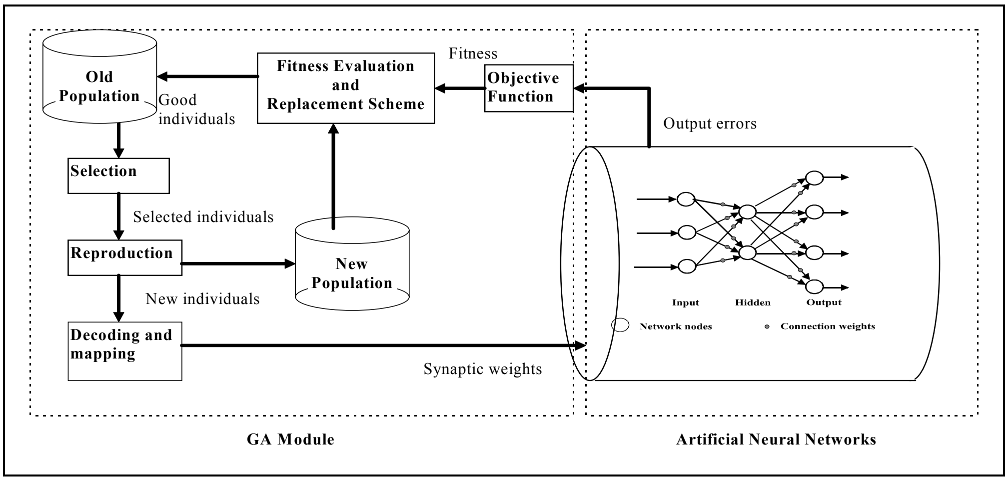


Figure 2. Block diagram representation of GA training method.

2.4 Hierarchical Distributed ANN (HDANN)

Hierarchical Distributed ANNs are advanced neural network architectures which have been developed recently[17]. HDANN consists of several level of ANNs. The outputs of lower level ANNs are connected to the inputs of higher level ANNs. A typical schematic of a HDANN is shown on Figure 3. The advantages of using a HDANN rather than a large conventional ANN are that the learning rate is faster, the number of training patterns required are smaller and the memory for storing the states of the neurons and synapses are thus smaller. Furthermore, each of the individual ANNs can be trained separately, 'the divide and conquer approach'. Hierarchical distributed artificial intelligent neural networks are being investigated within this project. Each of individual ANNs at level 3 is used to monitor a small section of a power system.

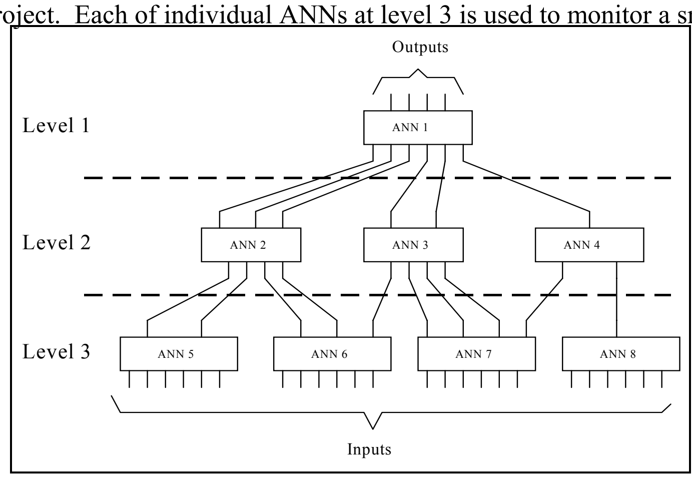


Figure 3.
Hierarchical Structured Artificial Neural Network

3.0 Experiments

In order to verify the principle of the early warning fault detection system, a simple ∏ circuit was selected and used as a target test circuit. The ANN based pre-fault detector was used as a monitor for the detection of partial faults on a simple Π circuit. The Π circuit consists of three complex components (impedances) representing the equivalent circuit for a transmission line. The circuit is represented in Figure 4.

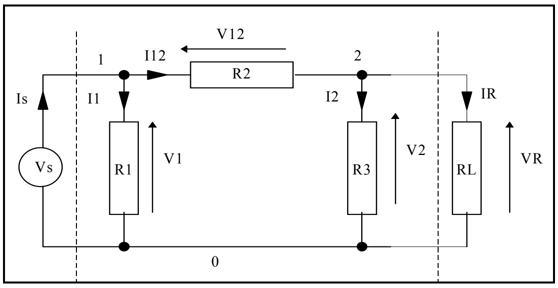


Figure 4.
The schematic diagram of the Π circuit.

For a physical transmission line, the only positions where measurements can easily made are at the junction points sending and receiving ends. Initially, only DC voltages and currents for the transmission line were considered in the feasibility study.

Training patterns for the ANNs were constructed based on the case of a constant input voltage source and a constant load. The values of the impedances in the Π circuit were varied in small incremental steps. The changes of impedance of the Π circuit affected states at both the sending and receiving ends of the transmission line. By specifying a certain degree of impedance change, for example 10% (see Table 1 and Figure 5), as a ‘soft’ fault, the states at both ends of the transmission line can be used to generate the training pattern for the ANN. Table 1 shows the pre-normalised training pattern for the ANN.

% of Degradation	Vs	Is	Vr	Ir	F1	F2	F3
-50% (R1)	1.0000	0.2667	0.3333	0.0333	1	0	0
-50% (R2)	1.0000	0.2000	0.5000	0.0500	0	1	0
-50% (R3)	1.0000	0.1750	0.2500	0.0250	0	0	1
-10% (R1)	1.0000	0.1778	0.3333	0.0333	1	0	0
-10% (R2)	1.0000	0.1714	0.3571	0.0357	0	1	0
-10% (R3)	1.0000	0.1679	0.3214	0.0321	0	0	1
-5% (R1)	1.0000	0.1719	0.3333	0.0333	0	0	0
-5% (R2)	1.0000	0.1690	0.3448	0.0345	0	0	0
-5% (R3)	1.0000	0.1672	0.3276	0.0328	0	0	0
Normal	1.0000	0.1667	0.3333	0.0333	0	0	0
+5% (R1)	1.0000	0.1619	0.3333	0.0333	0	0	0
+5% (R2)	1.0000	0.1645	0.3226	0.0323	0	0	0
+5% (R3)	1.0000	0.1661	0.3387	0.0339	0	0	0
+10% (R1)	1.0000	0.1576	0.3333	0.0333	1	0	0
+10% (R2)	1.0000	0.1625	0.3125	0.0313	0	1	0
+10% (R3)	1.0000	0.1656	0.3438	0.0344	0	0	1
+50% (R1)	1.0000	0.1333	0.3333	0.0333	1	0	0
+50% (R2)	1.0000	0.1500	0.2500	0.0250	0	1	0
+50% (R3)	1.0000	0.1625	0.3750	0.0375	0	0	1

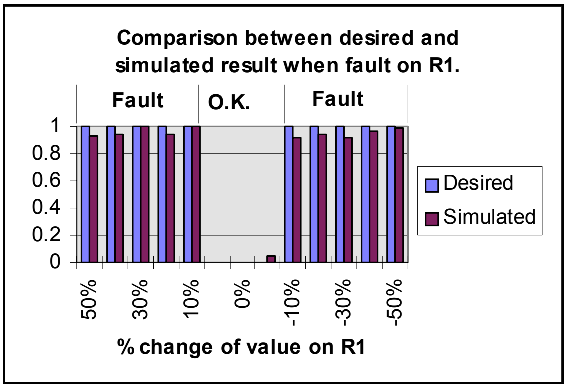
Where
Vs is sending end voltage;
Is is sending end current;
Vr is receiving end voltage;
Ir is receiving end current;
F1 = 1 indicates a fault on R1;
F2 = 1 indicates a fault on R2;
F3 = 1 indicates a fault on R3.

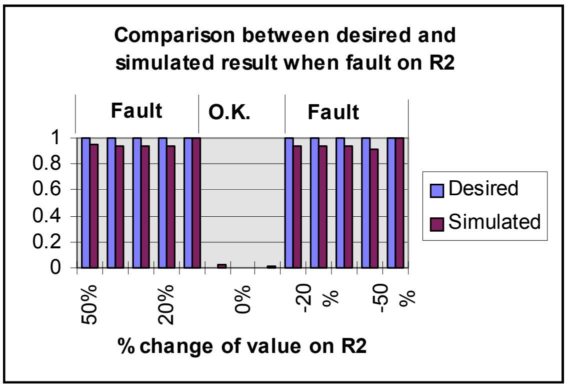
Table 1. Training patterns for the ANNs based ‘soft’ fault detector.

The first column lists changes to the resistances R1 to R3, while the four columns of numbers are the sending (Vs, Is) and receiving end (Vr, Ir) voltages and currents respectively. The last three columns represent the fault states, where a fault is represented by logic ‘1’ for resistance R1, R2 and R3 respectively. Each row of data was produced by changing the value of either R1, R2 and R3 by a small step. As can be seen for the data in each column, there is very little difference between these values. These relatively small differences in current and voltage make it very difficult for the ANN fault analyser to detect a ‘soft’ fault state. The solution to this problem is to pre-process the input data for the ANN. A normalisation pre-process method has been developed by the authors to maximise the differences among the data. The results from this experiment demonstrate that the pre-process (normalisation) method is essential to obtain a solution and it also helps to reduce the training process time.

3.1 Experiment Results

An ANN of structure 4-6-3 was developed for the purpose of soft fault analysis and detection, EFD. The voltages and currents of both sending and receiving end of the ∏ circuit (see Figure 4) are used as inputs to the ANN. The outputs of the ANN are used to indicate which impedance of the actual ∏ circuit exceeds the allowable tolerance limits. The results obtained were produced by an ANN, trained by the BP training method, within approximately 10,000 iterations. Figure 5 shows the results produced by the soft fault detector. As can be seen in Figure 5, the desired and all simulated results are closely matched and therefore the system may be used to accurately identify soft fault states.





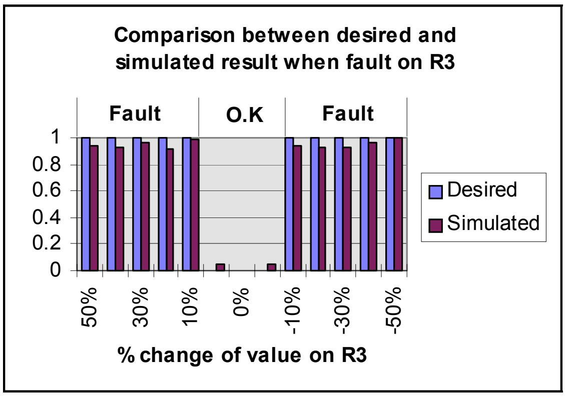


Figure 5 :
Comparison between desired and simulated results using BP.

4.0 Discussions and further work

A new concept and methods for EFD or soft fault detection has been outlined and tested. The preliminary results have been encouraging and show good potential for the algorithm to be successfully implemented in real power system environments. As fault detection is one of the important processes for reliable operation of any power system, an effective soft detection algorithm could eventually become a standard monitoring application essential for power system operational processes.

The transmission line (∏ circuit) validation experiments reported have indicated the capability of the ANN based soft fault detection algorithm. During the early stages of development, the ANN 'soft' fault detection could not learn to recognise small differences within the training data. The differences among these values of voltage and current in the ∏ circuit were simply too small and insignificant for the detector to analyse satisfactorily. Data pre-processing is essential for this system so that an ANN can learn the set of input fault states. This approach also considerably reduces the learning time.

The DC ∏ circuit fault detection test results were considered to be very satisfactory. A total of 37 sets of different testing cases were used to evaluate the detector. Half of the them were not part of the training set. All test sets produced satisfactory results with an accuracy of 95% or higher.

Further work is being carried out on balanced 3-phase a.c. circuits. Multiple 'soft' faults detection methods will also be considered. Evolutionary computing techniques such as the Genetic Algorithm will be used to further improve the performance of the ANN by devising operators specific to the domain. A significant advantage of this approach is that by measuring the states of external nodes within a system, it is possible determine the state of equivalent internal circuit elements and thereby detect, at an early stage, components which are gradually moving out of acceptable tolerance range, prior to possible failure.

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