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APPLICATIONS OF INTELLIGENT SOFTWARE SYSTEMS IN POWER PLANT, PROCESS PLANT AND STRUCTURAL ENGINEERING

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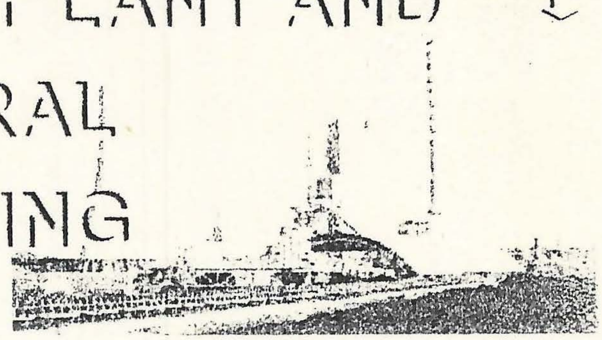

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Artificial Neural Networks Applied to Protection of Power Plant

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Abstract

The project of a power plant protection is nowadays limited to expected situations. To work with unforeseen or unknown data is a challenging task. The implementation of a pattern recognizer for a power plant protection diagnosis may provide great advances in the protection field. This paper presents the use of Artificial Neural Networks as a pattern classifier for a distance relay operation. The scheme utilizes the digitized form of three phase voltage and current inputs. Increase of performance for the distance relays is expected.

1-Introduction

Distance relaying techniques have attracted considerable attention for the protection of transmission lines. This principle measures the impedance at a fundamental frequency between a relay location and the fault point and thus determines if a fault is internal or external to a protection zone. Voltage and current data are used for these purposes and they generally contain the fundamental frequency component added with harmonics and DC component (noise).

With digital technology being ever increasingly adopted in power substations, more particularly in protection, distance relays have found some improvements mainly related to efficient filtering methods (such as Fourier, Kalman, etc.) and as a consequence shorter decision time has been achieved. The trip/no trip decision has been improved, compared to electromechanical/solid state relays. However, if unforeseen or incomplete data input occurs, the protection system may not act properly [1].

This paper presents the theory of Artificial Neural Networks (ANN) as being an alternative computational concept to the conventional approach based on a programmed instruction sequence. The ANN can provide solutions to problems with unknown determining factors. Its potential has brought power system researchers to look at it as a possibility to solve problems related to different subjects such as load forecasting, fault detection and location, economic dispatch, etc. [2],[3],[4].

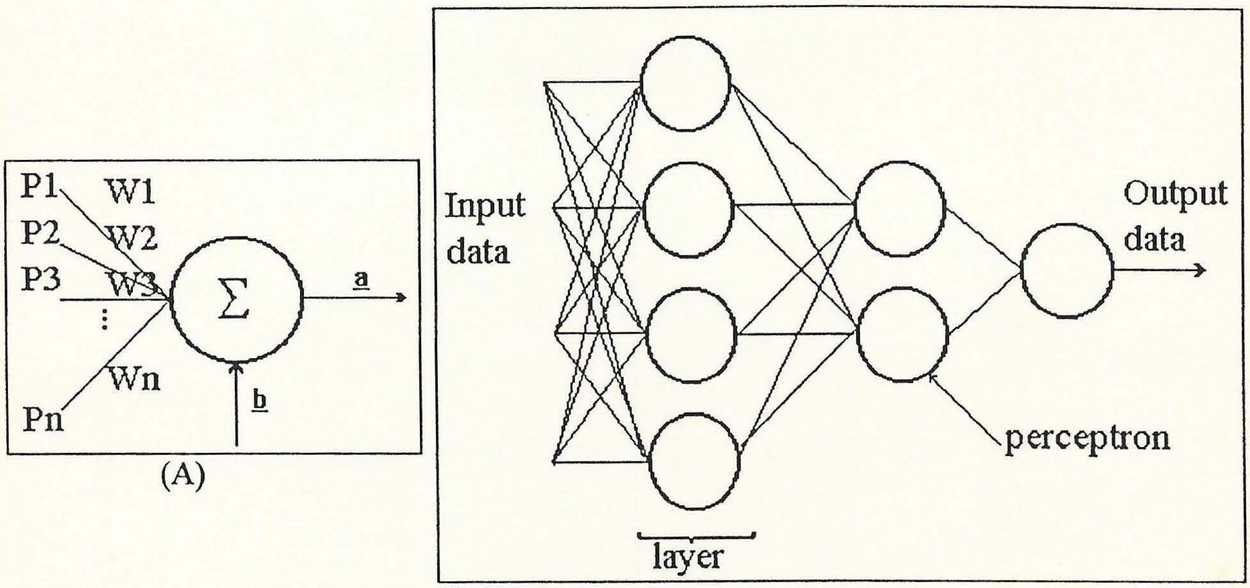
This work shows the application of ANN as a pattern classifier for distance relay operation in transmission lines. The scheme can work with unexpected or incomplete data, improving the performance of ordinary relays using the digital principle. The degree of accuracy for locating the faults in the different zones is also improved.

2-The Artificial Neural Network

The Artificial Neural Network (ANN) is inspired by biological nervous systems and it was first introduced as early as 1960. Nowadays the studies of ANN are growing rapidly, for many reasons[5]:

• ANN works with pattern recognition at large.
• ANN is prepared to work with incomplete and unforeseen input data.
• ANN has a high degree of robustness and ability to learn.

The neuron is the nervous cell and is represented in the ANN universe as a perceptron. The interconnection of the perceptrons can form a network which is composed of a single layer or several layers as seen in Figure 1(b).



(B)

Figure 1 - ANN diagrams
(A) - Perceptron representation
(B) - ANN multi-layer scheme

Figure 1(a) shows a simple model of a neuron characterized by a number of inputs $P_1,P_2,\ldots,P_N$, the weights $W_1,W_2,\ldots,W_n$, the bias adjust $\underline{b}$ and an output $\underline{a}$.

The neuron uses the input, together with information on its current activation state to determine the output $\underline{a}$, given as in equation (1).

$$\underline{a} = \sum_{k=1}^{n} W_k P_k + \underline{b} \qquad (1)$$

The ANN models may be "trained" to work properly. The desired response is a special input signal used to train the neuron. A special algorithm adjusts weights so that the output response to the input patterns will be as close as possible to their respective desired responses. In other words, the ANN must have a mechanism for learning. Learning alters the weights associated with the various interconnections and thus leads to a modification in the strength of the interconnections.

In order to use the ANN properly, it is necessary to know that empirical methods are the only way to find satisfactory results. The network scheme will have direct influence on the ANN performance. Problems may also arise from the ANN training. Depending on some factors, ANN may not converge and it could be necessary to change the training parameters. The sequence of the input data training, the initial weights used and the number of cases for the training data may affect the results.

The use of ANN in distance relays may result in a considerable advance for the correct diagnosis of operation. The ANN may solve the overreach and the underreach problems which are very common in the power plant protection project. ANN can be trained with data provided from a simulation of a faulted transmission line and "learn" the aspects related to that situation. The use of ANN make it possible to protect over 80% of the extension of the power system line. ANN can deal with unforeseen situations related to faults in the power plant.

3-Backpropagation Method

The Backpropagation algorithm is central to much current work on learning in neural networks. It was invented independently several times, by Bryson and Ho (1969), Werbos (1974), Parker (1985) and Rumelhart, Hinton, and Willians (1986). A closely related approach was proposed by Le Chun (1985). The Backpropagation method works very well adjusting the weights (Wjn) which are connected in successive layers of multi-layer perceptrons. The algorithm gives a prescription for changing the weights in any feed-forward network to learn a training set of input-output pairs $\{P_n,a_r\}$[6]. The use of the bias adjust in the ANN is optional, but the results may be enhanced by it. Trained backpropagation networks tend to give reasonable answers when presented with inputs that they have never seen. An elementary backpropagation neuron with R inputs is show below on Figure 2.

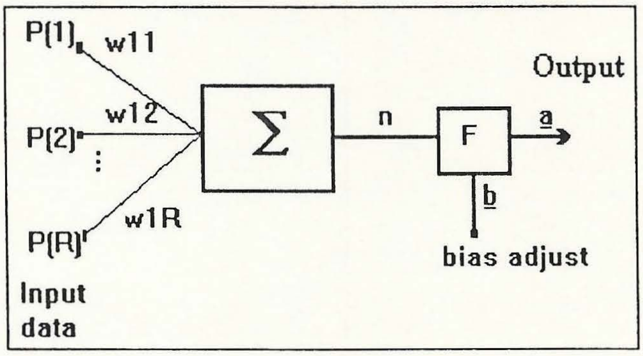


Figure 2 - Neuron with logsigmoid characteristic

where:

n	- n^{th} summation output	R	- number of inputs
W	- weights	$\underline{b}$	- bias adjust
F	- transfer function	$\underline{a} = F[w.P,\underline{b}]$	

$$\underline{a} = \log sig(n,\underline{b}) = \frac{1}{1+e^{-(n+\underline{b})}} \qquad (2)$$

Backpropagation networks often use the logistic sigmoid as the activation transfer function. The logistic sigmoid transfer function maps the neuron input from the interval $(-\infty,+\infty)$ into the interval (0,+1). The logistic sigmoid equation (2) is applied to each element of the proposed ANN [7].

4-Application of the Backpropagation Method for the Fault Location Problem

It is common, among the algorithms for digital distance protection, to use voltage and current waveforms taken from a busbar in order to solve the fault location problem in a power plant.

Figure 3 shows the ANN diagram chosen to solve the fault location problem using the backpropagation method. This scheme also uses the three phase values of current and voltage data. The Discrete Fourier Transform was used to filter this input data and extract the fundamental components. The transfer function used for the perceptrons was the logistic sigmoid described in the earlier section.

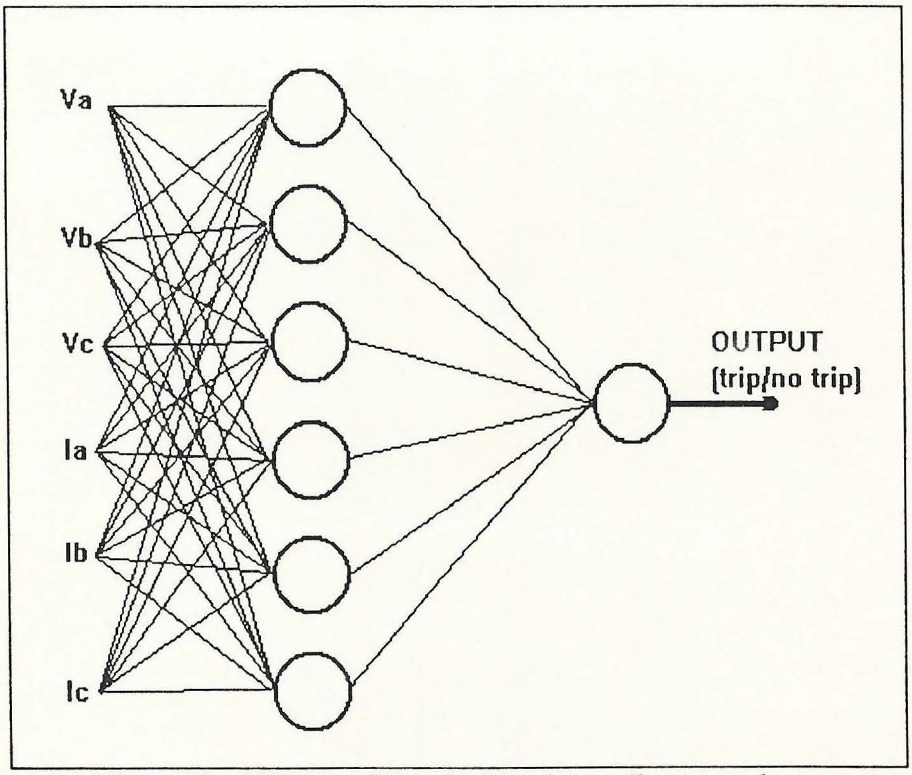


Figure 3 - ANN configuration used as a distance relay.

5-The Power Plant Diagram Used

In order to test the applicability of the scheme proposed earlier, a simulation of the transmission line in a faulted condition is needed. This paper makes use of a digital simulation of faulted EHV transmission lines developed by Johns and Aggarwall [8]. The 100Km transmission line used to train and test the proposed ANN is shown in Figure 4. The digitized output of voltage and current at the three phases are then used in real time to feed the ANN algorithm. Only one side of information was used in the referred method (from busbar A).

The primary situation used for training, considered the fault resistance as constant (as well as the other parameters such as source capacity, etc.) and phase A to ground faults only. The training values used in the ANN scheme considered the changes of the fault location along the transmission line as the main variation of the input data. However, flexibility for untrained or unforeseen data is expected for this kind of scheme.

Figure 5 shows the schematic diagram for the hardware needed in an ANN implementation, including the microprocessor based neural relay. The converged set of weights, which are worked in an off-line mode are then stored in the microprocessor for on-line application. The scheme works in a sample frequency of 4kHz.

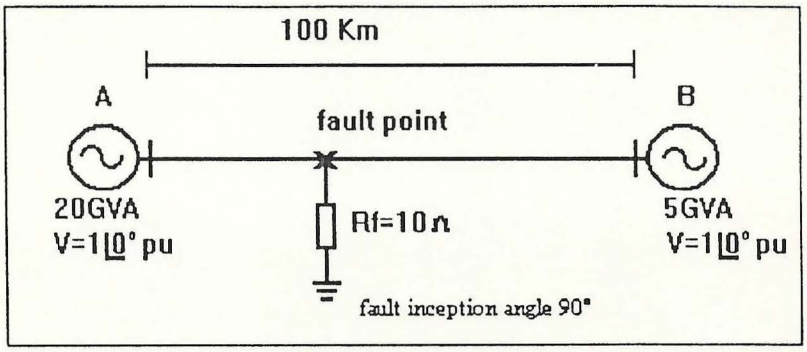


Figure 4 - Transmission line used for the ANN studies.

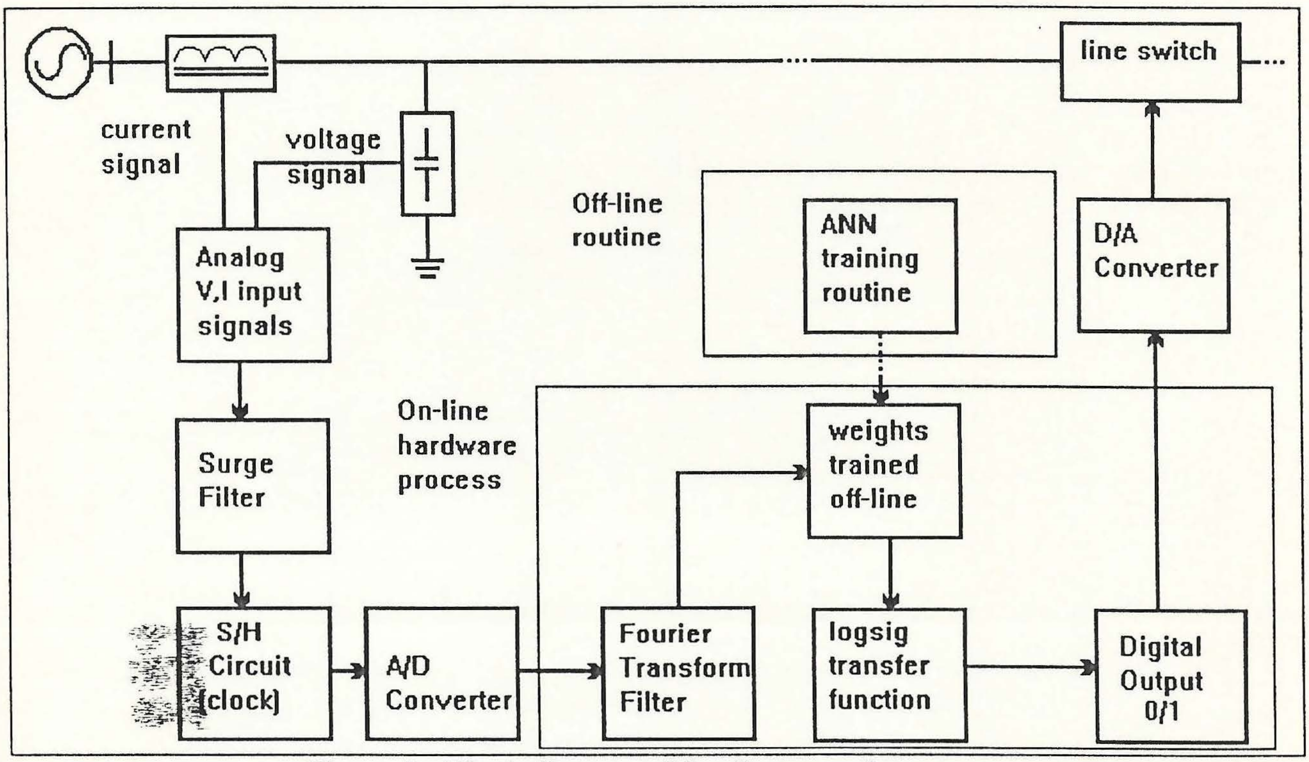


Figure 5 - Block diagram of the distance relay.

6-The Training Procedure and Test Results of the Proposed ANN

The "Neural Network Toolbox" from the software "Matlab™" [7] was used to create the ANN diagram, train it and obtain the weights as output. The initial weights as well as the initial bias used random values between 0-1.

59 different faulted cases were used in different locations of the transmission line in order to train and test the proposed ANN. In the referred scheme, a protection of 80% of the line was

chosen as the extension of the first zone of the relay. Points next to the region where trip/no trip condition exchanges (80Km for the line used) had special treatment. In this case, less degree of scarcity was taken between locations used for training.

Table 1 shows the results of an ANN model used as a distance relay. The ANN answer is shown, compared to the expected ones, for faults along the transmission line. It should be mentioned that the cases used for the tests are different from the ones used for the training.

The results presented in Table 1 show the efficiency of the proposed scheme. For all the cases, the ANN scheme correctly classifies the fault as been internal or external to the first zone of the relay.

Distance of the fault from point A (Km)	ANN answer	Correct answer	Distance of the fault from point A (Km)	ANN answer	Correct answer
2.0	1	1	56.0	1	1
4.0	1	1	60.0	1	1
6.0	1	1	61.0	1	1
8.0	1	1	64.0	1	1
10.0	1	1	65.0	1	1
11.0	1	1	68.0	1	1
13.0	1	1	71.0	1	1
16.0	1	1	73.0	1	1
20.0	1	1	74.0	1	1
22.0	1	1	75.0	1	1
26.0	1	1	76.0	1	1
29.0	1	1	77.0	0.9998	1
30.0	1	1	78.0	0.9941	1
33.0	1	1	82.0	$2.6845e^{-4}$	0
35.0	1	1	83.0	$1.0104e^{-5}$	0
37.0	1	1	84.0	$4.2734e^{-7}$	0
40.0	1	1	86.0	$1.1656e^{-9}$	0
42.0	1	1	87.0	$6.6594e^{-11}$	0
45.0	1	1	88.0	$3.9977e^{-12}$	0
46.0	1	1	89.0	$2.7110e^{-13}$	0
48.0	1	1	92.0	$2.0983e^{-16}$	0
52.0	1	1	94.0	$2.8801e^{-18}$	0
54.0	1	1	96.0	$5.3289e^{-20}$	0
55.0	1	1	98.0	$1.5577e^{-21}$	0

Table 1-Results for the ANN scheme.

7-Tests of the ANN for unforeseen data

In order to test the performance of the ANN scheme subjected to unknown data inputs, some changes were made to the power system parameters. As said before, Table 1 presents the relay results for the configuration presented in Figure 4. In order to test the ANN flexibility to unforeseen inputs, the fault resistance, power generation capability and fault inception angle suffered small variations. Table 2 shows the results of the ANN scheme subjected to such this case, the memberships (one of eigenvectors normalized for the greatest weight to be equal 1), after the calculation, will be give by the first normalized eigenvector in Figure 7.

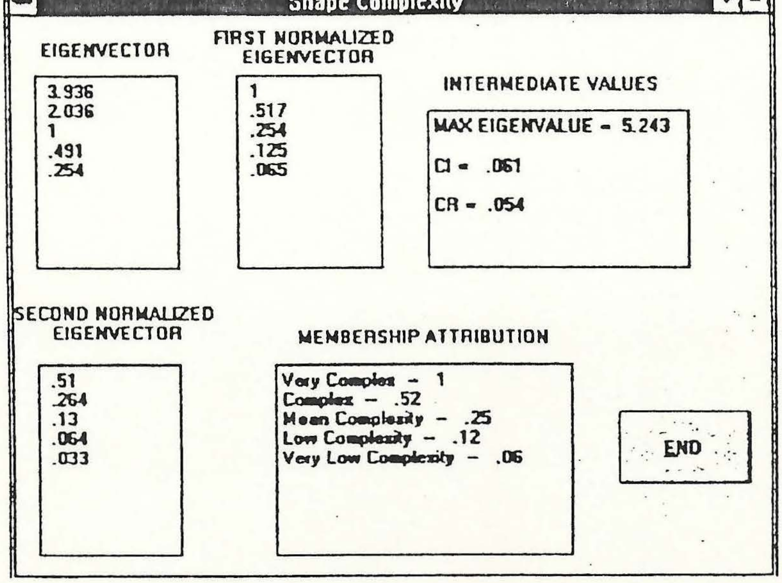


Figure 7 - Eigenvector for membership attribution

The values of memberships now will give a weight for each of the parts from the data base. These memberships represent the importance of complexity of shape for each part.

After the memberships for the several features (qualitative and quantitative) are calculated, now, it is necessary to have a procedure to obtain the clusters of similar parts.

4 - ANALYSIS OF SIMILARITY FOR THE FEATURES

A principle that can be used for the grouping is to choose a threshold value for the similarity. Once this threshold value is chosen, two elements will be in the same grouping if the similarity between them is larger than the value of comparison.

To estimate the resemblance between pairs of data, it is possible to use the convention of arranging the data in form of matrix. Each entry in this matrix will represent the proximity between two parts. This relationship, called S which is a matrix **n x n**, represents the similarity between different parts. To obtain this matrix it is possible to utilize several formulaes for the calculation of similarity, as examplified by the expressions (1), (2), (3), (4) and (5).

$$S(x_i, x_j) = \frac{\sum_{k=1}^{p} \min(\mu_k(x''_{ik}), \mu_k(x''_{jk}))}{\sum_{k=1}^{p} \max(\mu_k(x''_{ik}), \mu_k(x_{jk}))} \tag{1}$$

$$S(x_i, x_j) = \frac{\sum_{k=1}^{p} \min(\mu_k(x''_{ik}), \mu_k(x''_{jk}))}{\frac{1}{2}\sum_{k=1}^{p} (\mu_k(x''_{ik}) + \mu_k(x''_{jk}))} \tag{2}$$

variations. It could be noted that for most cases the ANN scheme still gives correct results, confirming its capability as a pattern classifier. The wrong diagnosis was presented in the case of small fault resistance where, as a consequence the current of a faulted phase increased. The wrong diagnosis was given because this case is similar to the situation of the fault occurring in the first zone of the relay trained earlier. However, it should be mentioned that such cases could be used in the training set in order to avoid such a problem.

Change of trained parameters	ANN Output	Correct Output
Fault inception angle set to 88°, fault distance=75Km from A.	1	1
Fault inception angle set to 88°, fault distance=85Km from A.	$1.5024.10^{-7}$	0
Fault inception angle set to 92°, fault distance=70Km from A.	1	1
Fault inception angle set to 92°, fault distance=85Km from A.	$3.3442.10^{-9}$	0
Fault resistance set to 0Ω, fault distance=70Km from A.	1	1
Fault resistance set to 0Ω, fault distance=90Km from A.	1 (wrong)	0
Fault resistance set to 5Ω, fault distance=85Km from A.	1 (wrong)	0
Fault resistance set to 5Ω, fault distance=70Km from A.	1	1
Fault resistance set to 8Ω, fault distance=70Km from A.	1	1
Fault resistance set to 8Ω, fault distance=95Km from A.	$2.0047.10^{-15}$	0
Fault resistance set to 12Ω, fault distance=70Km from A.	1	1
Fault resistance set to 12Ω, fault distance=90Km from A.	$5.8528.10^{-18}$	0
Fault resistance set to 15Ω, fault distance=70Km from A.	0.9192	1
Fault resistance set to 15Ω, fault distance=90Km from A.	$1.1459.10^{-21}$	0
Source at B set to 4.5GVA, fault distance=75Km from A.	1	1
Source at B set to 4.5GVA, fault distance=90Km from A.	$2.3569.10^{-13}$	0
Source at B set to 4GVA, fault distance=70Km from A.	1	1
Source at B set to 4GVA, fault distance=90Km from A.	$3.5749.10^{-12}$	0
Source at A set to 18GVA, fault distance=75Km from A.	1	1
Source at A set to 18GVA, fault distance=90Km from A.	$7.1024.10^{-15}$	0

Table 2-Results of the ANN for unforeseen data.

8-Conclusion

In this paper the use of ANN as a pattern classifier to work as a distance relay was investigated. The results obtained in this scheme are very encouraging. The ANN scheme can operate correctly in the location of the fault point. The scheme can be extended including some more variations of parameters in the training set in order to avoid misoperation as seen in the paper for the case of low fault resistance. It is also necessary to point out some problems related to the ANN application. The initial network configuration is totally empirical and may not result in the best performance for the scheme. The training points to be used can also be an expressive problem. These are some points that can influence the speed of the conversion of weights and consequently the performance of the scheme.

However, this tool opens a new dimension in relay philosophy which should be widely investigated in order to solve some of the various problems related to the distance protection of transmission lines.

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