Fuzzy-Neuro Approach to Fault Classification for Transmission Line Protection

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***Abstract*—This paper presents a new approach to real-time fault detection and classification in power transmission systems by using fuzzy-neuro techniques. The integration with neural network technology enhances fuzzy logic systems on learning capabilities. The symmetrical components in combination with three line currents are utilized to detect fault types such as single line-to ground, line-to-line, double line-to-ground and three line-to-ground, and then to define the faulty line. Computer simulation results are shown in this paper and they indicate this approach can be used as an effective tool for high speed digital relaying, as the correct detection is achieved in less than 10ms.**

1. INTRODUCTION

Protecting transmission lines is very important for safeguard of the power system. With the advent of microprocessors and digital electronics, digital-based relaying has been developed since the late 1960s. Research activity has covered virtually every protection technique, and many novel algorithms and associated hardware implementations have emerged [1-3]. Some of them such as representing transmission lines by either first- or second-order differential equations and traveling-wave techniques have resulted in several commercial developments [4, 5]. However, both these approaches are based on deterministic computations on a well defined model of the system to be protected. This results in difficulty in taking system variation into account as the rules are fixed. They do not have the ability to adapt dynamically to the system operating conditions, and to make correct decisions if the signals are uncertain.

Recently, many researchers have studied the application of neural networks to overcome most of the problems above outlined [6-8]. The fuzzy set theory is also used to solve uncertainty problems [9]. However, all these methods make use of either neural networks or fuzzy sets taking one at a time. The use of neural nets in applications is very sparse due to its implicit knowledge representation, the prohibitive computational effort and so on. The key benefit of fuzzy logic is that its knowledge representation is explicit, using simple "IF-THEN" relations. However, it is at the same time its major limitation. The power system operation in transient period cannot be easily described by artificial explicit knowledge, because it is effected by many unknown parameters. The integration of neural network into the fuzzy logic system makes it possible to learn from the prior obtained data sets.

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In our project, training patterns to be absorbed by the fuzzy-neuro model were generated using sequence current components and line currents under normal and fault conditions at various locations along a transmission line. Simulations were performed using an electromagnetic transient program, EMTDC/PSCAD [10] , on a sample three-phase power system. The line components were first processed using FFT algorithm and then derived the sequence components of the fundamental frequency. The performance of the proposed model was tested using a test set. Some of the test results are included in this paper.

2. FAULT ANALYSIS

The analysis of fault currents will give information about the nature of faults. In our paper, we consider the following components:

- symmetrical components
- three line currents

A. Symmetrical Components

Under normal or symmetrical fault (three line-to-ground) conditions, the zero and negative sequence components in the line currents are nearly zero. The presence of only the negative sequence component in the fault current indicates that a line-to-line (ll) fault has occurred. The presence of negative and zero components indicates that a fault of single line-to-ground (slg) or double line-to-ground (dlg) has occurred. The fault classification based on sequence components relaying have also been proposed in the past [8, 9]. The following equations give relationships between sequence components of fault currents at the fault point. For example, equation (1) gives the condition for single line-to-ground (slg) fault. Equation (2) does for double line-to-ground (dlg) fault. Where, $I_{fa}^{(0)}$, $I_{fa}^{(1)}$, $I_{fa}^{(2)}$ are zero, positive and negative sequence components respectively. $Z^{(0)}, Z^{(2)}$ are zero and negative sequence impedances respectively seen from the fault point. Z_f is the fault impedance. From the above equations, it can be seen that $I_{fa}^{(0)} / I_{fa}^{(1)}$ and $I_{fa}^{(2)} / I_{fa}^{(1)}$ of slg fault are higher than those of dlg. Our computer simulation results on a sample three-phase power system (Fig. 1) also show this relation.

$$I_{fa}^{(0)} = I_{fa}^{(1)} = I_{fa}^{(2)} \tag{1}$$

$$\left.\begin{aligned} & I_{fa}^{(0)} + I_{fa}^{(1)} + I_{fa}^{(2)} = 0 \\ & I_{fa}^{(2)} = -I_{fa}^{(1)} \left[\frac{Z^{(0)} + 3Z_f}{Z^{(2)} + Z^{(0)} + 3Z_f} \right] \\ & I_{fa}^{(0)} = -I_{fa}^{(1)} \left[\frac{Z^{(2)}}{Z^{(2)} + Z^{(0)} + 3Z_f} \right] \end{aligned}\right\} \tag{2}$$

This simulation has been accomplished, using EMTDC/PSCAD program, in order to analyze fault characteristics under different fault locations. Fig. 2 shows the ratio between the zero sequence component (Io) and the positive one (Ip) at the relay point versus the fault distance from the relay of slg and dlg fault. Similarly, Fig. 3 shows the ratio between the positive sequence component (Ip) under fault condition and the rated current (Irated) under normal condition. Fig. 4 shows the ratio between the negative sequence component (In) and the positive one of slg, ll and dlg fault.

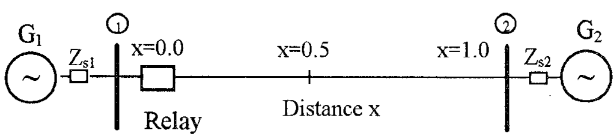


Fig. 1. A power system for EMTDC simulation.

It is very difficult to use a deterministic algorithm to make the correct judgment in terms of the above 3 figures because these figures still contain some ambiguities especially for slg and dlg faults. This leads to fuzzy approach to solve this problem. It should be noted that these components are extracted one period after fault occurs, using FFT algorithm, and they remain stable during the subsequent periods. However, for high speed digital relaying, it needs less than

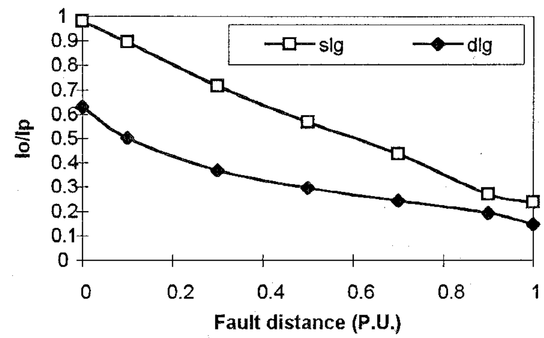


Fig. 2. Ratio Io/Ip

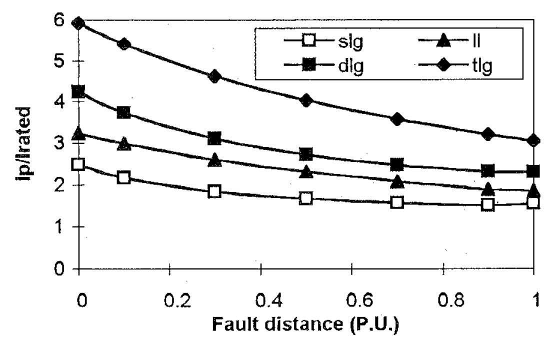


Fig. 3. Ratio Ip/ Irated

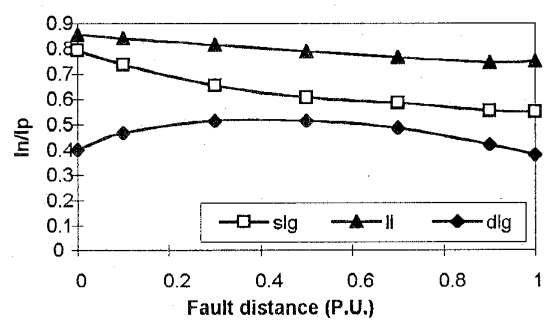


Fig. 4. Ratio In/Ip[1]

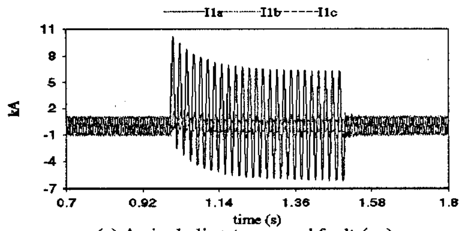
one period to make correct judgment. The system operation in transient period cannot be easily described by artificial explicit knowledge. But the information is contained in the field data. Consequently, we use fuzzy-neuro techniques in our case as shown in section 4.

B. Three Line Currents

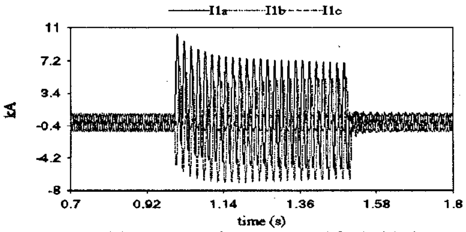
As above mentioned, sequence components relaying is an effective tool, but mere use of sequence components is not

[1] Io, In and Ip both decreases with the fault distance. Because the change of Io is very high Io/Ip still decreases, while In/Ip appears smooth.

very satisfactory for differentiating the slg fault with the dlg fault, which can be shown in section 4. To enhance the performance, line currents are used to confirm the judgment. When fault occurs, the fault line current often increases, greater than the currents in healthy lines. In case of slg fault, only one line current increases greatly, while in case of dlg fault, two line currents are greater than the 3rd line current. Followings are the fault currents of slg and llg, which can show the difference and can be used to derive a correct response.



(a) A single line-to-ground fault (ag).



(b) A double line-to-ground fault (abg).

Fig. 5. Current waveforms (a) a single line-to-ground fault (phase A to ground), (b) a double line-to-ground fault (phase A to phase B involving ground).

3. CONVENTIONAL PROTECTION ALGORITHMS

A. Algorithm Using Phase Currents and Voltages

This method belongs to the class of impedance algorithms which determine fundamental impedance by using a full-cycle or half-cycle fourier algorithms. When a full-cycle window algorithm is applied, the phasors that represent the fundamental component of the faulted voltage and current waveform can be expressed by the following equation,

$$\dot{U} = \frac{2}{N}\sum_{k=0}^{N} u_k e^{j\frac{k2\pi}{N}}$$
$$\dot{I} = \frac{2}{N}\sum_{k=0}^{N} i_k e^{j\frac{k2\pi}{N}} \qquad (3)$$

When a half-cycle algorithm is applied, the equation (3) change to equation (4),

$$\dot{U} = \frac{4}{N}\sum_{k=0}^{N/2} u_k e^{j\frac{k2\pi}{N}}$$
$$\dot{I} = \frac{4}{N}\sum_{k=0}^{N/2} i_k e^{j\frac{k2\pi}{N}} \qquad (4)$$

By taking the phasors we arrive at a relation for determining the impedance:

$$z = \frac{\dot{U}}{\dot{I}} = R + jX \qquad (5)$$

Using full-cycle algorithm, the DC and/or harmonic components are almost filtered out, however one period of samples are required to implement to the algorithm. This leads to processing times greater than 20 ms (f =50 Hz). While using half-cycle algorithm, it is faster than the former, but it has the disadvantage of introducing error, specifically due to any aperiodic component and/or even harmonics [1].

B. Algorithm Using Sequence Components

This algorithm by A.G. Phadke *et al.* [12] is based on the use of sequence components. When fault occurs, the voltage drops in the line can be defined as

$$\Delta E_0 = \Delta I_0 Z_0$$
$$\Delta E_1 = \Delta I_1 Z_1 \qquad (6)$$
$$\Delta E_2 = \Delta I_2 Z_2$$

where Z_0, Z_1, Z_2 are the sequence impedances of the entire line, ΔE_0, ΔE_1, ΔE_2 are the changes in the sequence voltage components, ΔI_0, ΔI_1, ΔI_2 are the changes in the sequence current components. By considering all possible fault types a general expression for the fault distance k can be obtained in the following form,

$$k = \frac{k_1 + k_2 k_2' + k_0 k_0'}{1 + k_0' + k_2' + k_l} \qquad (7)$$

where $k_0 = \frac{E_0}{\Delta E_0}$, $k_1 = \frac{E_1}{\Delta E_1}$, $k_2 = \frac{E_2}{\Delta E_2}$, $k_l = \frac{Z_1 \bar{I}_1}{\Delta E_1}$, $\bar{I}_1$ is the positive component of pre-fault current. $k_0' = \left|\frac{\Delta E_0}{\Delta E_1}\right|$,

$$k_2' = \begin{cases} 1 \text{ if } |\Delta E_2| \cong |\Delta E_1| \\ 0 \quad \text{otherwise} \end{cases}.$$

The sequence components are obtained by a linear transformation of the phase currents and voltages of fundamental frequency, which can be obtained by fourier analysis or other methods. The occurrence of harmonics and DC components will bring influence on the accuracy of this method. The above two examples of impedance algorithms demonstrate the problems inherent in attempting to consider all real-world effects using a mathematical model. In the next we will introduce the fuzzy-neuro techniques.

4. FUZZY-NEURO TECHNIQUES

In this paper, we use the architecture of fuzzy controller developed with the aid of relational neural networks (Fig. 6). In general, fuzzy sets and neural networks deal efficiently with the two very distinct areas of information processing. Fuzzy sets are good at various aspects of uncertain knowledge representation, while neural networks are efficient structures capable of learning from examples. Both techniques have their advantages and disadvantages, and they can be complementary too.

Fuzzy controller is inflected in three basic elements: fuzzification, fuzzy inference and defuzzification. In neural nets, the weights between the input and the first hidden layer as well as the last hidden layer and the output layer, determine the input/output behavior. In a fuzzy system, these parameters are found in the fuzzification and defuzzification routines and can thus be trained. Calculated degrees of membership in the fuzzifier layer are sent to the rule layers and operated in the neurons in the rule layers according to

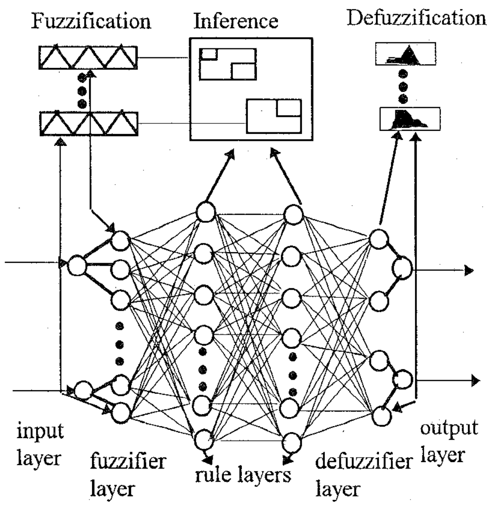


Fig. 6. Neurofuzzy technologies map a neural net to a fuzzy logic system.

IF-THEN rules. In this paper, the computation of the IF part uses minimum operator for AND aggregation and maximum operator for OR aggregation, i.e. AND: $\mu_{IF} = \min_i (\mu_i)$, OR: $\mu_{IF} = \max_i (\mu_i)$. To implement using Neural Networks, a degree of support (DoS) in the range 0 - 1 is introduced, $\mu_{THEN} = \mu_{IF} * \text{DoS}$, because neural training methods usually use error gradients to heuristically find the best search direction and a gradient cannot be calculated when discrete rules are used.

The neural network uses the error back propagation algorithm to learn from the data sets, and find a suitable fuzzy controller. In this work, Competitive Learning is used to increase the training capability. Each time only update the connection weight of the "winner neuron".

5. FUZZY-NEURO FAULT CLASSIFIER

A. Preparation of Training Patterns

A. 1. Selection and Generation

A simple three phase power system, shown in Fig.1, was chosen for the purpose of generating line currents under normal and fault conditions. A data base of line currents is built up for various types of faults at different locations , by using EMTDC/PSCAD simulation software (Fig. 5).

A. 2. Pre-processing and determination of the symmetrical components of line currents

In case of fault, the line currents are no longer sinusoidal, because of the likely presence of harmonic components. Moreover, an exponential decaying component exists depending on the power system's parameters and the instant when the fault occurs. It seems impossible to simulate all the conditions considering different fault locations and occurring times. One alternative is to perform a FFT algorithm to remove the high harmonic components and attenuate the exponential component greatly. Then symmetrical components can be obtained by means of a simple linear combination of the currents and voltages of fundamental frequency.

B. The Control Scheme

The whole control scheme of fault classification is shown as Fig. 7. The system consists of three main modules. The sequence components input to the sequence module to judge the different fault type: slg, ll, dlg and tlg. When the decision is slg or dlg, it needs the phase module 1 to confirm. After this, phase module 2 is used to define the faulty phase such as phase A to ground and so on. Phase module 1 and phase nodule 2 also utilize the line current RMS as inputs. Besides this, phase module 1 will consider the output of sequence module as a primary factor.

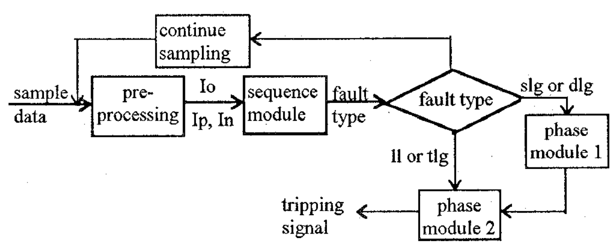


Fig. 7. The whole scheme of fault classification.

C. Training and Testing of Sequence Module

C. 1. Training

The fuzzy-neuro model used is executed by a structured computer software package [11] that can update the structure and parameters by interactive debug. It allows inserting the human previous experience, and during the training process the designer can control the whole process directly. Thus, the model is trained using the information from multiple sources: designer's experience and sample data. The following figure shows the final structure of this fuzzy system including input interfaces, rule blocks and output interfaces. The connecting line symbolize the data flow.

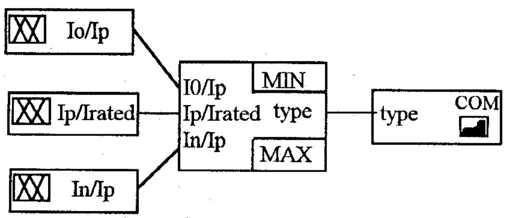
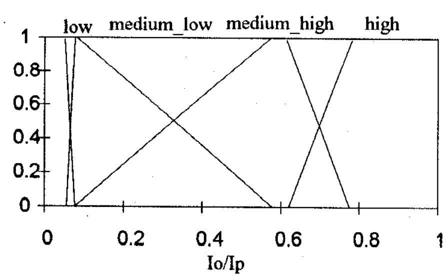
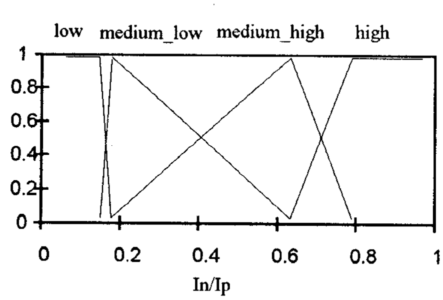


Fig. 8. Structure of sequence module.

It is worth while to note that the definition of the membership function is, an important but difficult procedure, based on the designer's knowledge and training sets. In this case, the membership functions should reflect different fault types and fault distances, as shown in Fig. 9. Considering the influence of different fault distances, the practical inputs are: I_O/Ip, Ip/Irated and In/Ip. Where, Io , Ip and In are zero, positive and negative sequence components respectively. Irated is the rated current of the transmission line. The output variable type, that indicates the nature of fault, shown in Fig. 10, is obtained by applying the rules listed in Table 1. All the rules are derived from the training of the fuzzy-neuro model based on the prior data-base.





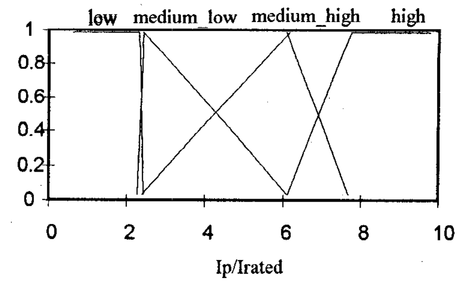


Fig. 9. Membership functions of input variables.

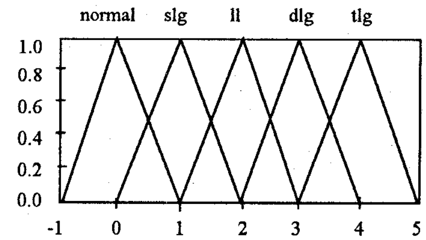


Fig. 10. Membership function of output type variable.

TABLE 1
Rules of the sequence module

IF			THEN	
In/Ip	**Ip/ Irated**	**Io/Ip**	**DoS***	**type**
low	low	low	0.96	normal
medium_low	low	medium_low	0.87	slg
medium_high	low	medium_low	1.00	slg
medium_high	low	medium_high	1.00	slg
high	medium_low	high	0.98	slg
medium_high	medium_low	high	0.20	slg
medium_high		low	0.63	ll
high		low	0.50	ll
medium_low	medium_low	medium_low	0.57	llg
medium_high	medium_low	medium_low	1.00	llg
medium_low	medium_low	medium_high	0.57	llg
medium_high	medium_low	medium_high	0.20	llg
medium_low	medium_high	medium_high	0.60	llg
medium_high	medium_high	medium_high	1.00	llg
medium_low	medium_low	high	1.00	llg
low	medium_high	low	0.95	tlg
low	high	low	0.80	tlg

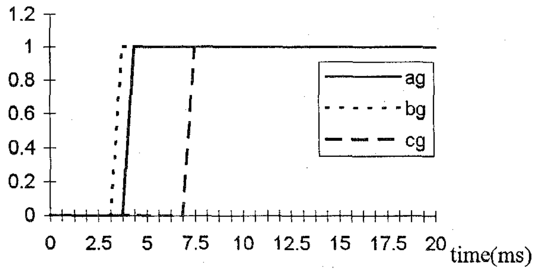
* DoS: Degree of support in the range 0 - 1 [10].

C. 2. Testing

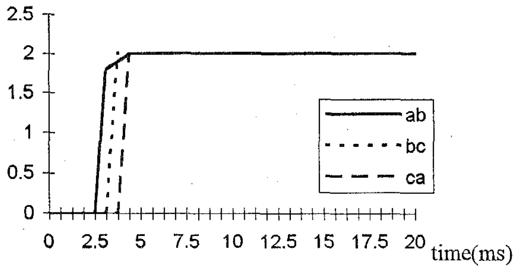
Trained fuzzy-neuro fault classifier was tested with a set of independent test patterns. The objective of this testing is to evaluate the reliability, speed, and generalization of the fuzzy-neuro fault classifier. Some results showing the performance of this fault classifier are presented here.

The faults at different fault distances have been simulated and the results at the fault location of 30% and 90% of the line length are shown in Fig. 11 and 12. In Fig. 10, when -1 ≤ output <0.5, we regard it as normal condition; 0.5≤ output <1.5, slg; 1.5≤ output <2.5, ll; 2.5≤ output <3.5, dlg; 3.5≤

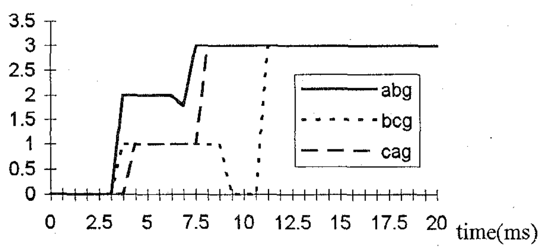
output <5, tlg. Fig. 13 shows the results of this evaluation of different fault phases from the random fault occurring instant, without any fault resistance, at the fault location of 10% along the line length. Suppose the fault occurs at t=0.



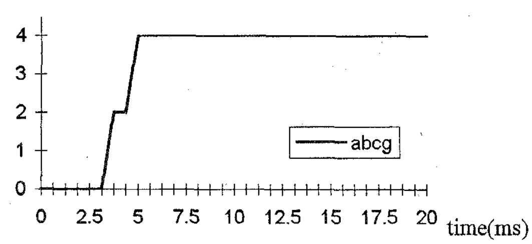
(a) Single line-to-ground



(b) Line-to-line



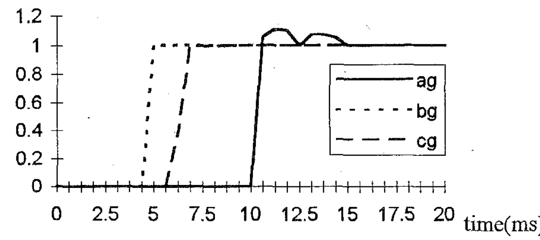
(c) Double line-to-ground



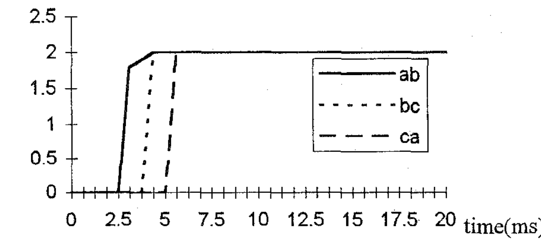
(d) Three line-to-ground

Fig. 11. Different type of fault located at 30% of the line length from relay (without any fault resistance).

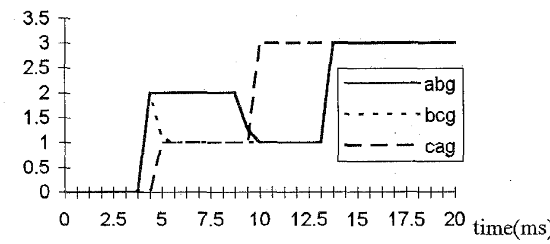
[2]ag: phase A to ground, ab: phase A to phase B, abg: phase A to phase B involving ground, abcg: three phase-to-ground. The others are similar in notation.



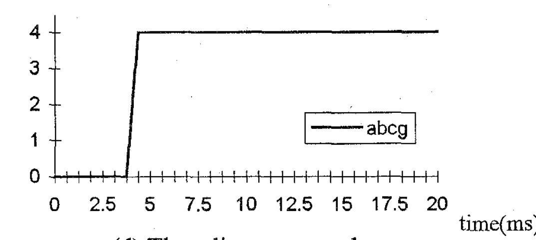
(a) Single line-to-ground



(b) Line-to-line

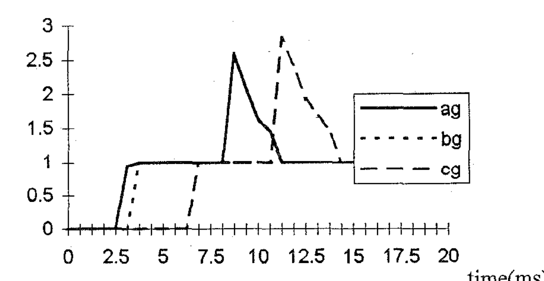


(c) Double line-to-ground

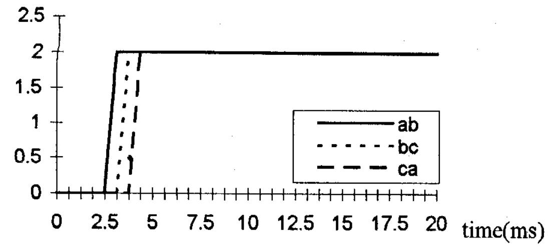


(d) Three line-to-ground

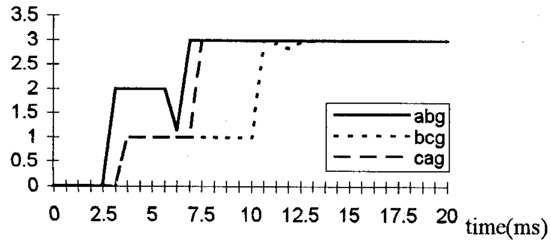
Fig. 12. Different type of fault located at 90% of the line length from relay (without any fault resistance).



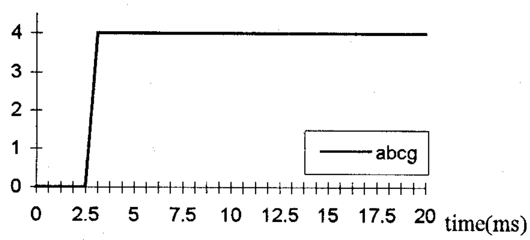
(a) Single line-to-ground



(b) Line-to-line



(c) Double line-to-ground



(d) Three line-to-ground

Fig. 13. Different type of fault located at 10% of the line length from relay (without any fault resistance).

Some faults with each having fault resistance of R_f=0.6X_l (X_l: line reactance) are also simulated for different fault locations. Fig. 14 shows the results of this condition for line-to-line fault located at 50% of the line length. In figures 15 and 16, line-to-ground faults at 10% and 90% of the line length are shown.

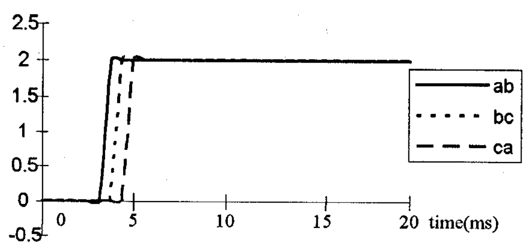


Fig. 14. Line-to-line fault located at 50% of the line length from relay (fault resistance R_f=0.6X_L).

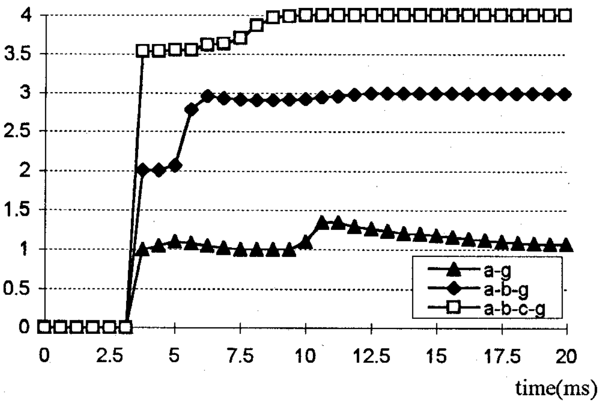


Fig. 15. Line-to-ground faults located at 10% of the line length from relay (fault resistance R_f=0.6X_L).

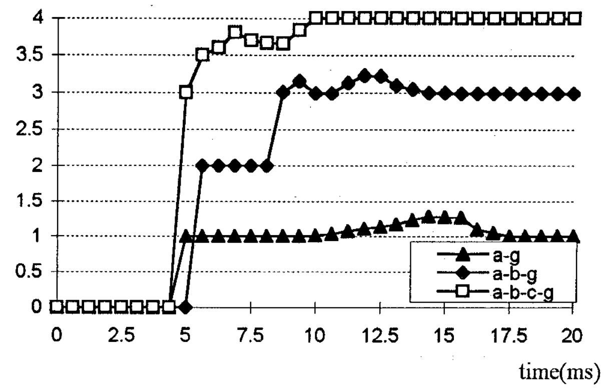
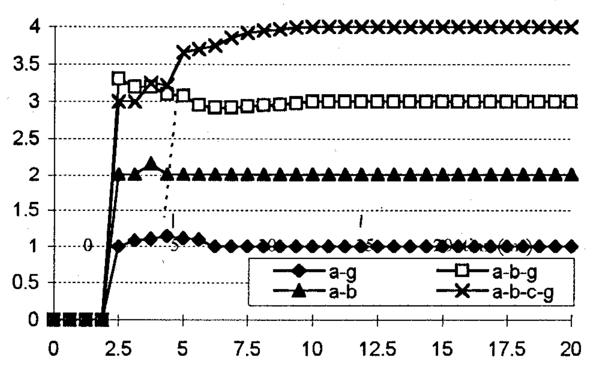
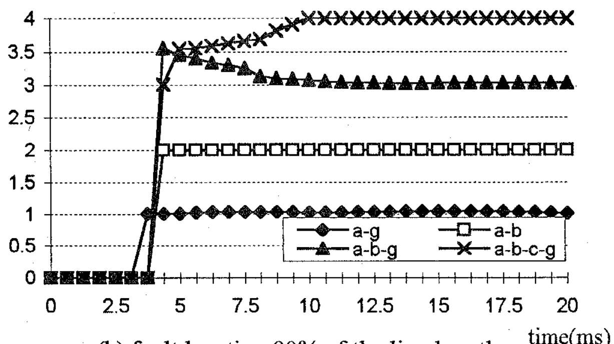


Fig. 16. Line-to-ground faults located at 90% of the line length from relay (fault resistance R_f=0.6X_L).

In power systems, the source to line impedance ratio (SIR) Z_S / Z_L can vary significantly, and a good protection scheme should not be affected by the SIR variations from 0.1 to 60 [13]. Fig. 17 and 18 show the results for different fault types at both end of the line for different SIR.

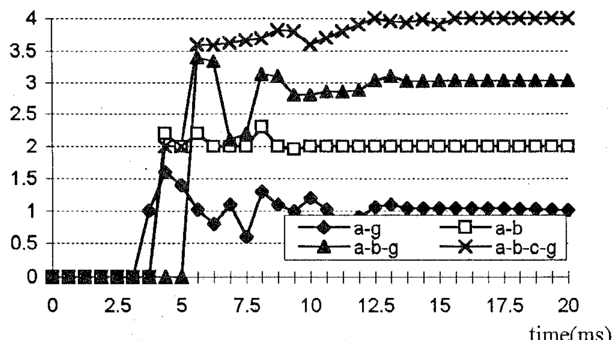


(a) fault location 10% of the line length

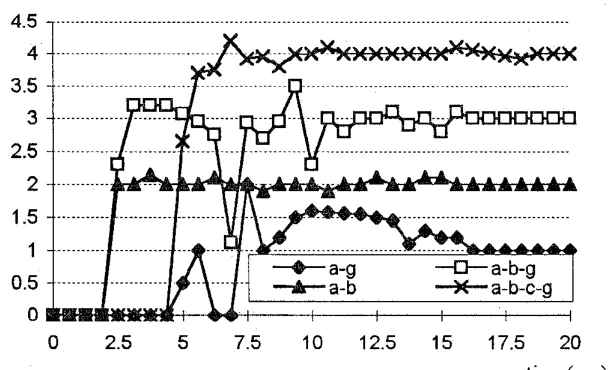


(b) fault location 90% of the line length

Fig. 17. Different type of fault with SIR=0.1.



(a) fault location 10% of the line length



(b) fault location 90% of the line length

Fig. 18. Different type of fault with SIR=60.

Test results show that the proposed fuzzy-neuro fault classifier is effective in determining the fault type under different fault locations, fault occurring times, phases involved, presence of fault distance and variations in source impedances. The classifier can detect the faults of ll and tlg about 5ms, but sometimes it need more time (over 10 ms) for slg and dlg fault. The following phase module 1 is used to improve the reliability and decision speed when the fault is slg or dlg.

We would now like to compare conventional methods and fuzzy-neuro fault classifier. Fig. 19 demonstrates the results of two conventional algorithms as already described [1,12], as well as the fuzzy-neuro network for a single line to ground fault. The output values of the conventional methods indicate the distance between the relay and the fault. The estimated distance is normalized to the length of the protected transmission line. The zero output means that it cannot detect the fault. Whereas those of fuzzy-neuro classifier are the outputs from the network to indicate the fault type.

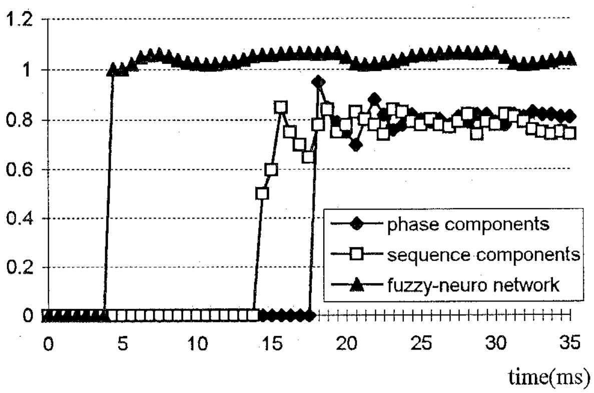


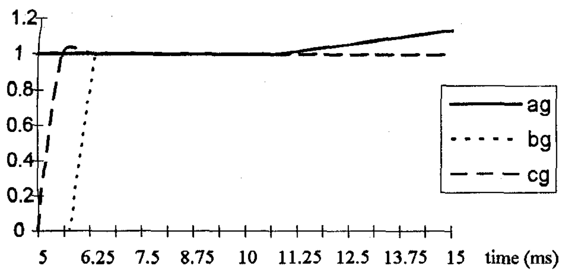
Fig. 19. Comparison, single-line-to-ground fault at 80%.

In Fig.19 fuzzy-neuro classifier has reached a stable status after 6 ms in contrast to the conventional methods which required more than 20 ms. As shown in Fig.16, fuzzy-neuro classifier can detect the fault when the fault resistance is involved. However in this case, the two conventional methods can only detect the fault near the relay while they are inadequate for the faults at the remote end of the transmission line.

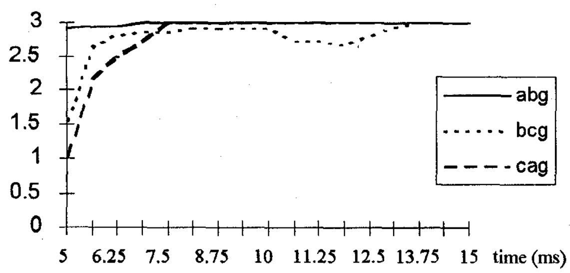
D. Training and Testing of Phase Module 1

To consider the effect of the sequence module, its output is considered as a input of the phase module 1. Consequently, the phase module 1 has 4 inputs: Ia, Ib, Ic, type (output from sequence module), and 1 output: fault type (the value below 2 means slg, while the value above 2 means dlg). The structure and learning procedure is as same as the above module. In this paper it is not discussed in detail.

Tests same as those of sequence module have been performed to compare the results and they show that the sequence components in combination with three line currents can differentiate dlg from slg efficiently and speedily. As we show in Fig. 16, the slg faults can be detected below 6.25ms, with dlg faults below 7.5ms. All the tests show that the slg and dlg faults can be detected below 10ms.



(a) Single line-to-ground



(b) Double line-to-ground

Fig. 20. Slg and dlg fault located at 10% of the line length from relay judged by phase module 1.

E. Training and Testing of Phase Module 2

When fault occurs, the faulty phase currents often rise up greatly, while non-fault phase current is less influenced. Similar to the above two modules, we can utilize fuzzy-neuro techniques to define the fault phases from the relative magnitude of three phase currents. Phase module 2 is tested when single line to ground fault occurs at different location point. The results are in close agreement with the actual fault type too.

6. IMPLEMENTATION

The proposed fuzzy-neuro fault classifier will form a part of a protective relay, which is being implemented on a TMS320C31-based DSP system with IBM-compatible microcomputer as a host machine. Floating point arithmetic is used in the implementation to increase the computer speed and satisfy the real time constraints. The on-line tests using Real Time Digital Simulator (RTDS) [10] are under development.

7. CONCLUSIONS

Classification of transmission system faults using fuzzy-neuro techniques has been achieved in real time. It is proved to be a fast, accurate and robust approach that would perform accurately for various system conditions. This means that the fuzzy-neuro model with further refinement can be implemented in an actual power system to monitor occurrence of faults and take necessary action.

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Discussion

M. Sanaye-Pasand and **O. P. Malik** (Department of Electrical and Computer Engineering, The University of Calgary, Calgary, Alberta, Canada T2N 1N4):

The authors have presented an algorithm for fault detection and classification utilizing symmetrical components, three phase currents and neuro-fuzzy techniques. Three different trained modules are used in series to perform the detection and classification job.

The discussors would like the authors to clarify and comment on the following points:

1. To enhance the performance, line currents are used to confirm the judgement of the sequence module. It is assumed that " for the case of *slg* fault, only one line current increases greatly, while in case of *dlg* fault, two line currents are greater than the 3rd line current". Current based classifiers get confused when the load current for heavily loaded transmission lines approaches the same order of magnitude as the fault current in the case of faults with resistance.
2. Two conventional methods are compared with the proposed algorithm. The conventional methods referred in the paper measure the fault distance and are not directly used as fault classifiers. Would it not be better to use a more appropriate algorithm, e.g. a neural network-based classifier method as proposed in the Ref. [A,B] for comparison? It is claimed in Ref. [A] that the fault classification could be performed in about one third of a cycle. Fault classification times of 7 *ms* are reported in Ref. [B].
3. According to Figs. 11c, 12c and 13c, it takes about 11 to 14 *ms* before the output of the sequence module reaches to its final state. However, in section 5.D it is mentioned that "all the tests show that the *slg* and *dlg* faults can be detected below 10 *ms*". Considering that the phase module 1 receives its fault type input from the preceding sequence module, the discussors wonder how the phase module 1 can determine the correct output before its input has stabilized.
4. Depending upon the number of inputs and membership functions, neuro-fuzzy structure may result in a big network. Three different networks in series is proposed in this paper. Each network should be trained and implemented separately which may need a lot of calculations and effort. In particular, the third network, phase module 2, behaves as an current level detector. The discussors wonder how a neuro-fuzzy structure could be justified to act as a level detector.
5. In Fig. 12c, the *abg* trajectory reaches the level of 3.0 at 13.75 *ms*. Does the relay not have to wait for some additional time to make sure that, it has reached a stable condition and not give a false signal?
6. It is stated in the Conclusions that "Classification of transmission system faults using fuzzy-neuro techniques has been achieved in real time". However, only simulation results are presented in the paper as stated in the Abstract. It is also stated in section 6 Implementation that "on-line tests using" RTDS are under development.
7. Would the authors please check section 5.D to see if reference to Fig. 16 in this section is correct?

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Huisheng Wang and **W W L Keerthipala:**

With reference to the above discussion we wish to furnish closing remarks as follows.

1. Under heavy load condition the positive sequence component (Ip/Irated) will never reach 2.0 pu. As a result the sequence module will not respond to over loading unless it accompanied with an increase in negative sequence (at least 15 % of Ip) currents. (Please refer to figure 10 and table 1 of the paper) The presence of negative sequence currents indicates an unbalanced fault with or without fault resistance.

2. We have not compared our results with those of [A] and [B]. However, we made comparison with a neural network technique [8] on a similar system. The comparison shows that both training time and computation are reduced greatly due to the application of Neuro-Fuzzy classifier.

3. It is true that the output of sequence module presented in figures 11c, 12c, and 13c takes about 11ms to 14 ms before reaching its final stage. However, the phase module 1 takes into account three line currents (Ia, Ib, Ic) simultaneously with the output of sequence module to determine the output of phase module 1. Hence the final decision is directly influenced by the line currents too making it possible for the phase module 1 to determine the correct output before the final establishment of the sequence module's output. Thus the overall detection time has been reduced to about 10 ms even for the dlg faults. Infact, the phase module 1 was introduced to speed up the decision process for the slg/dlg faults.

4. The training of neuro-fuzzy networks takes less time and effort compared to that of mere neural networks. The final trained network only comprises of several simple IF-THEN type of rules. For example for the system presented in this paper only twenty-nine rules were needed to represent all three modules.

5. Yes, the classifier will wait for a short delay and make decisions only when the same type of fault is detected more than certain number of times consecutively.

6. It is true that only the off-line simulation results are presented in the paper. However, we did have some preliminary results on real-time tests indicating the real feasibilty of real-time implementation. Those results were not included in this paper because of the page limit.

7. In section 5.D, the reference should be to figure 20 instead of figure 16.