On-Line Testing of a Fuzzy-Neuro based Protective Relay using a Real-Time Digital Simulator

W. W. L. Keerthipala
School of Electrical & Computer Engineering,
Curtin University of Technology, WA 6845,
Australia 6845.

Huisheng Wang
Research & Development Unit,
Creative Technology Ltd,
Singapore 609921.

Chan Tat Wai
School of Electrical & Electronic Engineering,
Nanyang Technological University,
Singapore 639798.

Abstract: This paper presents a new approach with a Fuzzy-Neuro based Protective Relay for real-time fault detection and classification in power transmission systems. The integration of neural network technology into the Fuzzy Logic Controller enables the Fuzzy Rules to be learned by examples of input / output pattern pairs. From the power system point of view, the symmetrical components in combination with three line currents are utilised 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. The operating principle of the Fuzzy-Neuro Protective Relay, which depends on currents alone (without having to make reference to the system voltage) is, by conventional definition of distance protection, a novel approach. One major advantage of this technique, therefore, is the potential savings on Voltage Transformers in the actual implementation. Real-time test results are presented in this paper and they indicate that this approach can be used as an effective tool for high speed digital relaying, as the correct detection is achieved within a cycle of the fault occurrence.

Keywords: Fuzzy-Neuro Fault Classifier, Real Time Digital Simulator (RTDS), Digital Protection of Power Systems.

I 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 [1,2,3,15,16]. Some of them such as representing transmission lines by either first- or second-order differential equations and traveling-wave techniques [15] 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 some 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" type of relations. However, it is at the same time its major limitation as the power system operation in transient period, which is effected by many unknown parameters, cannot be easily described by artificial explicit knowledge. The integration of neural network into the fuzzy logic system, however, makes it possible to learn from the prior obtained data sets.

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 simple three-phase power system. The line current 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.

Figure 1 shows a typical two-bus system used for real-time tests of the Fuzzy-neuro based fault classifier. This paper presents mainly the real-time implementation aspects of the Fuzzy-Neuro fault classifier and the results validating the real-time operation.

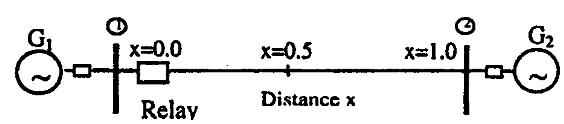


Fig. 1. A power system for relay testing.

A relay monitoring at busbar 1 senses the sequence components of the line currents due to a fault occurred at some point along the line. Such components are presented in figures 2, 3, and 4 against the distance to the fault point; where Ip, In, and Io are respectively positive, negative, and zero sequence components.

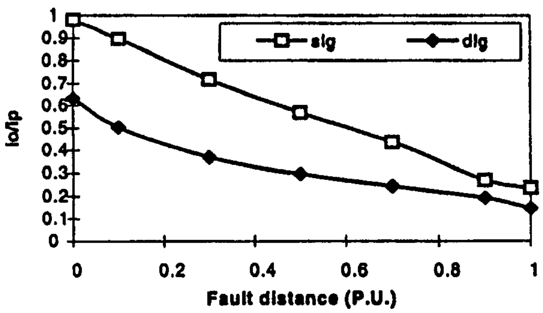


Fig. 2. Ratio Io/Ip

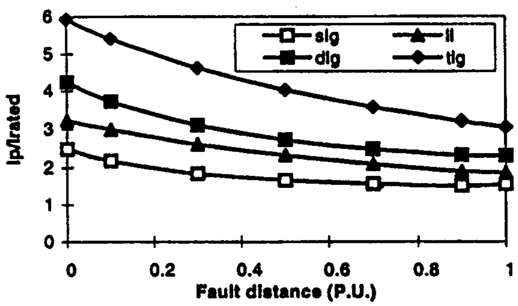


Fig. 3. Ratio Ip/ Irated

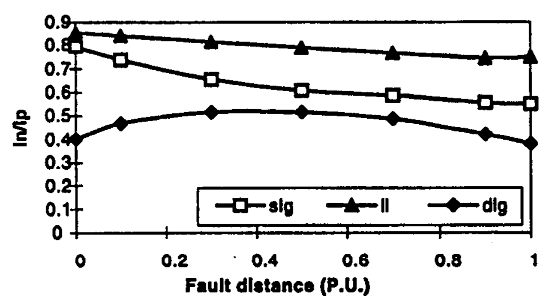


Fig. 4. Ratio In/Ip[1]

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 single-line-to-ground (slg) and double-line-to-ground (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 to make correct judgment within a cycle or so. The system operation in transient period cannot be easily described by artificial explicit knowledge. But the information (in implicit form) is contained in the field data. Consequently, we use fuzzy-neuro techniques to extract correct information from implicit field data.

A. Three Line Currents

As above mentioned, sequence components relaying is an effective tool, but mere use of sequence components is not very satisfactory for differentiating the slg fault with the dlg fault. 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.

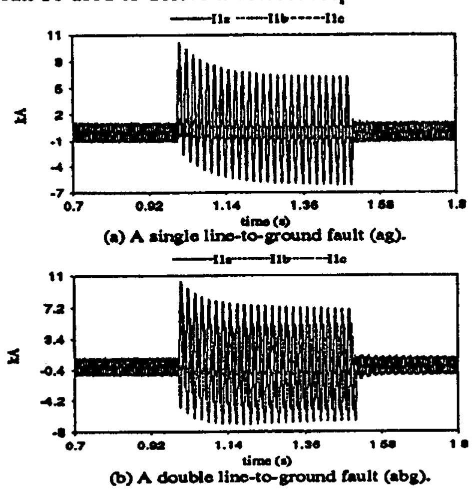


Fig. 5. Current waveforms (a) slg fault (phase A to ground), (b) dlg fault (phase A to phase B involving ground).

II FUZZY-NEURO FAULT CLASSIFIER

In this paper, we use the architecture of fuzzy controller developed with the aid of relational neural networks (Fig. 6).

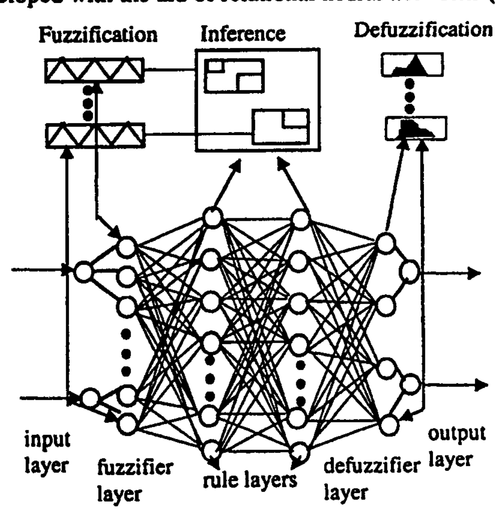


Fig. 6. Neurofuzzy technologies map a neural net to a fuzzy logic system.

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 if properly used.

A. Selection of Training Patterns

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). Details of training the controller can be found in reference [14].

B. Pre-processing and Symmetrical components

In case of fault, the line currents are no longer sinusoidal, because of the likely presence of harmonic components. Moreover, an exponentially 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 of fundamental frequency.

C. The Control Scheme

The whole control scheme of fault classification is shown in Fig. 7. The system consists of three main modules. The sequence components are 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 values) as inputs. Besides this, phase module 1 will consider the output of sequence module as a primary factor.

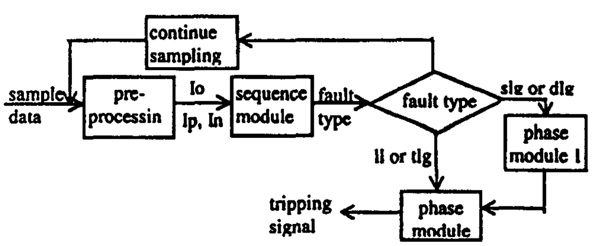


Fig. 7. The whole scheme of fault classification.

D. Training of Sequence Module

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.

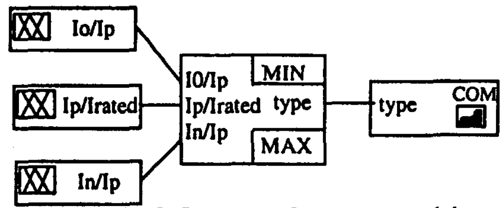


Fig. 8. Structure of sequence module.

It is worth while to note that the definition of the membership function is, an important procedure, based on the designer's knowledge and training sets. In this case, the membership functions should reflect different fault types and fault distances. 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. 9, is obtained by applying the fuzzy rules derived from the training of the fuzzy-neuro model [14] based on the prior data-base.

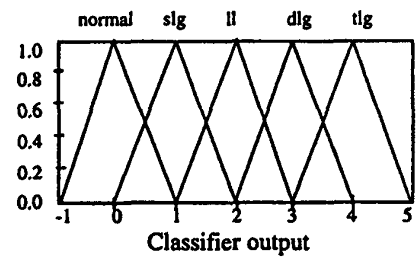


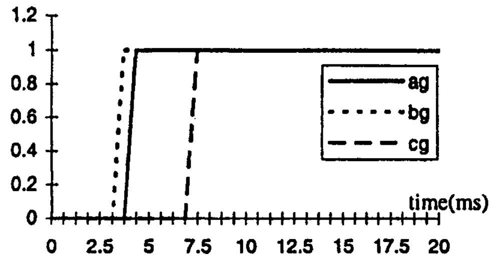
Fig. 9. Membership function of output (type) variable.

E. Testing

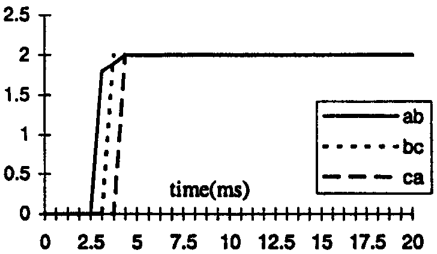
Trained fuzzy-neuro fault classifier was tested with a set of independent test patterns. The objective of this testing is to evaluate the reliability, speed, and generalization of the fuzzy-neuro fault classifier. Some results showing the performance of this fault classifier are presented here.

III OFF-LINE SIMULATION TEST RESULTS

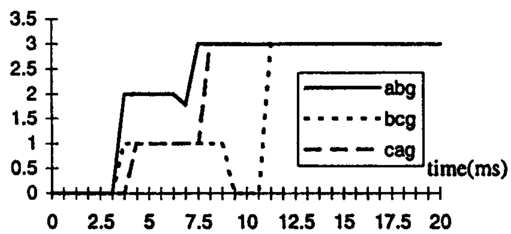
The faults at different fault distances have been simulated and only the results of the fault location of 30% and 90% of the line length are shown in Fig. 10 and 11. As per membership definition in Fig. 9, when $-1 \leq$ output <0.5, we regard it as normal condition; $0.5\leq$ output <1.5, slg; $1.5\leq$ output <2.5, ll; $2.5\leq$ output <3.5, dlg; $3.5\leq$ output <5, tlg. In each case the fault occurs at $t = 0$ instant.



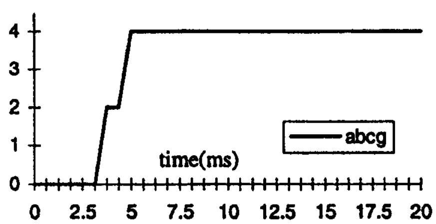
(a) Single line-to-ground



(b) Line-to-line

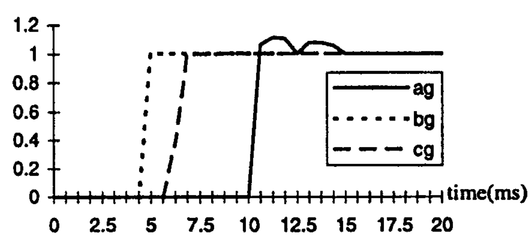


(c) Double line-to-ground



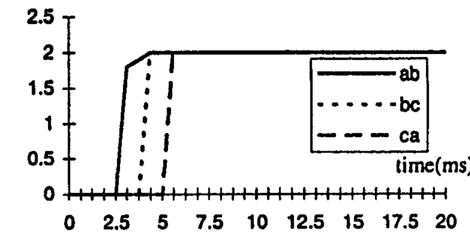
(d) Three line-to-ground

Fig. 10. Different types of fault located at 30% of the line length from relay (without any fault resistance).

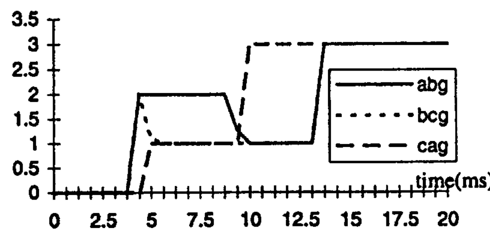


(a) Single line-to-ground

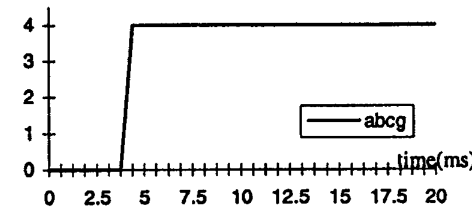
[2]ag: phase A to ground, ab: phase A to phase B, abg: phase A to phase B involving ground, abcg: three phase-to-ground. The others are similar in notation.



(b) Line-to-line



(c) Double line-to-ground



(d) Three line-to-ground

Fig. 11. Different type of fault located at 90% of the line ength from relay (without any fault resistance).

Test results show that the proposed fuzzy-neuro fault classifier is effective in determining the fault type under different fault locations, point on wave, phases involved, presence of fault distance and variations in source impedances. The classifier can detect the faults of ll and tlg in about 5ms, but sometimes it need more time (over 10 ms) for slg and dlg fault.

IV REAL-TIME IMPLEMENTATION

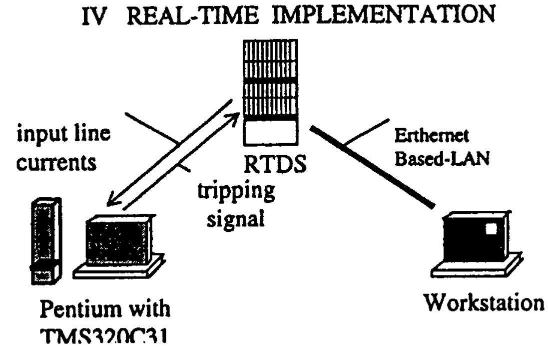


Figure 12: Apparatus set-up for Real-time tests

The proposed fuzzy-neuro fault classifier is part of a protective relay, which is 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 calculation accuracy and satisfy the real time constraints. The on-line tests using Real Time Digital Simulator (RTDS) [10] (as in figure 12) was conducted and the results are reported in section 5 of this paper.

V REAL TIME TEST RESULTS

The power system shown in figure 1 is simulated in real-time using the Real-Time Digital Simulator (RTDS), a massively parallel high speed (2000 MIPS) simulation facility, and the line current signals at the relay point are sent to the Fuzzy-Neuro Classifier residing in the Digital Signal Processor (TMS320C31). The Classifier output (as seen in figures 10 and 11) is used to generate a trip signal and sent in real time to the appropriate Circuit Breakers of the power system which is being run in the RTDS. Thus a circuit interruption can occur should a fault is detected in real-time.

Several instruments are connected to the RTDS including an a storage oscilloscope to capture important signals in real-time. The line current signals were monitored and recorded using the storage oscilloscope. Figures 13 to 16 show the records of three line currents under different types of faults. These photographs (oscilloscope screen) are taken from real-time tests for different faults at the fault location of 80% from the relay point. Each graph has three curves. The top one is the waveform of phase A current, with phases B and C sequentially. The right most dotted line represents the CB interruption point. From the graphs, we can see it needs nearly one cycle to detect the fault after it occurs at the time instant marked by the left dash-dot-dash line. The vertical line with tick marks is the y axis with a scale of 1.5 kA/div.

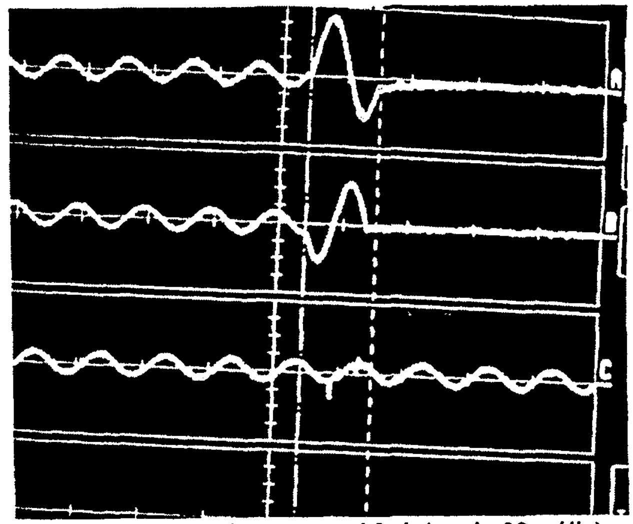


Figure 14: Double line-to-ground fault (x axis: 20ms/div)

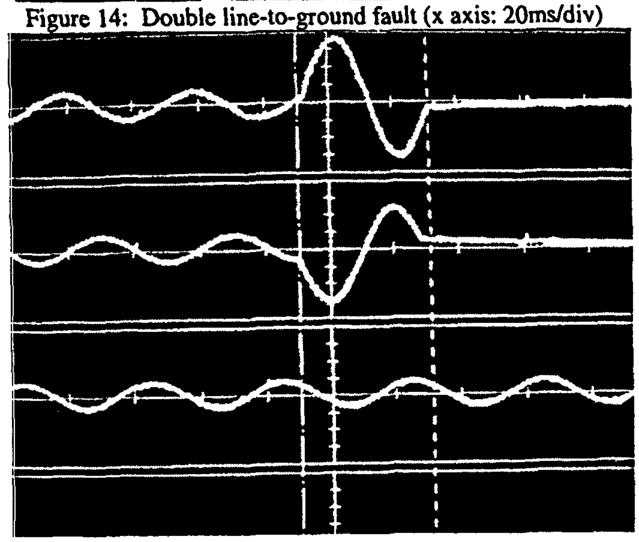


Figure 15: Line-to-line fault (x axis: 10ms/div)

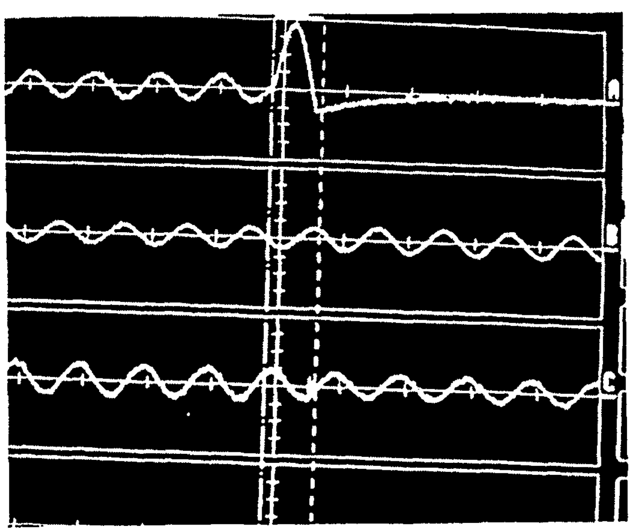


Figure 13: Single line-to-ground fault. (x axis: 20 ms/div)

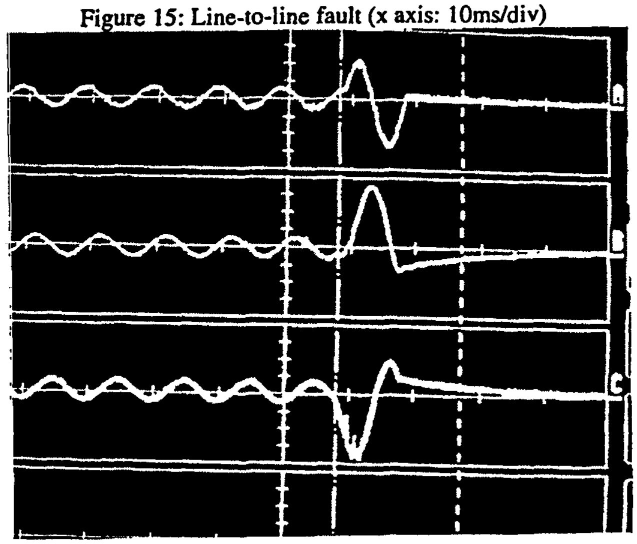


Figure 16: Three line-to-ground fault (x axis: 20ms/div)

VI CONCLUSIONS

Classification of transmission system faults, using only the current signals, with fuzzy-neuro techniques has been achieved in this work. It is proven to be a fast, accurate and robust approach that would perform accurately for various system conditions. Further, the results of real-time implementation is encouraging. This means that the fuzzy-neuro model with further refinement can be implemented in an actual power system to monitor occurrence of faults and to take necessary action. As this technique assumes no voltage reference it could potentially lead to huge savings on Voltage Transformers (VT and CVT) normally required for protection schemes.

VII ACKNOWLEDGEMENTS

The authors wish to thank the School of Electrical & Electronic Engineering, Nanyang Technological University, for providing facilities and a Research Grant (RP31/93) to conduct this research work and for providing a research scholarship to Miss Wang HuiSheng to work on this project.

VIII REFERENCES

[1] A.T. Johns and S.K. Salman, *Digital Protection for Power Systems,* published by Peter Peregrinus Ltd., on behalf of the Institution of Electrical Engineers, London, United Kingdom, 1995.

[2] A.T. Johns, M.A. Martin, A. Barker, E.P. Walker, P.A. Crossley, "A New Approach to e.h.v. Direction Comparison Protection Using Digital Signal Processing Techniques", *IEEE Trans. on Power Delivery,* PWRD-1, no. 2, Apr. 1986, pp. 24-34.

[3] M.B.Djuric and V.V.Terzija, "A New Approach To the Arcing Faults Detection for Fast Autoreclosure in Transmission Systems", *IEEE Transaction on Power Delivery,* Vol. 10, No. 4, October 1995, pp. 1793-1798.

[4] W.D. Breingan and M.M. Chen, "The Laboratory Investigation of a Digital system for the Prottection of Transmission lines", *IEEE Trans. 1979,* PAS-98, pp. 350-368.

[5] M.M. Mansour and G.W. Swift, "Design and Testing of a Multi-microprocessor Travelling Wave Relay", *IEEE Trans. 1986,* PWRD-1, pp. 74-82.

[6] T.S. Sidhu, H. Singh and M.S. Sachdev, "Design, Implementation and Testing of an Artificial Neural Network Based Fault Direction Discriminator for Protecting Transmission Lines", *IEEE Trans. on Power Delivery,* Vol. 10, No. 2, April 1995, pp. 697-706.

[7] Thomas Dalstein and Bernd Kulicke, "Neural Network Approach to Fault Classification for High Speed Protective Relaying", *IEEE Trans. on Power Delivery,* Vol. 10, No. 2, April 1995, pp. 1002-1009.

[8] W W L Keerthipala, Chan Tat Wai, and Wang HuiSheng, "Neural Network based Classifier for Power System Protection", *Journal of Electric Power Systems Research,* Vol. 42, pp. 109-114, Elsevier Science Publication, 1997.

[9] Alessandro Ferrero, Silvia Sangiovanni and Ennio Zappitelli, " A Fuzzy-Sets Approach to Fault-Type Identification in Digital Relaying", *IEEE Trans. on Power Delivery,* Vol. 10. No. 1 January 1995, pp 169-175.

[10] *"Electromagnetic Transients including D.C. (EMTDC/PSCAD) Program, and Real Time Digital Simulator (RTDS) manuals",* Manitoba HVDC Research Center, Winnipeg, Canada, 1994 release.

[11] "fuzzyTECH 4.1 User's Manual", Inform Software Corp., U.S.A, 1996.

[12] A.G. Phadke, T.Hlibka and M. Ibrahim, "Fundamental Basic for Distance Relaying with Symmetrical Components", *IEEE Trans. On PAS,* Vol. 96, No. 2, March/April 1977, pp635-646.

[13] "Protective Relays Application Guide", GEC Measurements, 1975.

[14] Wang Hui Sheng and W W L Keerthipala, "Fuzzy-Neuro Approach to Fault Classification for Transmission Line Protection", Paper accepted for the *IEEE Transactions on Power Delivery, Paper No. PE-815-PWRD-0-06-1997.*

[15] P A Crossley and P G McLaren, "Distance Protection Based on Travelling Waves", *IEEE Transactions, PAS-102,* 1983, pp. 2971-2983.

[16] P G McLaren and M A Redfern, "Fourier-Series Techniques applied to Distance Protection", *IEE Proceedings, Vol. 122,* 1975, pp. 1295-1300.

[17] Wang HuiSheng, "Neuro-Fuzzy Implementation of Digital Protection for Power Transmission Systems", Master of Engineering Thesis, Nanyang Technological University, Singapore, 1997.

IX BIOGRAPHIES

W W L Keerthipala (M'90) obtained his PhD degree from University of Cambridge, England, in 1989, in Power Systems and Drives, and later he worked at Nanyang Technological University, Singapore, until 1997 August. Currently he is a Senior Lecturer with Curtin University of Technology, Australia.

Wang HuiSheng obtained her Master of Engineering degree from Nanyang Technological University, Singapore, in 1997. Currently she is with Creative Technology Ltd. In Singapore as a Research Engineer in Digital Image processing.

Chan Tat Wai, David, is a Senior Lecturer with Nanyang Technological University, Singapore.