TWO NEW METHODS FOR VERY FAST FAULT TYPE DETECTION BY MEANS OF PARAMETER FITTING AND ARTIFICIAL NEURAL NETWORKS

Anton Poeltl
ABB Power T&D Company, Inc.
Greensburg, PA

Klaus Fröhlich, Senior Member, IEEE
Swiss Federal Institute of Technology Zurich
Zurich, Switzerland

Abstract: *A new method for the detection of the type of a fault in* generator circuits and transmission systems is introduced. Already within a quarter of a cycle after fault inception the method can distinguish between the various fault types. Fitting the parameters of a set of simple equations to voltage and current measurements immediately before and after a fault identifies the fault type. The procedure includes a new method for phasor computation and takes less than 1 ms computation time. As a variant of this method neural networks are employed. Verification using EMTP modeling proved satisfactory operation of both methods even when the current signals were superimposed with heavy noise. Fast decisions for single pole tripping and a crucial basis for algorithms for synchronous switching under fault conditions are provided.

Keywords: Fault location, Parameter estimation, Neural network applications

I. INTRODUCTION

Protective relaying in systems of generation and transmission of electrical power have been subject to significant development during recent years. With employment of digital electronic circuits, the relays became more sophisticated and to some extent faster than conventional circuits. In the context of intelligent protection schemes, two tasks are of major importance, namely the recognition of the fault type and determination of the fault location. Also in discussion is the determination whether the fault is arc-less, which indicates a permanent fault, or whether it is caused by an arc, which, at least for lines, is the indication of a temporary fault.

For faster fault analysis, in this paper a procedure is introduced which provides information on the fault type within a quarter of a cycle based on a deterministic method consuming a minimum of computer power. The error rate of the procedure is well below 5% even when the current signal is superimposed by a noise of 10%. It is also shown in the report how simple neuronal networks can be employed for fault type detection if the data containing voltage and current curves are properly preprocessed. The functioning of both procedures is verified by EMTP simulations.

There are several reasons for fault type detection. For proper tripping, the type of the fault should be known to the protection relay—in particular when single pole tripping is practiced by the utility. Development in recent years has resulted in digital high-speed relays with reaction times that came down to no more than a quarter of a cycle. Accordingly, the need for a short time interval for fault type recognition has arisen.

Among modern solutions for fault type analysis are the application of expert systems or artificial neural networks. In [1] an expert system is presented that uses the phasors of phase voltages and currents as well as their zero-sequence values to derive a criterion for each fault type. The reported procedure is not intended for real-time application but can be used for off-line diagnosis of data provided by digital fault recorders. In [2] artificial neural networks are introduced as an improvement of this approach. One of the reported advantages is that no phasor computation has to be performed. Since only Fourier transform is considered for phasor computation the data window has to cover a complete cycle or at least half-cycle, which indeed is not required for the application of neural networks. However, in this report a fast method for phasor computation will be presented that can be applied with data windows of any length.

Another neural network approach for fault type detection is presented in [3] and [4]. The reported method is suitable for high-speed protective relaying and identifies the fault type within 6...8 ms. However, extensive training with thousands of patterns is required. Furthermore the execution of the neural networks in real time requires more computation power than the parameter fitting method described in this report.

A further application, which has not been discussed in literature so far, is fault type detection as a basic information for synchronous switching under fault conditions by circuit breakers, either in generator/transformer circuits or on the bus and the transmission line. As shown in [5], algorithms to synchronize the contact travel of a breaker to the fault current wave, for minimization of contact wear, need to know the fault type in order to be sufficiently fast. This means information on the fault type has to be available within a quarter of a cycle if the synchronizing procedure should not delay the operation of high speed relays.

PE-326-PWRD-0-10-1998 A paper recommended and approved by the IEEE Power System Relaying Committee of the IEEE Power Engineering Society for publication in the IEEE Transactions on Power Delivery. Manuscript submitted June 22, 1998; made available for printing November 10, 1998.

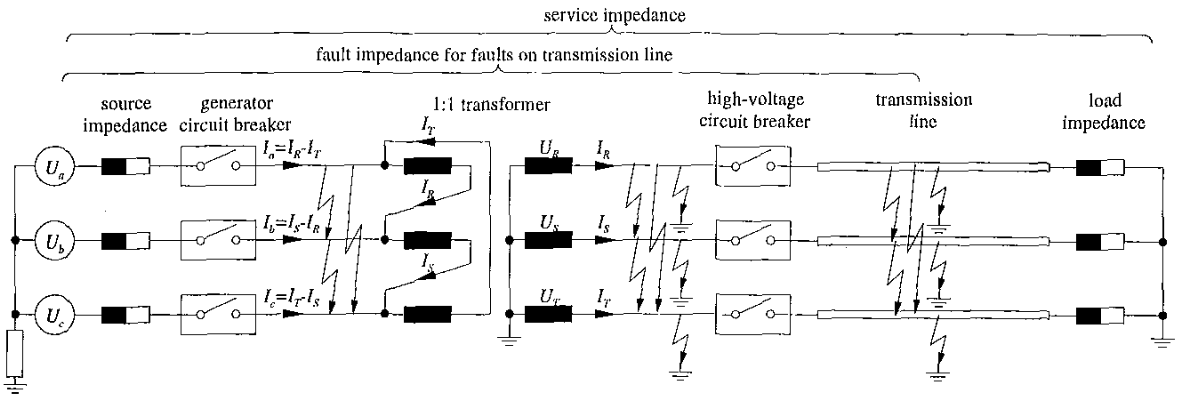

Fig. 1. Equivalent circuit of a typical power system

II. FAULT TYPES

Fig. 1 shows the simplified equivalent circuit of a typical power system consisting of generator, transformer, transmission line and load. As shown, faults can occur on both the high-voltage side and the low-voltage side of the transformer. The HV circuit breaker (HV CB) is used to clear faults on the transmission line, whereas the generator circuit breaker (GCB) has to clear generator fed faults located between the GCB and the HV CB. In general, these faults may occur inside the transformer as well as between the terminals of the transformer [6].

From Fig. 1 ten fault types on the high-voltage side can be derived, namely

- 3 phase-to-ground faults on phase (Rg, Sg and Tg),
- 3 phase-to-phase faults (RS, ST, RT),
- 3 two-phase-to-ground faults (RSg, STg, RTg),
- three-phase faults with or without ground connection.

On the low-voltage side line-to-ground faults are not considered, since the Y-point of the generator is assumed to by grounded via high impedance. Therefore, only

- 3 phase-to-phase faults (ab, bc, ca) and
- 1 three phase fault (abc)

can occur.

Inside the transformer, faults can be classified as

- 3 faulted low voltage windings (ab, bc, ca),
- 3 faulted high voltage windings (Rg, Sg, Tg).

Note that not all of the 20 above-mentioned fault types are totally different. For instance, a fault between two low-voltage phases behaves similar to a fault between a high-voltage phase and ground. Using these similarities, the various faults are grouped into the 10 fault types shown in Table 1.

The relation of various fault types shown in Table 1 is important for the functionality of the method described in this report. First, the method identifies the fault as one of the 10 fault types listed in Table 1. Next, the fault impedance, which is a by-product of the previous step, can be used to further differentiate between faults on the low-voltage side, on the high-voltage side, or inside the transformer. Similar to a distance protection relay, the method uses only the voltages and currents measured at the location of the breaker for this task.

III. PRINCIPLE OF THE PARAMETER FITTING METHOD

The core part of the fault type detection method is a set of equations that approximately describe the steady state of the phase currents during a fault. For each of the fault types in Table 1 the corresponding equations are listed in Table 2. These equations introduce the service admittance Y_S and the fault admittance Y_F as parameters. The service admittance is

TABLE 1
CONSIDERED FAULT TYPES

fault type	transformer windings	LV side	HV side
1	Rg, ab	ab	Rg
2	Sg, bc	bc	Sg
3	Tg, ca	ca	Tg
4			RSg
5			STg
6			TRg
7			RS
8			ST
9			TR
10		abc	RST

TABLE 2
EQUATIONS FOR THE FAULT TYPES OF TABLE 1

fault type	$I_{F,R}$	$I_{F,S}$	$I_{F,T}$
1	$U_R Y_F$	$U_S Y_L$	$U_T Y_L$
2	$U_R Y_L$	$U_S Y_F$	$U_T Y_L$
3	$U_R Y_L$	$U_S Y_L$	$U_T Y_F$
4	$U_R Y_F$	$U_S Y_F$	$U_T Y_L$
5	$U_R Y_L$	$U_S Y_F$	$U_T Y_F$
6	$U_R Y_F$	$U_S Y_L$	$U_T Y_F$
7	$(U_R-U_S) Y_F + U_R Y_L$	$(U_S-U_R) Y_F + U_S Y_L$	$U_T Y_L$
8	$U_R Y_L$	$(U_S-U_T) Y_F + U_S Y_L$	$(U_T-U_S) Y_F + U_T Y_L$
9	$(U_R-U_T) Y_F + U_R Y_L$	$U_S Y_L$	$(U_T-U_R) Y_F + U_T Y_L$
10	$U_R Y_F$	$U_S Y_F$	$U_T Y_F$

the reciprocal of the service impedance which comprises all impedance in effect prior to fault inception (see Fig. 1). Accordingly, the fault impedance includes all impedance from the voltage source to the location of the fault. Whereas the service admittance can be calculated from the voltages and currents measured immediately before fault inception, the fault admittance can only be determined if the fault type is already known—or if a fault type is arbitrarily assumed. This latter observation leads to the principle for fault type detection shown in Fig. 2.

Each triple of equations in Table 2 is used as a model for the particular fault that calculates the phasors of the currents after fault inception I_{FR}, I_{FS} and I_{FT} from the voltage phasors U_R, U_S and U_T. Besides the service admittance Y_S, the calculated currents for each model depend on the fault admittance Y_F, which is an unknown and thus free parameter. Therefore, Y_F can be used to tune the output of each model in order to match the phasors of the measured currents as well as possible. However, even though the fault admittance Y_F for each model is selected to minimize the deviation between the currents calculated by the model and the currents measured after fault inception all but one model will deliver significant differences. Only the output of the model that describes the type of the fault that has actually occurred will closely match the measured currents. Hence, the fault type can be identified by searching for the smallest absolute difference ΔI (see Fig. 2) between the output of the model and the measured currents.

Since the equations used to model the various fault types apply only to the steady state and do not take into account effects such as the transients caused by a synchronous generator or non-linearity caused by saturation of the transformer, none of the models will exactly describe the measured currents. However, an exact model is not required as long as the model describing the actual fault type matches better than all other models. As will be shown, there are indeed orders of

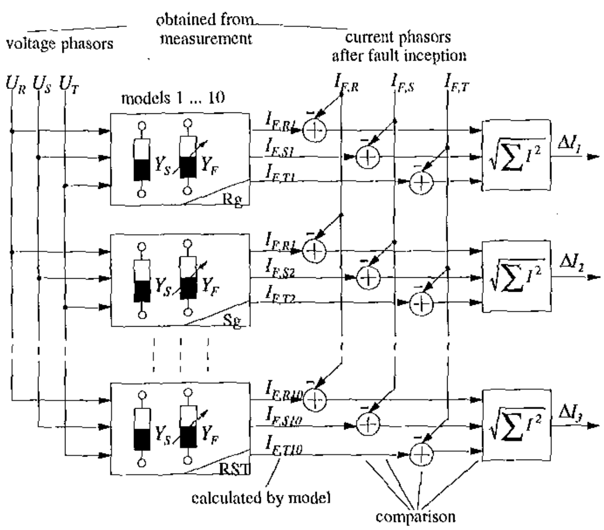

Fig. 2. Principle for fault type detection via parameter fitting

magnitude between the absolute difference ΔI of the model describing the correct fault type and the differences of all other models.

IV. IMPLEMENTATION

A. Set of equations

The equations used to model the currents after fault inception on the high-voltage side of the system (comp. Fig. 1) are listed in Table 2.

These equations, however, apply only if the phase currents and phase voltages are measured on the high-voltage side. In order to obtain the appropriate equations in case the phase voltages and currents are measured on the low-voltage side the following substitutions have to be made:

$$\begin{aligned} U_R &= U_a - U_b \\ U_S &= U_b - U_c \\ U_T &= U_c - U_a \end{aligned} \tag{1}$$

which allows to calculate the currents on the low-voltage side according to

$$\begin{aligned} I_a &= I_R - I_T \\ I_b &= I_S - I_R \\ I_c &= I_T - I_S \end{aligned} \tag{2}$$

Although equations (1) and (2) are based on a 1:1 transformer ratio (see Fig. 1) they can be applied to all delta–wye connected transformers, since the actual ratio introduces only a scaling factor into the calculation of the fault admittance but does not affect detection of the fault type.

B. Service Admittance

The service admittance Y_S is calculated from the phasors of the voltages U_R, U_S, U_T and the currents $I_{L,R}$, $I_{L,S}$, and $I_{L,T}$ immediately before fault inception,

$$Y_S = \frac{1}{3}\left[\frac{I_{L,R}}{U_R} + \frac{I_{L,S}}{U_S} + \frac{I_{L,T}}{U_T}\right]. \tag{3}$$

With (1) and (2), an expression based on the voltages U_a, U_b, U_c and the currents $I_{L,a}$, $I_{L,b}$, $I_{L,c}$ on the low-voltage side can also be derived,

$$Y_S = \frac{1}{3}\left[\frac{I_{L,a}}{3U_a} + \frac{I_{L,b}}{3U_b} + \frac{I_{L,c}}{3U_c}\right]. \tag{4}$$

C. Phasor Calculation

In terms of fast reaction times, the calculation of the voltage and current phasors is the most crucial part of fault type detection. If, for instance, Fourier transform is used to calculate the phasors of the fault currents sampling of the current has to be continued for one cycle or at least one half-cycle after fault inception. Therefore it takes at least 8.3 ms in a 60 Hz system before the algorithm for fault type detection can even start. As a remedy, the application of neural networks has been suggested in [2], since neural networks, as opposed to Fourier transform, do not require data windows of a particular length.

However, a decomposition into its sine, cosine and dc components according to

$$i(t) = c_1 \cos(\omega t) + c_2 \sin(\omega t) + c_3 = i_{ac}(t) + c_3 \qquad (5)$$

can also performed via least squares fitting [7] [8]. By replacing the time t in (5) with the instants $t_1, t_2, \ldots t_n$, at which consecutive samples of the current were taken, an equation system results which can be solved by means of least squares. The so-called pseudo-inverse [9], which is required for solving this equation system, can be computed in advance since it does not depend on the values unknown prior to fault inception. Hence, the computation effort in real-time is reduced to a matrix multiplication, which can be done in parallel with acquisition of the samples.

Therefore, the presented method for phasor computation is both flexible and fast. Any length of the data window that meets the accuracy requirements can be selected. In general, a quarter of a cycle is sufficient to produce sufficiently accurate results even in noisy environments.

Once the coefficients $c1$, $c2$, and $c3$ have been computed the current phasor I in compliance with

$$i_{ac}(t) = \mathrm{Re}\left\{ I \cdot e^{j\omega t} \right\} \qquad (6)$$

can be calculated using

$$I = c_1 - j \cdot c_2 . \qquad (7)$$

The phasors for voltage and current prior to fault inception can be calculated in a similar way. However, in order to be still available for phasor computation, the courses of the phase voltages and currents prior to fault inception must not be overwritten with those after fault inception. Therefore it is necessary to store the past few cycles of the course of the phase voltages and currents.

D. Reaction time

The reaction time of the fault detection method is the sum of the data window length required for phasor computation plus the time needed to execute the fault type detection algorithm. On a digital signal processor (TMS320-C31), for instance, execution time is 500 µs. In combination with a data window length of a quarter cycle the total reaction time is therefore

$$t_r = \frac{1}{4 \cdot 60\,\mathrm{Hz}} + 500\,\mu\mathrm{s} = 4.7\ \mathrm{ms} \qquad (8)$$

in 60 Hz power systems.

V. APPLICATION OF NEURAL NETWORKS

There are multiple ways to apply neural networks to fault type detection. In [2] neural networks are trained to recognize the fault type based on raw samples of the phase currents, whereas in [3] the neural networks are fed with "features" extracted form the course of the phase currents.

In this report, neural networks will be applied to identify a fault type based on the phasors of the currents after fault inception. Since several steps of the parameter fitting method, such as phasor computation and the evaluation of the equations of Table 2, will be used for preprocessing the neural network approach can be considered a variant of the parameter fitting method.

The principle of the application of neural networks is shown in Fig. 3. The current and voltage phasors are preprocessed before they are used as inputs for the neural network. Each of ten neural networks has been trained to recognize one of the fault types of Table 1. The output of a particular neural network is 1 if it identifies the fault type and 0 otherwise.

The purpose of preprocessing is to simplify the task of the neural networks. Thereby, neural networks with a simpler structure can be used. The input of the preprocessing procedure is a "phasor diagram" consisting of the voltage phasors and the current phasors after fault inception. The following steps are performed:

1. Rotation of the phasor diagram to assume a standard position,
2. Compensation of the load currents based on the equations in Table 2,
3. Normalization of the current phasors using the maximum length of all phasors.

The result of the preprocessing procedure is a standardized phasor diagram for the currents of a particular fault type. This diagram is nearly independent of the voltage phase angle at fault inception, the load currents and the actual magnitude of the phasors. Therefore it is possible to use neural networks with only 10 hidden neurons. The neural networks were

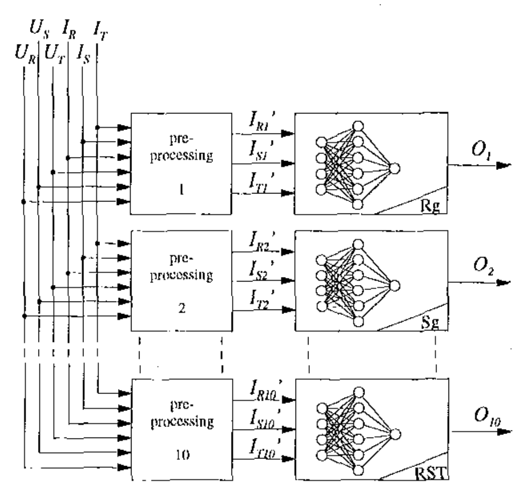

Fig. 3. Application of neural networks for fault type detection

trained with 100 different fault situations: 10 fault types with 10 different voltage phase angles at current inception. For testing, basically the same set of training data was used but with a different load, a different fault location and other 10 voltage phase angles. As shown in the next section the neural networks were able to generalize, i.e. to correctly process even data that were not used for training.

VI. PERFORMANCE VERIFICATION

In order to verify both fault type detection methods various faults were simulated using EMTP (Electro-Magnetic Transients Program). The underlying model was a synchronous generator followed by a step-up transformer as shown in Fig. 1. The phase currents and voltages were calculated for the low-voltage side, which is the more sophisticated case for fault type detection.

Both methods were applied to only 6 different fault types, since the remaining fault types can be obtained by permutation of the phases.

1. phase-to-phase fault at low-voltage side: ab (corresponds to Tg)
2. three-phase fault at low-voltage side: abc (corresponds to RST)
3. phase-to-ground fault at high-voltage side: Rg
4. two-phase-to-ground fault at high-voltage side: RSg
5. phase-to-phase fault at high-voltage side: RS
6. three-phase fault at high-voltage side: RST

Each fault type was simulated with 10 different voltage phase angles at fault initiation time, yielding 60 simulation cases. All of the simulated faults were classified correctly by both fault type detection methods.

Fig. 4 shows an example for fault type detection using parameter fitting as well as neural networks. The fault currents correspond to a phase-to-ground fault (phase R) at the terminals of the high-voltage windings of the transformer. Due to the delta-star connected transformer the phase-to-ground fault at the high-voltage side behaves like a phase-to-phase fault at the low-voltage side (cf. Table 1), which is characterized by two equal currents with opposite sign. The influence of the load currents, however, obscures this feature.

The result of the parameter fitting method shows how closely the approximation equations for each considered fault type can describe the actually measured (simulated) fault currents. It can be seen that the approximation equation for phase-R-to-ground (Rg) fits much better than all other equations. Thereby the fault type is correctly recognized as Rg.

Also, fault type classification using neural networks works satisfactorily. The neural network trained for Rg recognizes the fault currents ($O = 1$), whereas the remaining networks are certain that the considered fault currents do *not* represent the

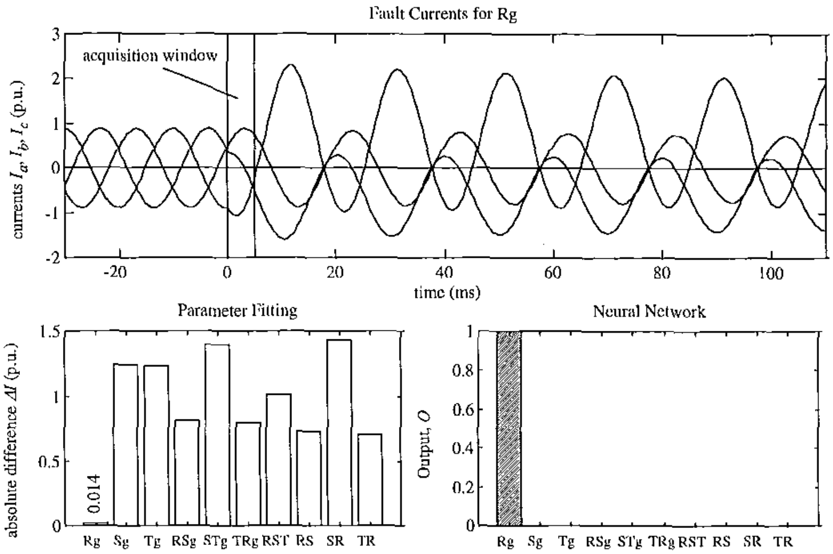

Fig. 4. Example for fault type classification tested with EMTP-simulations. Both methods are based on the short time window confined by the two vertical lines.

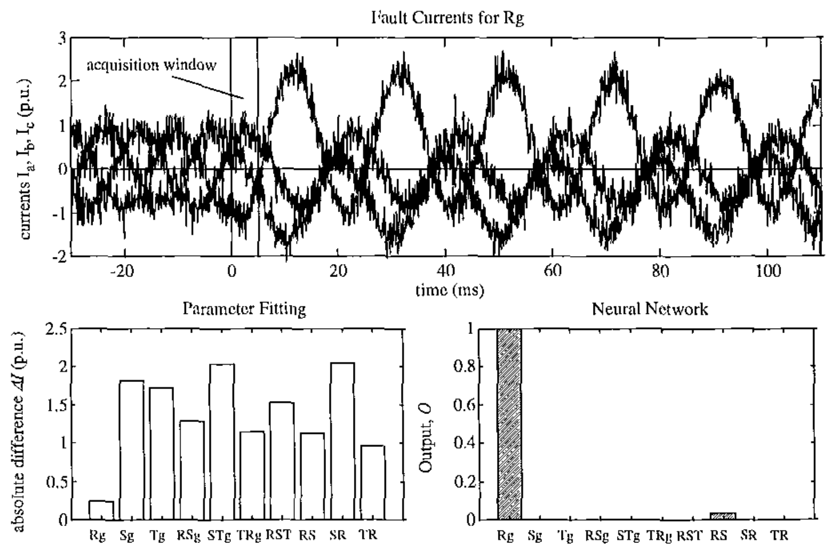

Fig. 5. Evaluation of robustness against noise.

fault type, they were trained for ($O = 0$).

In order to test the robustness of the fault classification methods, a random noise signal was added to the simulated fault currents prior to fault classification. Both methods worked 100% error-free with noise levels corresponding to a reasonable measurement accuracy. Finally, at a noise level of 10%, which is already unrealistically high, some classification errors occurred. Even then the percentage of correct classifications was 96% for parameter fitting and 93% for neural networks. Fig. 5 shows an example, where both methods produced a correct result, in spite of the high noise level. Due to the calculation errors caused by the noise signal the approximation equation for Rg does not fit as closely as in Fig. 4. However, the difference is still significantly lower than for all other fault types. Likewise, the fault currents are still recognized by the neural network trained for Rg, whereas most of the remaining networks are certain *not* to recognize the fault type they were trained for. Only one neural network tends to confuse Rg with RS, although its output is still below 0.5.

VII. CONCLUSIONS

The methods introduced in this report are able to identify the type of a fault within a quarter of a cycle, which means reaction times of less than 5 ms in 60 Hz systems.

The methods can be used for generator circuits including the transformer as well as for transmission lines.

Because of the short reaction time they may be applied for fast decision in case of single pole tripping. Also, they are an essential tool if an algorithm for synchronous switching under fault condition should be applied, which for the time being is not practiced but which certainly has future potential as e.g. implied by the work of CIGRE Working group 13.07.

VIII. REFERENCES

[1] M. Kezunovic, C.W. Fromen, "An Expert System for Transmission Substation Event Analysis", *IEEE Transactions on Power Delivery*, Vol. 8, No. 4, October 1993.

[2] M. Kezunovic, I. Rikalo, "Detect and Classify Faults Using Neural Nets", *IEEE Computer Applications in Power*, October 1996.

[3] Th. Dalstein, B. Kulicke, "Neural Network Approach to Fault Classification for High Speed Protective Relaying", *IEEE Transactions on Power Delivery*, Vol. 10, No. 2, April 1995.

[4] Th. Dalstein et al., "Multi-Neural Network Based Fault Area Estimation for High Speed Protective Relaying", *IEEE Transactions on Power Delivery*, Vol. 11. No. 2, April 1996.

[5] A. Pöltl, *Synchrones Abschalten von Kurzschlüssen mittels Hochspannungsleistungsschaltern und Generatorschaltern*, Ph.D. thesis, Vienna University of Technology, 1997.

[6] B. Culver, K. Fröhlich, L. Widenhorn, "Prevention of Tank Rupture of Faulted Power Transformers by Generator Circuit Breakers", *European Transaction on Electrical Power*, pp. 39-42, vol. 6, No. 1, Jan./Feb. 1996.

[7] W.H. Press, *Numerical Recipes in C*, Cambridge University Press, 1992.

[8] Ch.W. Therrien, *Discrete Random Signals and Statistical Signal Processing*, Prentice-Hall International Editions, pp. 518-535.

[9] A. Weinmann, *Uncertain Models and Robust Control*, Springer 1991, pp. 645-647.

IX. BIOGRAPHIES

Anton Poeltl (1968) studied Electrical Engineering at the Vienna University of Technology in Austria, leading to the degree of Dipl.-Ing. in 1992. From 1993 to Feb. 1998 he belonged to the scientific staff of the Institute of Switching Devices and High Voltage Technology of the Vienna University of Technology. His research on algorithms for synchronous switching under fault conditions led to a Ph.D. in 1997. Presently, he works as a development engineer for intelligent circuit breakers at ABB Power T&D Company Inc. in Greensburg, Pennsylvania (U.S.A).

Klaus Fröhlich (1945) studied Electronic Engineering at the Vienna University of Technology in Austria, leading to the degree of Dipl.-Ing. in 1972, followed by a Ph.D. in Technical Science in 1976. From 1973 to 1979 he was a scientific staff member at the Institute of Switchgear at the Vienna University of Technology, dealing with high voltage phenomena on oil and vacuum breakers. In 1979 he joined Brown Boveri AG in Baden, Switzerland, where he specialized on high power testing techniques of HV circuit breakers. In 1986 he became head of the BBC High-Voltage Laboratory, where he was mainly involved in the development of gas-insulated switchgear (GIS). In May 1990 he became a full professor at the Vienna University of Technology and headed the Institute of Switching Devices and High-Voltage Technology until 1997. Since May 1997 he is the head of the High Voltage Laboratory at the Swiss Federal Institute of Technology, Zurich, Switzerland. He is a senior member of IEEE, a member of CIGRE Study Committee 13 and chairman of CIGRE Working Group 13.07 (Controlled Switching).

DISCUSSION

Toshihisa Funabashi, (Senior Member, Meidensha *Corporation, Tokyo, 103-8515, Japan*):

In this paper two new methods for fault type detection are presented. The methods might be useful for single pole tripping and synchronous switching under fault conditions in real power systems. The authors' comments on the following points would be appreciated.

1) In the proposed method by parameter fitting, admittance matrices Y_F and Y_L are used rather than impedance matrices. In most digital distance protections, impedance matrices are used. Why the admittance matrix was chosen? Does it relate to the consistency of voltage phasors compared to that of current phasors?

2) Is the fault resistance considered in the simulation? This "fault resistance" is, I believe, the sum of the fault resistance and the fault arc resistance. Fault arc may behave non-linearly due to the variation of its physical characteristics. In such cases, the parameter fitting method is in error due to the non-linearity of the fault resistance.

3) In the simulation for performance verification of the proposed method, a random noise signal is considered. The real power system often has a harmonic distortion. In such cases, low-pass or band-pass filters are needed to eliminate a high harmonic signal. Thus, longer time is needed for identification of the type of a fault.

4) In the proposed method by neural networks, the pre-processing seems to succeed in simplifying the task of the neural networks. Among the three steps, i.e. rotation of the phasor, compensation of the load currents, and normalization of the current phasors, which is most effective? Are all three steps necessary for the good performance of neural networks?

Manuscript received March 29, 1999.

A. Poeltl and **K. Fröhlich**:

The authors wish to thank Mr. Toshihisa Funabashi for his valuable contribution for discussion of this paper and hopes that the following will answer Mr. Funabashi's questions.

1) Using admittance values seems to be more practical, since it is possible to express the fact that - for instance the high voltage circuit breaker is open - by using 0 for the corresponding admittance rather than ∞ for the impedance value.

2) The simulation used an EMTP model of a synchronous generator and a delta-wye connected transformer. The arc resistance/voltage was not modeled, even though it would have been a valuable addition for the purpose of evaluating the method. However, the simulation demonstrated that the method, in spite of being based on a very simplified theory, was able to distinguish between different types of faults based on data stemming from a quasi-realistic simulation. Therefore the author, without proof, is confident that the method is also applicable to arcing faults. Furthermore the author likes to point out that from the view point of modeling current wave forms the model used for parameter fitting makes a considerable error. However, for the differentiation between different fault types the model proves to be adequate.

3) Noise as well as higher harmonics are eliminated in the first step of the method where amplitude, phase and dc-component is calculated via least square fitting. Therefore there is no need for additional filters or further time consuming numerical pre-processing.

4) The described method using neural networks mimics the parameter fitting method, which is why it can work with very simple structured neural networks. Unless more sophisticated neural networks are used at least the rotation and normalization of the current phasors should be performed. The task of recognizing a particular fault type in the presence or absence of load current, however, could be left to neural network. As reported by the cited literature, neural networks have also been used with less or even without pre-processing for this purpose.

Manuscript received May 5, 1999.