A Novel Algorithm for Fault Classification in Transmission Lines Using a Combined Adaptive Network and Fuzzy Inference System

Sang-Min Yeo* and Chun-Hwan Kim**

Abstract - Accurate detection and classification of faults on transmission lines is vitally important. In this respect, many different types of faults occur, such as *inter alia* low impedance faults (LIF) and high impedance faults (HIF). The latter in particular pose difficulties for the commonly employed conventional overcurrent and distance relays, and if undetected, can cause damage to expensive equipment, threaten life and cause fire hazards. Although HIFs are far less common than LIFs, it is imperative that any protection device should be able to satisfactorily deal with both HIFs and LIFs.
Because of the randomness and asymmetric characteristics of HIFs, their modeling is difficult and numerous papers relating to various HIF models have been published. In this paper, the model of HIFs in transmission lines is accomplished using the characteristics of a ZnO arrester, which is then implemented within the overall transmission system model based on the electromagnetic transients program (EMTP).
This paper proposes an algorithm for fault detection and classification for both LIFs and HIFs using Adaptive Network-based Fuzzy Inference System (ANFIS). The inputs into ANFIS are current signals only based on Root-Mean-Square (RMS) values of 3-phase currents and zero sequence current.
The performance of the proposed algorithm is tested on a typical 154 kV Korean transmission line system under various fault conditions. Test results demonstrate that the ANFIS can detect and classify faults including LIFs and HIFs accurately within half a cycle.

Keywords: Adaptive network, Fuzzy inference system, Fault classification, Transmission line

1. Introduction

Since the complexity of modern power systems is increasing (longer lines, increased power transfer over existing lines due to the limitations imposed by environmental pressures, etc.), traditional analogue relaying is no longer capable of coping with performance requirements. Hence there is an advantage to employing digital protection relays, which are much better suited to handling the modern-day protection problems, particularly in terms of speed and accuracy. The purpose of a protective relaying system is to detect the abnormal signals indicating faults on a transmission system and isolate the faulted component from the rest of the system thereby preventing the propagation of the fault into other areas [1].

In this respect, there is now ongoing work to further improve the performance of digital protection relays. Protecting transmission lines is one important task to safeguard electric power systems. Faults on transmission lines need to be detected, classified and located accurately so that they can be cleared as quickly as possible. Fast and reliable fault classification is thus paramount in the overall protection strategy [1]-[2].

Many researchers have studied the application of neural networks to overcome many of the aforementioned problems [3]-[11]. Hitherto, the algorithms developed include the high frequency voltage signal method [5], a statistical method [6], a numerical algorithm [7]-[8], wavelet transform [9], the neural network and the neuro-fuzzy network [10]-[11].

Jang and Sun introduced the adaptive network-based fuzzy inference system (ANFIS). This system makes use of a hybrid learning rule to optimize the fuzzy system parameters of the first order Sugeno system [12]-[13]. It is composed of five layers. Each layer is a component of the fuzzy inference system and performs different actions. Using the back propagation method of training a neural network, fuzzy premise and consequent parameters are tuned properly.

This paper develops an algorithm of fault classification using ANFIS. The inputs for ANFIS are RMS values of 3-phase currents and zero sequence current. The performance of the proposed algorithm is evaluated for a typical 154 kV Korean transmission line system under various fault conditions.

* School of Information and Communication Engineering, Sungkyunkwan University, Korea. (harc@chollian.net)
** School of Information and Communication Engineering, Sungkyunkwan University, Korea. (chkim@skku.edu)
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2. Fault Classification Algorithm

2.1 System model studied

In the work presented herein, the model system studied is the Korean 154 kV system as shown in Fig. 1.

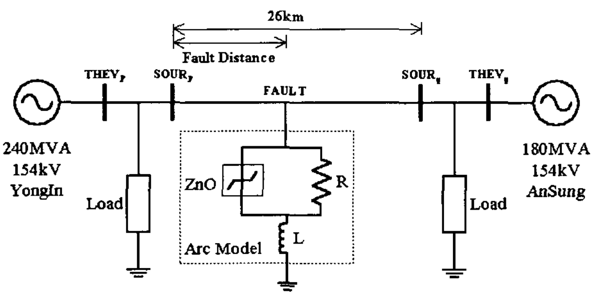

Fig. 1 Simulation model of 154 kV system

It is comprised of a 26 km line length terminated in two sources of 240 MVA and 180 MVA each at both ends of the line. Fault data is generated for fault conditions such as variation in fault distance, fault inception angle and fault types, at a sampling rate of 64 samples per cycle. The HIF simulation is based on a ZnO arrester model [14]-[17] which is embedded into the overall transmission line model, and the impedance of HIF is approximately 200Ω.

Table 1 details source and line parameters of the model system considered and Table 2 shows the various fault conditions.

Table 1 Source and line parameters

		Zero Seq.	Pos. Seq.
Line Constants	R[Ω /km]	0.2293	0.0419
	L[Ω /km]	1.0050	0.3316
	C[μmho/km]	1.6260	4.8309
YongIn Substation	Capacity	240MVA	
	Power Factor	0.91	
	Z_{source}[Ω]	$Z_0 = 1.128 + j0.0155$	
		$Z_1 = 0.820 + j6.7482$	
	Z_{load}[Ω]	$Z_Y = 89.93+ j40.96$	
AnSung Substation	Capacity	180MVA	
	Power Factor	0.91	
	Z_{source}[Ω]	$Z_0 = 1.5050 + j7.5775$	
		$Z_1 = 0.9400+ j8.6595$	
	Z_{load}[Ω]	$Z_Y = 119.90 + j54.62$	

Table 2 Fault conditions

	Test Condition
Type	SLG, DLG, DLL, 3ϕG, HIF
Inception Angle	0°, 30°, 60°, 90°
Location	5.2(20%), 13(50%), 20.8(80%) [km]

2.2 The characteristics of fault currents

Generally, when faults occur on transmission lines, magnitudes of faulted phase currents are increased and are often manifested with either harmonic or dc-offset components. However, the increase in fault phase current(s) in the case of HIFs is much smaller in comparison to LIFs.

Fig. 2 typifies the RMS values of currents for each fault type. As expected, the increase in fault currents under LIFs is much higher than under HIFs. Thus, in principle, fault classification between LIFs and HIFs can be achieved through knowledge of RMS values of currents. However, deducing only change of RMS values is insufficient to classify fault type between double line-to-ground faults and line-to-line faults because of similarities of change in the two types of faults and other means of accurately classifying these types of fault must be found.

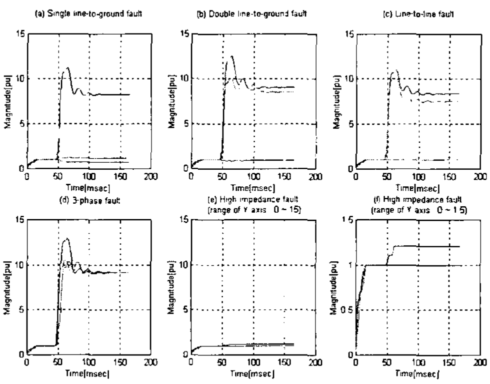

Fig. 2 RMS values of current for each fault type

In this paper, this problem is overcome by developing a fault classification algorithm using RMS values of phase currents combined with the zero sequence current as shown below.

Zero sequence current is calculated by equation (1).

$$I_o = \frac{1}{3}(I_a + I_b + I_c) \tag{1}$$

However, zero sequence current in the case of HIFs is increased at a much smaller rate in comparison with LIFs and thus in the technique developed herein, equation (1) is modified into the following equation:

$$I_o = (I_a + I_b + I_c) \tag{2}$$

As can be seen, although the magnitude of the modified zero sequence current is increased, it still retains the characteristics of the zero sequence current. Fig. 3 shows the RMS values of zero sequence current for each fault type. As expected, magnitudes of the zero sequence currents are near zero for fault types such as line-to-line fault, 3-phase fault, and normal state, but a fault involving ground has a non-zero value.

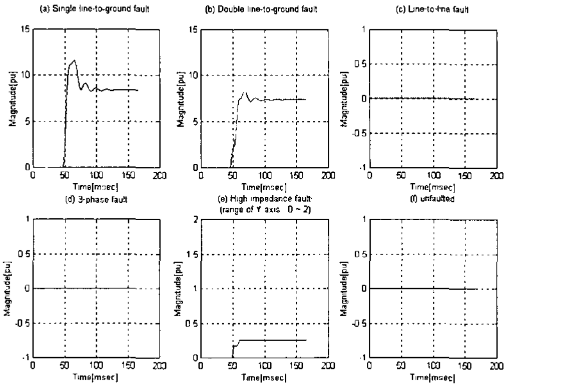

Fig. 3 RMS values of zero sequence current for each fault type

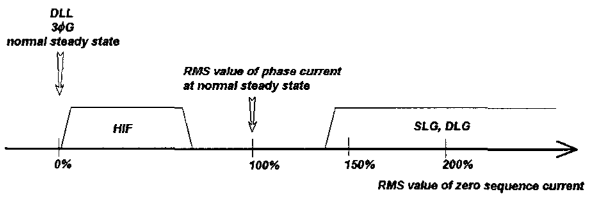

Fig. 4 Distribution for RMS values of zero sequence currents

Table 3 Fault characteristics for each fault type

Fault Type		Phase Voltage	Phase Current	Zero Seq. Current compared with normal state current
SLG	a	decrease	Much increase	large
	b	decrease	Much increase	large
	c	decrease	Much increase	large
DLG	ab	decrease	Much increase	large
	bc	decrease	Much increase	large
	ca	decrease	Much increase	large
DLL	ab	decrease	Much increase	0
	bc	decrease	Much increase	0
	ca	decrease	Much increase	0
3ϕG	abc	decrease	Much increase	0
HIF	a	very little variation	very little variation	small
	b	very little variation	very little variation	small
	c	very little variation	very little variation	small

Fig. 4 shows the distribution region of RMS values of zero sequence currents for each fault type on condition that the magnitude of RMS value of a phase current at normal steady state is set to be 100%. Results of Fig. 4 are summarized in Table 3.

2.3 Fault classification algorithm

In the case of transmission line faults, the characteristics of fault currents are mentioned above. In particular, since the level of fault current at high impedance fault is similar to the level of overload currents, it is difficult to detect high impedance faults. Of course, by using zero sequence current, it is possible to classify the fault as a low impedance fault or not. But, the purpose of this paper is to classify detailed types of faults. Therefore, the zero sequence current is inadequate for the proposed algorithm. In this paper, the proposed algorithm detects high impedance fault by level of zero sequence current, and classifies types of faults by the phase current.

Moreover, the algorithm of fault classification has adaptability for various characteristics of the power system. ANFIS makes use of a hybrid learning rule to optimize the fuzzy system parameters of the first-order Sugeno system. And using the back propagation method for training a neural network, fuzzy premise and consequent parameters are tuned properly. Also, ANFIS adapts to characteristics of the system, so the proposed algorithm can be applied to various system configurations.

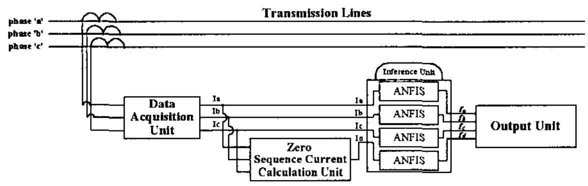

Fig. 5 Diagram of the proposed algorithm

As shown above, the fault classification algorithm is developed using ANFIS based on the characteristics of faults. Fig. 5 shows the diagram of the proposed algorithm. The proposed algorithm is comprised of 3 basic steps.

(1) Acquire three phase currents
(2) Calculate zero sequence current
(3) Deduce fault type using ANFIS

If inference results are zero, then this signifies a situation without faults. However, if inference results are non-zero, then the technique indicates both the presence of a fault and a fault type.

Fig. 6 shows the ANFIS architecture adopted herein. It consists of five layers, but since the ANIFS based algorithm employed herein has only one input, layer 2 can be combined with layer 1.

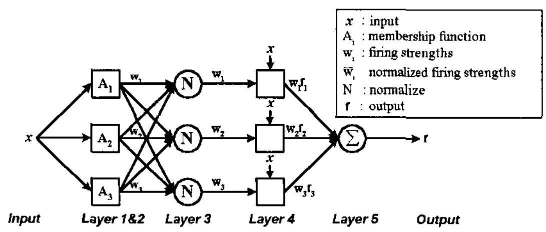

Fig. 6 ANFIS architecture

The following three rules are used:

Rule 1: If x is A_1 then $f_1=p_1x+r_1$.
Rule 2: If x is A_2 then $f_2=p_2x+r_2$.
Rule 3: If x is A_3 then $f_3=p_3x+r_3$.

The various layers can be described as follows.

Layer 1: Fuzzification (membership) - Here the trapezoid function is used as a membership function and is specified by four parameters $\{a_i, b_i, c_i, d_i\}$ as follows:

$$trapezoid(x : a_i, b_i, c_i, d_i) = \max\left(\min\left(\frac{x-a_i}{b_i-a_i}, 1, \frac{d_i-x}{d_i-c_i}\right), 0\right) \quad (3)$$

where the input x represents RMS values of phase currents and zero sequence current for the proposed algorithm, and, the membership functions used in ANFIS are depicted in Fig.s 7 and 8. It is apparent that the two types of membership functions are very different from each other; $\{a_i, b_i, c_i, d_i\}$ is the set parameter and the parameters in this layer are referred to as premise parameters.

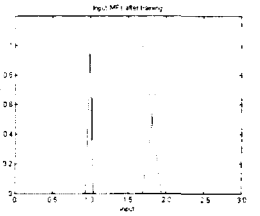

Fig. 7 Membership function for phase current

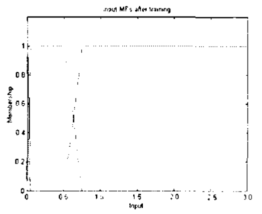

Fig. 8 Membership function for zero sequence current

Layer 2: Conjunction - Every node in this layer multiplies incoming signals for multi-input. But since only one input is adopted in the proposed algorithm (see equation (4)), multiplication of incoming signals is avoided.

$$O_{2,i} = O_{1,i} \quad , i = 1, 2, 3 \quad (4)$$

Layer 3: Normalization - This architecture has three rules. Each node in this layer calculates the ratio of the i^{th} rule's firing strength to the sum of all the rules' firing strengths:

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2 + w_3} \quad , i = 1, 2, 3 \quad (5)$$

Layer 4: Defuzzification - Each node i in this layer is an adaptive node with a node function.

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x + r_i) \quad (6)$$

where $\bar{w}$ is the output of layer 3 and $\{p_i, r_i\}$ is the parameter set.

Layer 5: Summation - The single node in this layer computes the overall output as the summation of all incoming signals.

$$O_{5,1} = f = (\bar{w}_1 x)p_1 + (\bar{w}_1)r_1 + (\bar{w}_2 x)p_2 + (\bar{w}_2)r_2 + (\bar{w}_3 x)p_3 + (\bar{w}_3)r_3 \quad (7)$$

The consequent parameters, $p1$, $q1$, $r1$, $p2$, $q2$ and $r2$, are linear. Therefore, the hybrid learning algorithm developed in the previous section can be applied directly. More specifically, in the forward pass of the hybrid learning algorithm, node outputs progress until layer 4 and the consequent parameters are identified by the least squares method. In the backward pass, the error signals propagate backward and the premise parameters are updated by gradient descent. The consequent parameters thus identified are optimal under the condition that the premise parameters are fixed. Accordingly, the hybrid approach converges much faster, since it reduces the dimension of the search space of the original back-propagation method. In this paper, sample signals for training are acquired by the EMTP simulation.

Table 4 Definition of outputs

Fault Type		ANFIS			
		Ia	Ib	Ic	Io
SLG	a	2	0	0	2
	b	0	2	0	2
	c	0	0	2	2
DLG	ab	2	2	0	2
	bc	0	2	2	2
	ca	2	0	2	2
LL	ab	2	2	0	0
	bc	0	2	2	0
	ca	2	0	2	0
3ϕG	abc	2	2	2	0
HIF	a	1	0	0	1
	b	0	1	0	1
	c	0	0	1	1
Unfaulted		0	0	0	0

The proposed algorithm developed herein consists of 4 ANFIS for 'a', 'b', 'c'-phase currents and zero sequence current, respectively. The inputs to the ANFIS are RMS values of 3-phase currents and zero sequence current. The values of output signify four categories associated with the 'a', 'b', 'c'-phase and zero sequence currents. If any of the outputs from the first 3 ANFIS (i.e. Ia, Ib, Ic) is '1' then this indicates an HIF, in the case of '2', it is LIF, and in the case of '0', there is no fault. For the 4th ANFIS (i.e. Io) considered, '2', '1' and '0' signify a ground fault for LIF, HIF or a fault clear of ground, respectively. This criterion is summarized in Table 4.

3. Simulation and Results

In this section, results illustrating the performance of the proposed algorithm are presented.

Fault cases studied are described in Table 2. As mentioned before, the performance of the proposed algorithm is tested for the Korean model system under various fault conditions such as fault inception angle, fault distance and fault types.

3.1 Results of the simulation under LIF

Figs 9 ~ 10 typify the outputs of the various ANFIS for fault classification for single line-to-ground fault, double line-to-ground fault, line-to-line fault and 3-phase fault, respectively. As expected, all results show accurate outputs for each of the fault conditions considered. Importantly, the entire process of fault detection and classification is achieved in approximately 5msec from the time the fault initiates. A more comprehensive performance of the technique under LIF is summarized in Table 5.

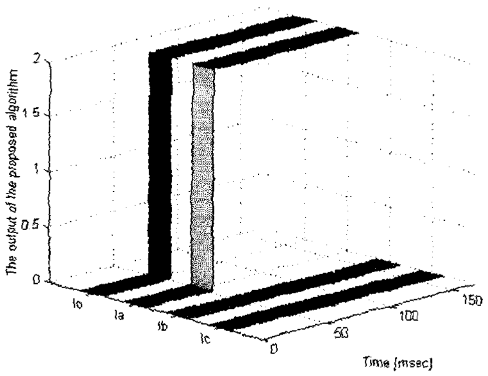

Fig. 9 Result for single line-to-ground fault
('a' phase, at 20% of line and at a fault inception angle of 90°)

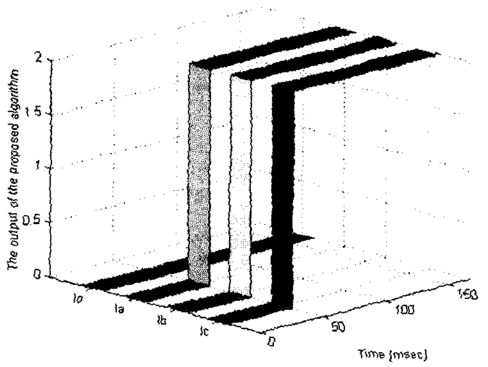

Fig. 10 Result for 3-phase fault
(at 80% of line and at a fault inception angle of 90°)

3.2 Results of the simulation under HIF

As mentioned before, because of the randomness, asymmetry and low levels of fault currents, HIFs pose particular difficulty in detection and classification when employing traditional protection techniques. Nevertheless, Fig. 11 graphically depicts the satisfactory performance of the technique for a high impedance single line-to-ground fault under HIF. Again, a more comprehensive performance is summarized in Table 5.

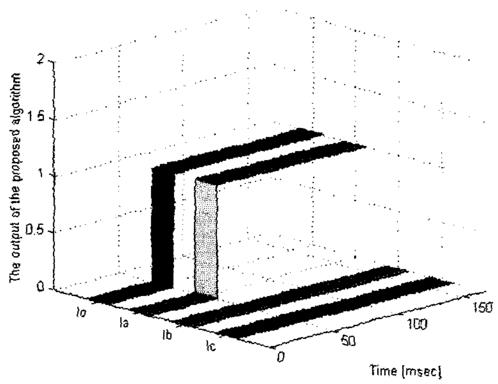

Fig. 11 Result for high impedance fault
('a' phase, at 20% of line and at a fault inception angle of 0°)

As expected, the ANFIS technique also gives the correct output (i.e. all 0's) under normal steady-state conditions, and Fig. 12 shows the result of the proposed algorithm for an unfaulted situation.

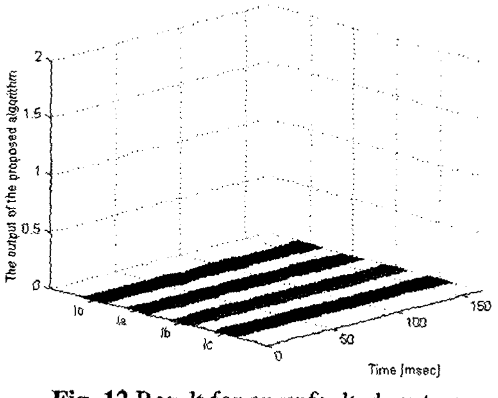

Fig. 12 Result for an unfaulted system

3.3 Summary

Table 5 summarizes the performance of the proposed algorithm for all the faulted and unfaulted cases studied. The classification time is calculated as the interval time from fault inception time to the fault classification type time, and error rate is calculated as:

$$(\text{error rate}) = \frac{\text{error samples}}{\text{total samples}} \times 100(\%) \tag{8}$$

Table 5 Summary table

Fault Type	Fault Inception Time [msec]	Classification Time [msec]			Error Rate		
		5.2km (20%)	13km (50%)	20.8km (80%)	5.2km (20%)	13km (50%)	20.8km (80%)
SLG('a', 0°)	45.8	3.9	4.4	4.7	0%	0%	0%
SLG('a', 90°)	50.0	2.6	2.9	3.1	0%	0%	0%
SLG('b', 60°)	45.8	2.6	2.9	3.4	0%	0%	0%
SLG('b', 30°)	50.0	3.1	4.4	6.5	0%	1.41%	2.66%
SLG('c', 30°)	45.8	2.6	3.1	3.4	0%	0%	0%
SLG('c', 60°)	50.0	2.9	3.4	3.7	0%	0%	0%
DLG('ab', 0°)	45.8	2.9	3.1	3.7	0%	0%	0%
DLG('ab', 90°)	50.0	4.2	5.0	5.5	0.63%	0.94%	0.94%
DLG('bc', 60°)	45.8	3.9	4.4	5.0	0%	0%	0%
DLG('bc', 30°)	50.0	3.9	4.2	4.4	0.78%	0.78%	0.63%
DLG('ca', 30°)	45.8	2.9	3.4	3.9	0.16%	0.16%	0.31%
DLG('ca', 60°)	50.0	3.4	6.0	6.8	0%	2.34%	2.81%
DLL('ab', 0°)	45.8	1.8	2.1	2.3	0%	0%	0%
DLL('ab', 90°)	50.0	1.6	1.8	2.6	0%	0%	0%
DLL('bc', 60°)	45.8	1.0	1.3	1.6	0%	0%	0%
DLL('bc', 30°)	50.0	2.9	3.4	3.7	0%	0%	0%
DLL('ca', 30°)	45.8	4.4	4.7	5.2	0%	0%	0%
DLL('ca', 60°)	50.0	1.3	1.6	1.8	0%	0%	0%
3ϕG(0°)	45.8	1.6	1.8	1.8	0.31%	0.16%	0%
3ϕG(90°)	50.0	0.5	0.8	0.8	0%	0%	0%
HIF('a', 0°)	45.8	5.0	5.2	5.7	0%	0%	0%
HIF('a', 90°)	50.0	2.1	2.3	2.6	0%	0%	0%
HIF('b', 60°)	45.8	2.3	2.6	2.9	0%	0%	0%
HIF('b', 30°)	50.0	6.5	6.8	7.0	0%	0%	0%
HIF('c', 30°)	45.8	6.5	7.8	8.3	0%	0%	0%
HIF('c', 60°)	50.0	3.7	3.9	4.2	0%	0%	0%
Normal	-	0	0	0	0%	0%	0%
Average	-	3.1	3.6	4.0	0.07%	0.21%	0.27%
Maximum	-	6.5	7.8	8.3	0.78%	2.34%	2.81%
Minimum	-	0.5	0.8	0.8	0%	0%	0%

As shown in Table 5, the proposed algorithm can classify fault types under LIF and HIF in less than half a cycle, with low error rate.

The output of the proposed algorithm carries two meanings; one is detection of faults and the other is classification of faults. In other words, if all of the outputs are not zero, this means that a fault has occurred and also implicit is the type of fault. The classification error signifies that the output indicates an incorrect fault type.

The cause of classification error is based on the transient phenomena. The fault current has been divided into two components, a steady-state component and a transient component. The steady-state component has the frequency of the applied voltage, but is shifted in phase by the angle and the constant angle of the system impedance, and with a magnitude that is determined by the magnitude of the applied voltage and of the system impedance. The transient component has two parts. One depends on the angle of the voltage wave at which the fault is applied and the other component is a function of the prefault current that is flowing at the instant the fault is applied.

In the case of a multi-phase fault such as double line-to-ground fault and line-to-line fault, the prefault current of each phase has different magnitude and phase angle from each other at the fault initiation instant. Accordingly, the transient current of each phase is different from each other. Such a difference of the transient current causes incorrect classification results. Importantly, the latter still indicates that a fault has occurred and due to the behavior of the signals with time, the classification error is only for a very short period and hence the impact of the classification error is not very significant. For example, as shown in Table 5, a DLG fault (distance: 80%) has a maximum error of 2.81% and this is equivalent to just 18 samples, i.e. about a quarter cycle of the fundamental frequency. After this initial period of error, the output of the algorithm starts to indicate correct fault classification.

4. Conclusions

Any fault detection and classification technique should be capable of performing satisfactorily under a wide variety of system and fault conditions, including contingencies such as HIFs. Conventional techniques, however, have difficulties in dealing with such faults (they either fail to detect the fault or fail to discern between double line-to-ground and line-to-line faults) principally due to the limitations imposed by the low levels of fault currents.

In this paper, a novel algorithm for fault detection and classification of LIFs and HIFs has been developed using ANFIS, which overcomes the aforementioned problem. Equally important, this algorithm can detect and classify fault type in a transmission line based on RMS value of phase currents and zero sequence current in one single algorithm.

The performance of the proposed algorithm is tested on a typical 154 kV Korean transmission line system under various fault conditions and the results presented clearly demonstrate that the proposed algorithm can detect faults and classify fault types accurately, in less than about half a cycle. In addition, the proposed algorithm has a very low error rate and excellent adaptability. The proposed algorithm has been developed for real time implementation and can be coded into existing digital relay hardware.

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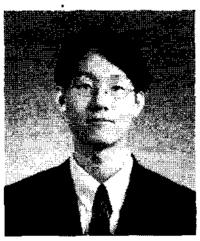
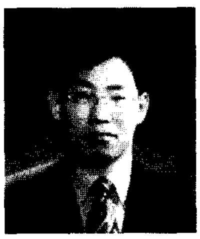


Sang-Min Yeo

He received his B.S. and M.S. degrees in Electrical and Computer Engineering from Sungkyunkwan University, Korea, in 1999 and 2001, respectively. Currently, he is studying to obtain his PhD at Sungkyunkwan University. His current research interests include power system protection and computer applications using EMTP software and signal processing.



Chul-Hwan Kim

He received his B.S. and M.S. degrees in Electrical Engineering from Sungkyunkwan University, Korea, in 1982 and 1984, respectively. He received his PhD in Electrical Engineering from Sungkyunkwan University in 1990 at which time he joined Cheju National University, Cheju, Korea, as a Full-time Lecturer. From 1998-2001, he was a Visiting Research Professor at the University of Bath, UK. Since March 1992, he has been a Professor at the School of Information and Communication Engineering, Sungkyunkwan University, Suwon, Korea. His research interests include power system protection, neural network applications, modeling/protection of underground cable and EMTP software.