Fault Classification in EHV Transmission Lines Using Artificial Neural Networks

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ABSTRACT

This paper investigates a new approach based on Artificial Neural Networks (ANNs) for real-time fault classification in power transmission lines which can be used in digital power system protection. The technique uses sampled current and voltage data of each phase at one terminal as inputs to the corresponding ANN. The ANN outputs indicate the type of the fault within a time less than 5 ms. The ANN-based classifier is tested under different fault types, fault location, fault resistance and fault inception angle. All the test results show that the proposed fault classifier can be used for supporting a new generation of very high speed protective relaying systems.

I. INTRODUCTION

Reliable detection and isolation of transmission lines fault is very important for maintaining safe, continued and economic operation of power systems. The design of high performance protective techniques is a subject to significant development within the academic community and in industry. Various approaches of fault detection and classification have been proposed in the literature. In almost all these protective techniques, sampled voltage and current data at the relaying point are used for fault recognition.

The most common used technique is based on the estimation of the phasor quantities of the fundamental power frequency. This method is based on the symmetrical components theory and requires computation of symmetrical component phasors, resulting in positive, negative and zero sequence phasors. This technique assumes that the transmission line is ideally transposed and may have difficulty to classify a double line to ground fault [1]. Different techniques have been proposed to estimate the phasor quantities based on discrete Fourier transform [2, 3], Walsh functions [3], Kalman filter [1, 4], etc. These techniques are computationally time consuming and do not have the ability to adapt dynamically to the system operating conditions and they are likely to make incorrect decisions if the signals are noisy.

Protective relaying techniques based on artificial intelligent tools such as fuzzy logic [5], artificial neural networks (ANNs) [6, 7] and neuro-fuzzy techniques [8, 9] are promising alternatives to the conventional ones.

Neural networks are highly interconnected processing elements with strong learning and generalization capabilities. They have the ability to learn the desired input-output mapping based on training patterns, without looking for an exact mathematical model. Once an appropriate neural network is trained exactly, the weights of the ANN will contain a representation of the non-linearity of the desired mapping between the inputs and outputs. ANNs can utilize directly the instantaneous current and voltage sample values without computation of phasors and sequence components. The advantage is that current and voltage data are processed directly without the need to perform extensive filtering to obtain phasors. In addition, the window length can be quite short and does not need to satisfy particular rules for the phasor computation.

Different approaches have been published describing the application of artificial neural networks in fault detection and classification. A neural network approach for fault type detection is presented in [10]. The reported method is suitable for high-speed protective relaying and identifies the fault type within 5 to 7 ms. The method uses a single ANN. Five consecutive sample (at 1kHz sample rate) points of current and voltage of each line are used as input of the ANN with a window length of 4ms. The output layer is composed with 11 nodes; each output is responsible for one fault type and the “normal state”. However using one simple ANN with many outputs requires a large amount of data in the training stage and can not handle all fault types. In [11], the authors use different types of input signals currents and/or voltages and one or three cycles. One cycle is composed by 33 samples at 2 kHz. The fault is identified within 15 ms. In [12] ten neural networks are applied to identify a fault type based on the currents and voltages phasors after fault inception. Each of the ten neural networks is trained to recognize one of the fault types. The fault is identified in a time period less than 5 ms. In [13] one ANN is used to identify the fault, and three samples at 800 Hz of the currents and voltages are used as inputs to the ANN. Each output of the ANN corresponds to phase conductors and the ground.

In this paper a novel fault classification technique is presented. The technique is based on Artificial Neural Networks (ANNs) and uses sampled current and voltage data of each phase at one terminal as inputs to the corresponding phase and ground ANN (four ANNs, one for each phase and an other for the involvement of the ground). The system state is defined through the identification of the associated voltages and currents patterns by ANNs.

II. PROPOSED ANN-BASED FAULT CLASSIFIER

CONSTITUTION

The proposed Fault Classifier (FC) consists of four independent artificial neural networks, one for each phase (L1, L2, L3) and one for the involvement of ground (E), which are termed ANNA, ANNB, ANNC and ANNG ; respectively. The ANN for the phase is named Phase Fault Detector (PFD) and the ANN for the involvement of ground during the fault is named Ground Fault Detector (GFD). The inputs of the ANNs are the current and voltage signals while the outputs are the logic values (“0” or “1”). The outputs of the PFDs (A, B, C, D) and the GFD (G) are used to realize the classification of the fault via a logic circuit. The fault type classification is assured by the Fault Classifier (FC). The basic functional bloc of the FC is shown in **Fig. 1**.

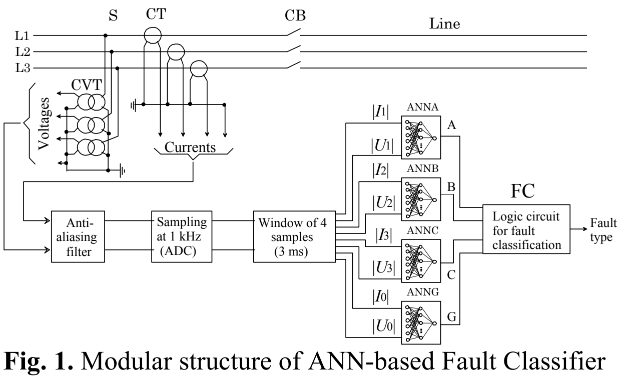


Fig. 1. Modular structure of ANN-based Fault Classifier

The phase fault detectors ANNA, ANNB and ANNC are designed to indicate the presence or the absence of a fault of any type in the respective phase. The ground fault detector ANNG detects the involvement of the ground during the fault. The occurrence of the fault and the involvement of the ground are determined by identifying the power system state directly from instantaneous current and voltage data from one terminal line.

INPUTS AND OUTPUTS

To evaluate the performance of the proposed neural network-based FC, a 400 kV, 150 km transmission line extending between two sources is considered in this study. The transmission line is represented by distributed parameters and the frequency dependence of the line parameters is taken into account. The physical arrangement of the conductors is resumed in **Fig. 2** and the line characteristics can be found in [14].

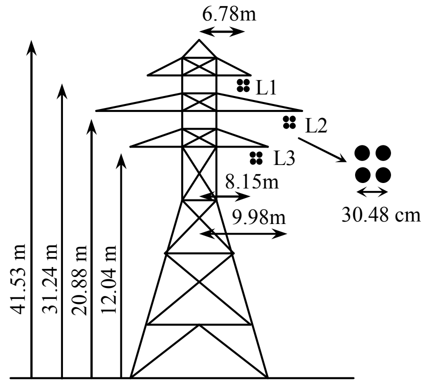


Fig. 2. Transmission line configuration

Input and output data used for training and testing FDC are generated from the S end of the sample power system model. A highly accurate transmission line simulation technique [15] was utilized to generate voltage and current waveforms for different fault types and conditions.

In order to build up an ANN, the inputs and outputs of the neural network have to be defined for pattern recognition. Inputs to the network should provide a true representation of the situation under consideration. The current and voltage signals extracted from the simulation at the relay location (Sending end S) are used as inputs to the ANN. The process of generating input patterns to the ANN is depicted in **Fig. 1**. The current and voltage signals are calculated as a string of samples corresponding to a 100 kHz sampling frequency. These signals are processed so as to simulate a 1 kHz sampling process (20 samples per 50 Hz cycle). This sampling rate is compatible with sampling rates presently used in digital relays. It should be mentioned that the input current and voltage samples have to be normalized (scaled) in order to reach the ANN input level (±1). The current and voltage signals are sampled at 1 kHz and used as input data to the ANN. The ANN output is indexed with either a value of “1” (presence of a fault) or “0” (non-faulty situation) for the PFD and “1” (involvement of the ground) or “0” (non-involvement) for the GFD.

NEURAL NETWORK STRUCTURES

The FC tasks can be formulated as a pattern classification problem. A fully-connected multi layer (input, hidden and output) feed-forward neural network (FFNN) has been used to classify faulty/non-faulty data sets. The number of inputs to the network and the number of neurons in the input and hidden layers are decided empirically through extensive simulations. Various network configurations are trained and tested in order to establish an appropriate network with satisfactory performance. Performance criteria are fault tolerance, time response and generalization capabilities. The three layer FFNN is selected to implement the algorithm for single ended fault detection using current and voltage data. Data strings of four consecutive samples of the current and voltage signals taken every 1 kHz are found to be appropriate inputs to the neural network. This represents a moving window with a length of 3 ms.

In order to obtain a good neural network model, it is vitally important to train and test it correctly. With supervised learning, each ANN is trained with various input patterns corresponding to different types of fault (L1-E, L2-E, L3-E, L1-L2-E, L1-L3-E, L2-L3-E, L1-L2, L1-L3, L2-L3, L1-L2-L3 and L1-L2-L3-E, where L1, L2, and L3 are related to the phases and E refers to the ground) at various locations for different fault inception angles and fault resistances. Different network structures (number of hidden layers and different number of neurons in each hidden layer) with different parameters (learning rates and transfer functions) are evaluated in order to optimize the neural networks architecture to achieve the best results. After a series of training and testing it has been found that three-layer architecture leads to the best performance for the ANN-phase and ground fault detectors. The proposed neural phase and ground fault detector architectures are resumed in **Tab. 1**. The variables $\underline{I}_1$, $\underline{U}_1$, $\underline{I}_2$, $\underline{U}_2$ and $\underline{I}_3$, $\underline{U}_3$ are the normalized sampled currents and voltages of phase L1, L2 and L3; respectively. The variables $\underline{I}_0$ and $\underline{U}_0$ are the normalized sampled zero sequence current and voltage; respectively. The back-propagation training algorithm with dynamic learning rate [16] has been used throughout. While the sigmoid transfer function was used in the hidden and the output layers.

Tab. 1. Architectures of the neural fault detectors

Phase and ground fault detector	Input variable	Number of neurons		
		Input layer	Hidden layer	Output layer
ANNA	$\underline{I}_1$, $\underline{U}_1$	8	18	1
ANNB	$\underline{I}_2$, $\underline{U}_2$	8	15	1
ANNC	$\underline{I}_3$, $\underline{U}_3$	8	18	1
ANNG	$\underline{I}_0$, $\underline{U}_o$	8	12	1

The ANN structures for the PFD (ANNA) and the GFD (ANNG) are shown in **Fig. 3** and **Fig. 4**; respectively.

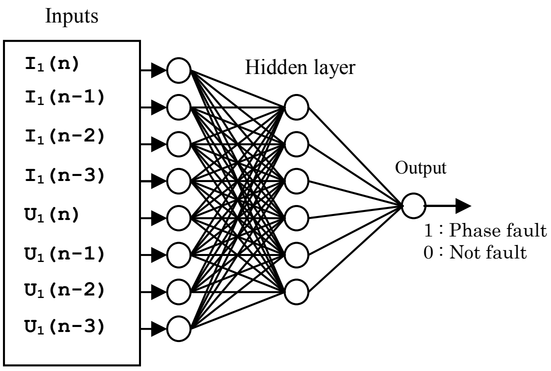


Fig. 3. ANNA structure

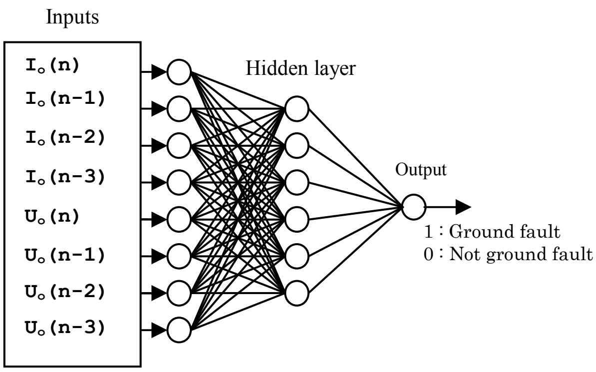


Fig. 4. ANNG structure

ANN TRAINING AND TESTING

The design process of the ANN-based fault detectors goes through the following steps:

- Preparation of suitable training data set that represents cases the ANN needs to learn.
- Selection of a suitable ANN structure for a given application.
- Training of the ANN.
- Evaluation of the trained ANN using test patterns until satisfied with its performance.

In **Tab. 2** and **Tab. 3** are given the parameter values used to generate data training sets and test patterns, respectively.

Tab. 2. Parameter settings for generating training patterns

Fault location l_f in km	3, 40, 80, 120, 147
Fault inception angle θ_f in deg.	0, 45, 90
Fault resistance R_f in Ω	0, 40, 100

Tab. 3. Parameter settings for generating test patterns

Fault location l_f in km	3, 10, 20,...130, 147
Fault inception angle θ_f in deg.	0, 30, 60, 90
Fault resistance R_f in Ω	0, 5, 40, 80, 100

In **Fig. 5** are shown the sending end current and voltage waveforms for a double phase (L1-L3) fault located at 50 km with a fault inception angle of 90° which corresponds to the occurrence of the fault at time 31 ms.

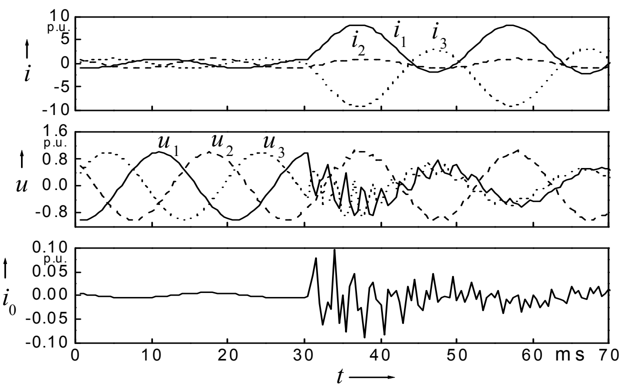
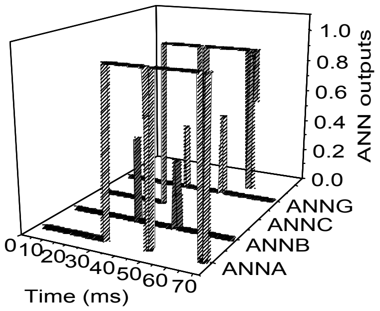
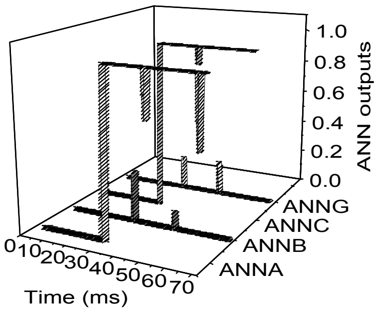


Fig. 5. Sending end current and voltage waveforms for a (L1-L3) fault with $l_f = 50$ km, $\theta_f = 90°$ and $R_f = 0\ \Omega$

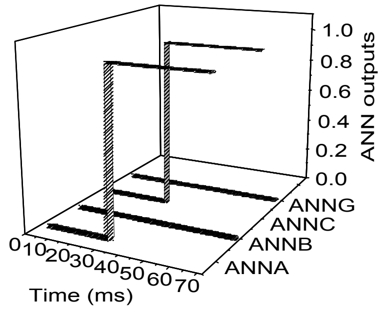
Initially, each PFD is trained with 4046 patterns while 2100 patterns were used to train the GFD. As it can see from **Fig. 6a**, the ANN output exhibits some disturbances for the later fault condition (L1-L3 fault). This indicates the necessity to increase the number of training patterns. Other training was performed with 5880 patterns for each PFD and 3010 for the GFD and the results are depicted in **Fig. 6b** which indicates again few incorrect responses. Finally, a new training with 7686 patterns for each PFD and 4170 for the GFD was considered leading to a better result as demonstrated by **Fig. 6c**.



a) ANN outputs when each PFD is trained with 4046 patterns and the GFD with 2100



b) ANN outputs when each PFD is trained with 5866 patterns and the GFD with 3010



c) ANN outputs when each PFD is trained with 7686 patterns and the GFD with 4172

Fig. 6. Training steps of the ANN phase and ground fault detectors for a (L1-L3) fault

The criteria for evaluating the performance characteristics of an ANN are:

- The stability of ANN output values in the normal steady-state and under fault conditions.
- The minimal response time, this is the difference between the actual time value and the desired time value.
- Generalization capabilities.

A good ANN fault detector is obtained when the response time is minimal; the ANN output values are stable in the normal operating conditions (i.e. 0) and under fault conditions (i.e. 1) and capable of providing fast and accurate fault detection under a variety of fault situations.

III. IMPLEMENTATION AND EVALUATION OF THE FAULT CLASSIFIER

FAULT CLASSIFIER IMPLEMENTYATION

The fault classifier FC implementation is obtained by gating ANNA, ANNB, ANNC and ANNG outputs through a logic circuit to indicate the type of the fault (L1-E, L2-E, L3-E, L1-L2-E, L1-L3-E, L2-L3-E, L1-L2, L1-L3, L2-L3, L1-L2-L3) as shown in **Fig. 7**.

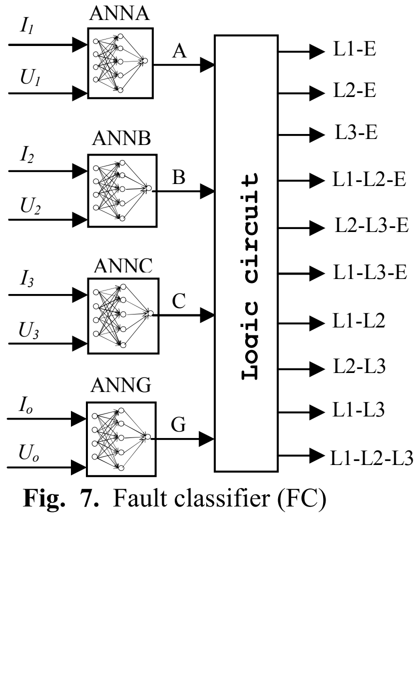


Fig. 7. Fault classifier (FC)

FAULT CLASSIFIER PERFORMANCE

After training, the FC was tested with 90 new fault conditions for each type of fault. These conditions included different fault locations, different fault inception angles θ_f (0, 30, 60 and 90 degrees) and different fault resistances R_f (0, 5, 40, 80 and 100 Ω). **Fig. 8** to **Fig. 11** show the response of the proposed fault classifier for some fault types and conditions.

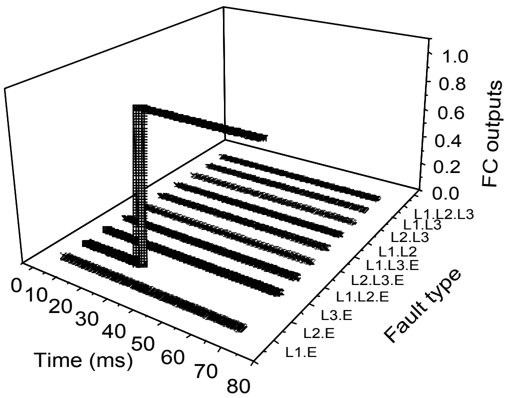


Fig. 8. FC outputs for L2-E fault with l_f = 147 km, θ_f = 30° and R_f = 5 Ω

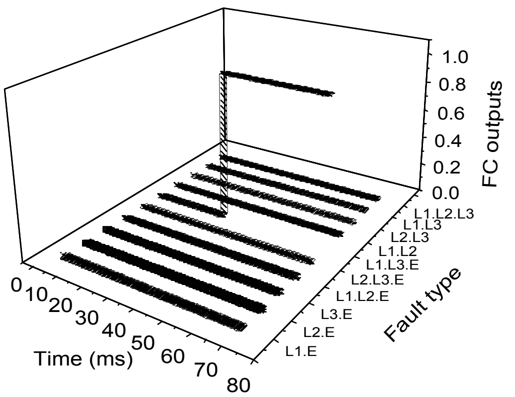


Fig. 9. FC outputs for L1-L3-E fault with l_f = 10 km, θ_f = 90° and R_f = 40 Ω

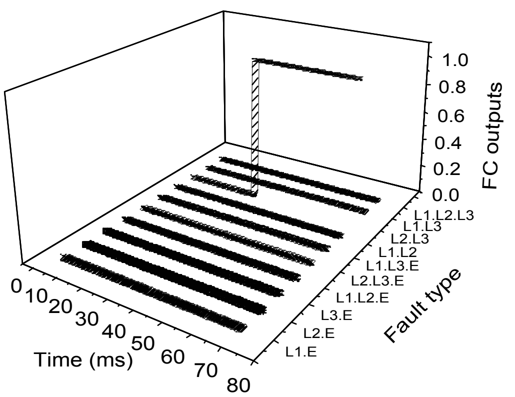


Fig. 10. FC outputs for L2-L3 fault with l_f = 50 km, θ_f = 60° and R_f = 0 Ω

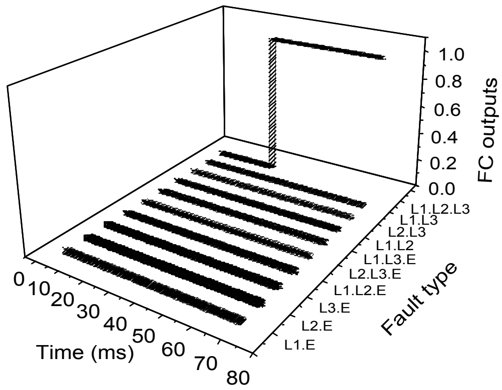


Fig. 11. FC outputs for L1-L2-L3 fault with l_f = 90 km, θ_f = 0° and R_f = 0 Ω

The results demonstrate the ability of the fault classifier to accurately indicate the type of the fault in all simulation tests considered and generalize the situation from the provided patterns.

The results show that in the fault cases presented, there is a very rapid transition in the FC outputs as the window moves from the pre-fault to the fault states. This clearly confirms the effectiveness of the proposed fault classifier.

The response time of the fault classifier t_r^c, difference time between the obtained time of fault classification t_o^c and the time fault occurrence t_f, is used as a criterion for performance evaluation of the classification function.

$$t_r^c = t_o^c - t_f \qquad (1)$$

Tab. 4 gives actual time and response time of the fault classifier corresponding to the test cases obtained for different fault types and four fault inception angles θ_f (0, 30, 60, and 90 degrees) for a fault at 50 km without fault resistance.

Tab. 4. FC test results for different fault types and fault inception angles with l_f = 50 km and R_f = 0 Ω

Fault type	Actual time and fault classifier response time in ms							
	θ_f = 0° (t_f =27 ms)		θ_f = 30° (t_f =28 ms)		θ_f = 60° (t_f =30 ms)		θ_f = 90° (t_f =32 ms)	
	t_o^c	t_r^c	t_o^c	t_r^c	t_o^c	t_r^c	t_o^c	t_r^c
L1-E	29	2	30	2	31	1	34	2
L2-E	28	1	30	2	33	3	35	3
L3-E	31	4	32	4	32	2	33	1
L1-L2-E	29	2	30	2	34	4	35	3
L2-L3-E	31	4	32	4	33	3	35	3
L1-L3-E	31	4	32	4	33	3	34	2
L1-L2	29	2	30	2	34	4	36	4
L2-L3	32	5	33	5	34	4	35	3
L1-L3	31	4	32	4	31	1	34	2
L1-L2-L3	31	4	32	4	33	3	35	3

It can be seen from **Tab. 4** that the fault inception angle has an influence on the fault classification time and the minimum value of t_r^c is 0.5 ms and its maximum value is 3 ms, obtained in cases of L3-E, L1-L3-E, L1-L3 and L1-L2-L3 faults when $\theta_f = 30°$.

Tab. 5 gives the response time of the FC corresponding to the test cases obtained for different fault types and two fault inception angles θ_f (0 and 90 degrees) for a fault at 130 km with three fault resistance values of 0 Ω, 40 Ω and 100 Ω, respectively.

Tab. 5. FC test results for different fault types and fault resistances with $l_f = 130$ km and $\theta_f = 0°$ and 90°

Fault type	Fault classifier response time t_r^c in ms					
	$\theta_f = 0°$ (t_f =27 ms)			$\theta_f = 90°$ (t_f =32 ms)		
	Fault resistance R_f			Fault resistance R_f		
	0 Ω	40 Ω	100 Ω	0 Ω	40 Ω	100 Ω
L1-E	3	3	3	2	2	2
L2-E	1	1	1	4	3	3
L3-E	4	3	3	1	1	2
L1-L2-E	2	2	2	3	4	4
L2-L3-E	4	4	4	3	3	3
L1-L3-E	4	4	4	2	2	2
L1-L2	2	2	2	4	4	4
L2-L3	5	5	5	3	3	3
L1-L3	4	4	4	2	2	2
L1-L2-L3	4	4	4	3	3	3

It can be seen from **Tab. 5** that the fault resistance has an influence on the fault classification time. The minimum value of t_r^c is 1 ms while its maximum value is 4.5 ms which corresponds to an L1-L3-E fault with a fault inception angle of 0° and fault resistance of 40 Ω.

The same set of 90 fault conditions for each fault type (11 types of fault) which represent 990 fault cases as in FD is used to investigate the performance of the FC. **Tab. 6** gives the percentage of fault test cases versus t_r^c for single-phase-to-ground, double-phase-to-ground, double-phase, triple-phase fault type and all fault types; respectively.

Tab. 6. Number of test cases (in %) versus t_r^c under different fault types.

t_r^c in ms	Number of test cases in %				
	Fault type				
	L1-E L2-E L3-E	L1-L2-E L2-L3-E L1-L3-E	L1-L2 L2-L3 L1-L3	L1-L2-L3	All faults
1	31,74	1,59	3,17	0,0	10,95
2	25,39	26,98	30,15	0,0	24,76
3	31,70	34,92	15,87	61,90	30,95
4	11,12	36,50	38,10	38,10	29,52
5	0,0	0,0	12,70	0,0	3,80

It can be seen that the minimum and maximum values of t_r^c are 1 ms and 5 ms respectively. In other words the fault can be classified in a minimum time of 1 ms and a maximum time of 5 ms (obtained in case of dl faults, 3.80% of all faults) which represents a good time error for the fault classification. All faults (100%) are classified within a time lower than 5 ms. A number of 100% of slg fault cases, 100% of dlg faults, 100% of tl faults are classified within a time lower than 4 ms. A number of 96.2% of all fault cases are classified within a time lower than 4 ms.

IV. CONCLUSION

A new ANN-based approach to real-time fault classification in power transmission systems which can be used in digital power system protection has been proposed in this paper. The technique uses sampled current and voltage data of each phase at one terminal as inputs to the corresponding ANN. The Fault Classifier (FC) consists of four independent ANNs, corresponding to the L1, L2, and L3 phases and the ground E. The ANN outputs are used to indicate the type of the fault within a very small time less than 5 ms. The ANNs are tested under different fault types, location, resistance and fault inception angle. All the test results show that the proposed fault detector and classifier can be used for supporting a new generation of very high speed protective relaying systems.

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