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A Novel Protective Scheme for Double Circuit Transmission Line Based on Modular Neural Network of Combined Structure

Abstract. *A novel application of neural network approach to protection of double circuit transmission line is demonstrated in this paper, to enhance the solution of problems associated with distance protection of parallel transmission lines. Concept of modularity is applied to the neural network structure to reduce its complexity and processing time. Results of performance evaluation studies show that the proposed modular neural network-based relay can improve the performance of conventional protection algorithms.*

Streszczenie. *W artykule opisano wykorzystanie sieci neuronowych do zabezpieczenia linii przesyłowej. Dla zmniejszenia złożoności układu przy dużych odległościach zaproponowano modularną strukturę sieci neuronowej. (**Nowa metoda zabezpieczenia dwuobwodowej sieci przesyłowej bazująca na modularnej sieci neuronowej**)*

Keywords: Double Circuit Transmission Lines, Modular Neural Network, Distance Protection Relays.
Słowa kluczowe: linia przesyłowa, zabezpieczenie, sieć neuronowa

Introduction

The basic operation of distance relays, the fundamental component of almost all transmission line protection, depends on the impedance measured at the relay location. For the conventional digital distance relays, the impedance seen at the relay location is calculated from the fundamental component of the voltage and current signals. The accuracy of the impedance estimation depends on how accurately the fundamental components of voltage and current signals are extracted. This requires using appropriate filtering algorithms. In order to minimize the error caused by non-fundamental components, the size of sampling window should be increased. Thus, the accuracy of an impedance estimate reduces with the increase in the speed at which that estimate is obtained [1]. In addition, when a fault happens on a transmission line, the power system goes through a transient period. It might not be easy to determine current/voltage signal magnitudes immediately and accurately during the transient period after the occurrence of the fault. Hence, the overall fault clearance time increases.

A proposed scheme based on high frequency traveling waves was introduced in [2]. However, such schemes may fail to detect faults under certain conditions such as close-up faults and small inception angle faults [3]. Adaptive distance protection scheme is proposed in [4], in which a correction factor, based on the information of the surrounding system of the protected line under different operating conditions, is used in the impedance calculation. The main drawback of this technique is the need to process a large quantity of information from power system. In [5], a proposed technique based on comparing of currents in the corresponding phases of the two lines to detect faults and discriminate between faulty and healthy phases in one cycle of fundamental component. In [6], phase currents comparison between the two circuits and positive sequence current level detection was used in conjunction with parallel line's zero sequence current compensated impedance calculation. In [7], A three-stage algorithm is proposed; fast fault detection and phasors estimation using Wavelet Transform (WT), magnitudes comparison of two circuits' line currents, and backup distance protection for some types of faults. In [8], a back-propagation neural network-based fault classifier was introduced.

In this paper, a novel scheme based on modular neural networks for the protection of parallel transmission lines is introduced.

ANNs

The technique described herein depends on the fact stating that the majority of power system protection techniques are involved in defining the system state through identifying the patterns of the associated voltage and current signals. So, the development of a protection scheme can be essentially treated as a problem of pattern recognition [9]. In this respect, Artificial Neural Networks (ANNs) are ideally suited to deal with the complex transmission line protection problems [10], [11]. Thus, ANNs were chosen to be the tool used in the proposed relay for pattern recognition. A single neuron processing unit (NPU) can handle the simplest of the pattern recognition problems. To handle complicated situations, Multi-layer Feed Forward Neural Networks (MFFNNs) are needed [12]. MFFNNs are trained in a supervised manner; i.e. both inputs and target outputs are available during the training process. Back-propagation algorithm is used to adapt weights. Thus, pattern classifiers trained with supervision require data with labels that specify the correct class during training. In unsupervised learning, there are no target outputs. A typical unsupervised learning network is the Kohonen network. The network neurons learn to distribute themselves over the input space, thus dividing it into separate unlabeled clusters. Back-propagation networks are smaller in size compared to combined unsupervised/supervised networks. However, training of a Backpropagation network is very slow (time consuming) and needs much larger training sets. Furthermore, retraining the Back-propagation network with new training data is more difficult. The Kohonen network has many advantages over the Back-propagation network but, in view of the fact that the network is without an output layer, it is not recommended to be used on its own for pattern classification. Rather, it is used as a first stage followed by an output layer with supervised training (Back-propagation network). A comparison between supervised and combined unsupervised/supervised training techniques was investigated in [13].

The modularity concept [14] in ANNs means subdividing a complex task into a set of simple subtasks. These subtasks are performed by a number of ANN modules. The solution of the overall task is achieved by combining the result of each module on conditions that each module is independent of other modules, each module responds to a certain subset of the overall inputs, and each module has a simpler architecture as compared to the system as a whole [15]. Such modular structure can be built with different types of neural networks, including the MFFNNs.

Power System Model

The single line diagram of the high voltage power system model studied in this work is shown in Fig. 1. The transmission line-to-line voltage is 220 kV. The utilized data is modeled from an existing transmission line linking Alexandria and Matrouh cities in the northern coast of Egypt. The transmission line is divided into three sections TL1, TL2 and TL3. The protected section is TL2, so the two relays shall be placed at both ends of the transmission line TL2. The tripping decision is made for faults occurring in TL2, while faults in TL3 are considered out of zone faults (external faults). The protection scheme disconnects TL3 after a sufficient time delay for external fault case. For faults occurring in TL1, the proposed scheme considers it a reverse fault, hence, no tripping decision is made and a special status flag is set by the algorithm.

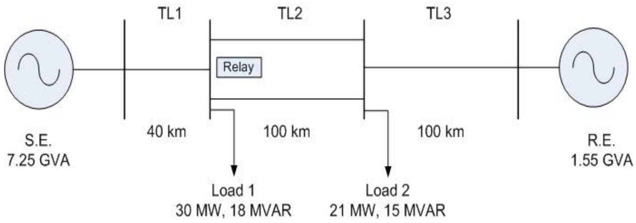

Fig. 1. Single-line diagram for power system model.

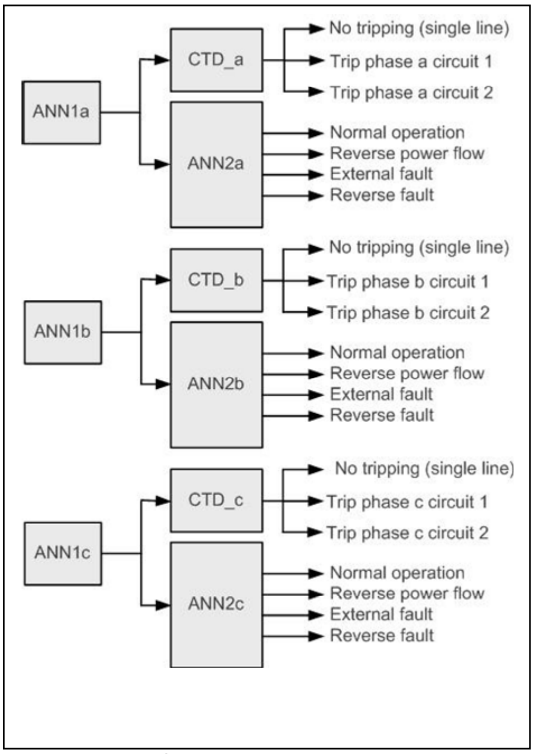

Fig. 2. Modularity of proposed structure

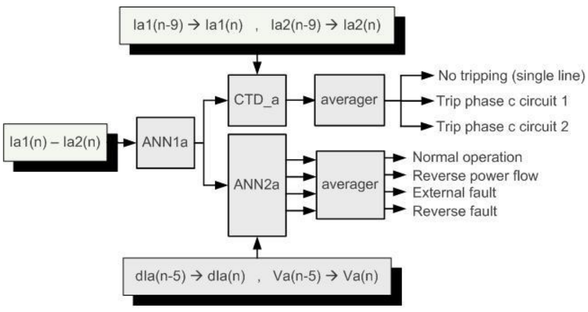

Fig. 3. Inputs and outputs of phase (a) protective modules

Proposed Technique

Modular structure

In this work, the modular concept is introduced to ANNs. The relay consists of two modules of ANNs to protect each phase resulting in a total of six modules. First module (ANN1) discriminates internal fault case only from all other cases. A Circuit Tripping Discrimination (CTD) algorithm is triggered if an internal fault is recognized by ANN1 module. CTD algorithm gives tripping decision for the faulted circuit of the two parallel lines.

The second module (ANN2) is triggered if no internal fault was recognized by ANN1 module. No fault detector is necessary since the first module identifies internal faults. Each module uses the corresponding samples of input signals related to its operation. This simplifies the neural network task further with redundant inputs being eliminated. The modular structure of ANNs for the proposed relay is shown in Fig. 2. Each ANN module is of a combined Kohonen/back-propagation neural networks structure.

Preprocessing

An ANN has a parallel processing ability which is an advantage in improving the processing speed. In order to further decrease the computational time, it is necessary to reduce the dimensionality of the inputs for classification. The preprocessing stage can significantly reduce the size of the neural networks based relay, which in turn improves the performance and speed of the training process [16]. For most applications utilizing ANNs, voltage and current input information is processed first by a conventional algorithm, e.g. a Discrete Fourier Transform (DFT) based distance measurement relaying algorithm, to calculate the appropriate phasor. The output of this algorithm is then processed by suitable neural networks [17], [18]. Using DFT makes the total algorithm more complex. Higher processing and computational capabilities are required to process the whole algorithm. A compromise between pre-processing stage complexity and neural networks structure is accomplished in most protection schemes in literature.

The approach adopted herein is based on a time domain window for each input variable. No digital filtering algorithms are needed in the pre-processing stage. This directly reduces the processing time of the whole algorithm, and as a result, increases its speed. After carefully considering different relay outcome requirements, it has been decided to use the three phase voltage signals and all six current signals (three phase currents of each circuit) as inputs to the relay. These inputs shall be sufficient to feed the relay with the required data, representing all fault and non-fault conditions. Input signals are first filtered using second order low pass Butterworth filter with a cutoff frequency of 400 Hz to attenuate high frequency components. Butterworth filter has been chosen because it has maximally flat response in the passband [19]. Decaying DC component attenuation is then performed for the input current samples. In this paper, a fast and efficient technique is proposed to attenuate the decaying DC. The technique is based on incremental current values of current samples. Incremental current values replace current samples introduced to the relay. Incremental signals are obtained by calculating current deviation of successive current samples.

The proposed DC attenuation technique almost removes DC component, while keeping information of current signals available to the neural network.

Sampling frequency

Through an extensive series of studies involving retraining of the ANNs, a sampling rate of 1000 Hz was selected [20].

Outputs

Regarding ANN1 modules, they are trained to give an output value of 1 if the input vector corresponds to a fault within the zone of protection (internal fault), and an output value of -1 if not. Each ANN1 module operates as a selector for the next processing stage. If ANN1 module output is 1, the CTD algorithm is triggered and the outputs of ANN2 module are deactivated.

The CTD algorithm has a single output for each phase representing tripping decision for the two conductors of the parallel transmission line. It gives an output value of 1 to trip circuit 1 of the corresponding phase conductors, an output value of 2 to trip circuit 2 and an output value of 0 for no tripping. If ANN1 module output is -1, then ANN2 module is triggered and the outputs of CTD algorithm are deactivated. ANN2 module has four outputs for each phase; 1) normal operation, 2) reverse power flow, 3) external fault, 4) reverse fault. It gives an output value of 1 for the recognized case and an output value of -1 for all other cases. A post-processing unit is used to smooth up the outputs by averaging the five outputs of each phase and rounding their values to the nearest distinct states. Inputs and outputs of phase (a) protective modules are shown in Fig. 3.

Flow chart

The flow chart of the proposed algorithm is shown in Fig. 4. The flow chart represents phase (a) only. The algorithm is repeated for the other two phases and processed in a parallel manner through three parallel microprocessors. Parallel processing is one of the advantages of applying modularity concept in ANN architecture.

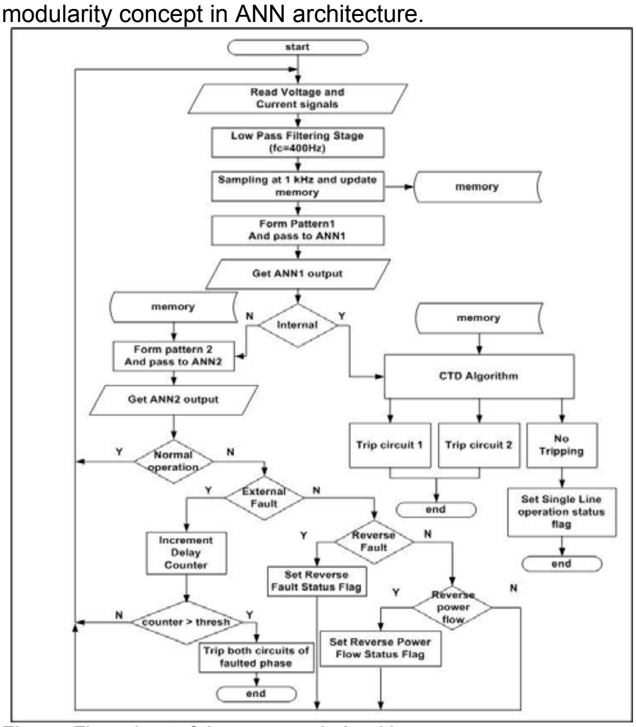

Fig. 4. Flow chart of the proposed algorithm.

Training results

Training epoch for ANN1 modules contains generated training patterns resulted from EMTDC simulations. A total of 2520 patterns were generated for training ANN1 modules. Training epoch for ANN1 module consists of two main parts. First part contains training patterns of internal fault cases at different locations of the protected line section, inception angles, and fault resistances. Second part contains training patterns of different cases including normal operation, external faults, reverse power flow, and reverse faults.

A total of 3960 patterns were generated for training ANN2 modules. Training epoch for ANN2 module consists of four main parts; 1) training patterns of reverse fault cases, 2) training patterns of external fault cases, 3) training patterns of normal operation cases, 4) training patterns of reverse power flow cases. Both External and reverse faults are simulated at different locations, inception angles, and fault resistances. Each case covers three consecutive cycles of power frequency. Each module is trained by combined unsupervised/supervised training algorithms for its two layers of Kohonen and back-propagation neural networks. To check modular ANN training result, each module was checked separately to isolate the training errors. Since the unsupervised layer has no target output, training was checked by studying the neurons distribution over the pre-trained input feature space.

Each ANN1 module consists of 7 neurons and each ANN2 module consists of 60 neurons. The neurons divided the input space into two separate regions for ANN1, while for ANN2 the input space is divided into four separate regions corresponding to the four output distinct states of ANN2. The supervised layer is evaluated by the training error obtained from the difference between the actual network output and the target output. Resultant error value is less than 0.1% which is reached through 10 epochs for ANN1 module and 25 epochs for ANN2 module.

Performance evaluation

Power system model is simulated using PSCAD/EMTDC program to generate voltage and current signals. The proposed algorithm is implemented under MATLAB environment for ANNs processing and algorithms execution. To evaluate the performance of the proposed relay, it must be tested with different cases from a validation set containing part of the training data and a new data that the neural networks were not trained with before. A validation data set consisting of different cases is generated by the power system model simulation tool (PSCAD/EMTDC).

Different cases are considered in the validation set including: 1) Normal operation; 2) Internal fault condition; 3) External fault condition; 4) Reverse fault condition; 5) Reverse power flow operation. For fault conditions, many parameters were changed such as fault type, fault location, fault inception angle, fault resistance and pre-fault power flow direction. The validation set also contained some extreme cases including faults near to busbar location, which is considered one of the most difficult fault conditions to be identified by the protective relay and internal faults through high resistance. Performance evaluation results show that the relay operates successfully and gives correct decision in all test cases. Some results are introduced herein. The notations used in this chapter are:

- NO: Normal operation
- RPF: Reverse power flow
- EF: External fault
- RF: Reverse fault

Fig.5 shows relay outputs for a “b1-g” fault occurring at 10 km from the relay point. Fault inception angle is 45º and the fault resistance is 0 ohm. ANN1b module gives an output value of “1” indicating that an internal fault is detected in phase “b”. Then CTD_b algorithm gives an output value of “1”. This leads to a tripping signal to circuit 1 of phase “b”. Hence, the faulted circuit is disconnected. ANN2 modules are deactivated in this case because of the detection of an internal fault. Tripping decision takes 3 ms.

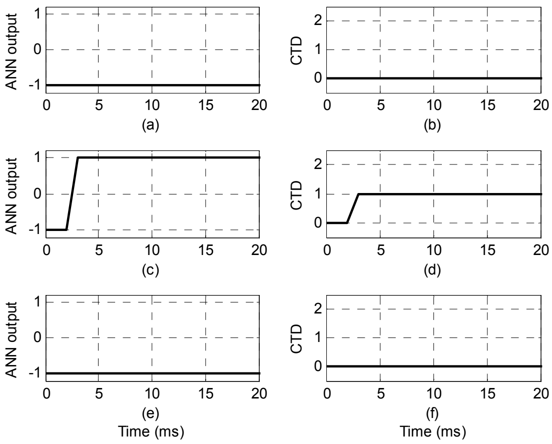

Fig. 5. ANN1 modules and CTD algorithms outputs
a) ANN1a output, b) CTD_a algorithm output,
c) ANN1b output, d) CTD_b algorithm output,
e) ANN1c output, f) CTD_c algorithm output.

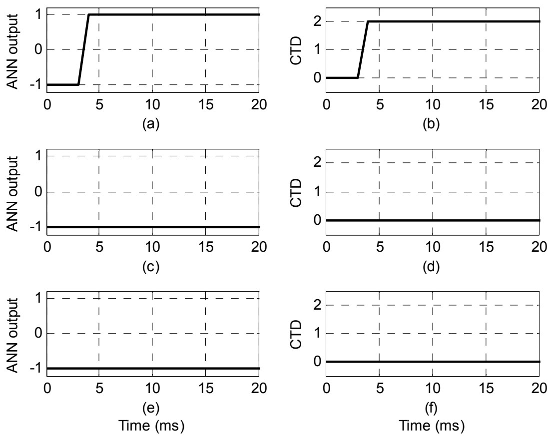

Fig. 6. ANN1 modules and CTD algorithms outputs
a) ANN1a output, b) CTD_a algorithm output,
c) ANN1b output, d) CTD_b algorithm output,
e) ANN1c output, f) CTD_c algorithm output.

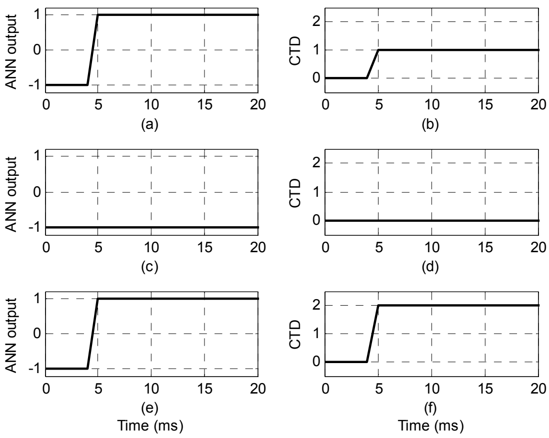

Fig. 7. ANN1 modules and CTD algorithms outputs
a) ANN1a output, b) CTD_a algorithm output,
c) ANN1b output, d) CTD_b algorithm output,
e) ANN1c output, f) CTD_c algorithm output.

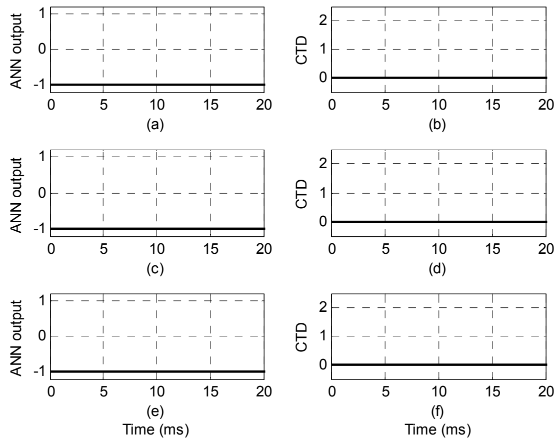

Fig. 8. ANN1 modules and CTD algorithms outputs
a) ANN1a output, b) CTD_a algorithm output,
c) ANN1b output, d) CTD_b algorithm output,
e) ANN1c output, f) CTD_c algorithm output.

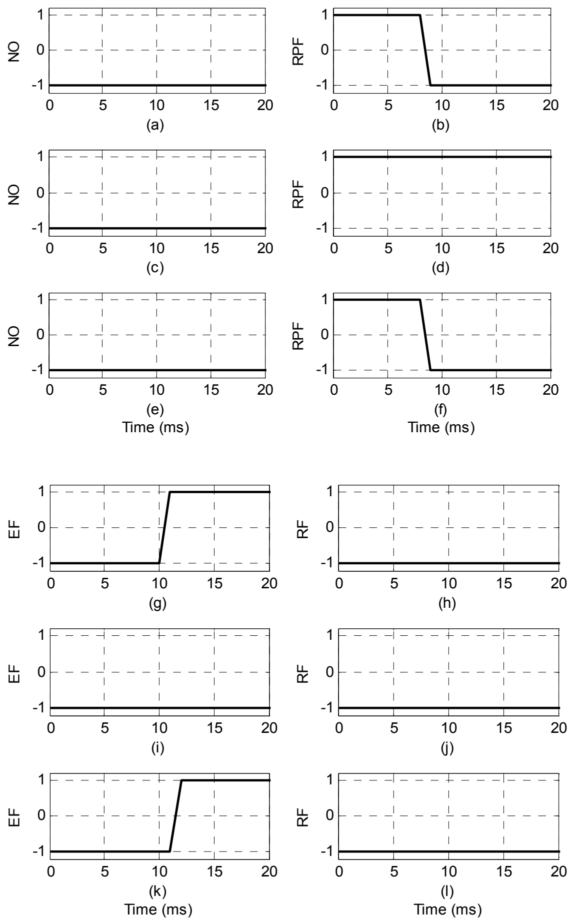

Fig. 9. ANN2 modules outputs
a) ANN2a NO output, b) ANN2a RPF output,
c) ANN2b NO output, d) ANN2b RPF output,
d) ANN2c NO output, e) ANN2c RPF output,
f) ANN2a EF output, g) ANN2a RF output,
h) ANN2b EF output, i) ANN2b RF output,
j) ANN2c EF output, k) ANN2c RF output.

Fig.6 shows the relay outputs for an “a2-g” fault occurring at 70 km from the relay point. Fault inception angle is 60º and the fault resistance is 20 ohm. ANN1a module gives an output value of “1” indicating that an internal fault is detected in phase “a”. Then CTD_a algorithm gives an output value of “2”. This leads to an instantaneous tripping signal to circuit 2 of phase “a”. Hence, the faulted circuit is disconnected. ANN2 modules are deactivated in this case because of the detection of an internal fault. The fault recognition takes 4 ms.

Fig.7 shows relay outputs for an “a1-c2-g” fault occurring at 90 km from the relay point. Fault inception angle is 90º and the fault resistance is 30 ohm. ANN1a and ANN1c modules give output values of “1” indicating that an internal fault is detected in phases “a” and “c”. Then CTD_a and CTD_c algorithms give output values of “1” and “2” respectively. This leads to an instantaneous tripping signal to circuit 1 of phase “a” and circuit 2 of phase “c”. Hence, the faulted circuits are disconnected. ANN2 modules are deactivated in this case due to the detection of an internal fault. Fault recognition takes 5 ms.

Fig.8 shows relay outputs for an “a-c” fault occurring at 120 km from the relay point. Fault inception angle is 90º and the fault resistance is 0 ohm. All ANN1 modules give output values of “-1” since no internal fault is detected. CTD algorithms give “0” outputs since it is deactivated by ANN1.

Fig. 9 shows ANN2 outputs. The pre-fault decision of all ANN2 modules is reverse power flow since power flow direction is from receiving end to sending end. The reverse power flow status flag is set. After fault inception, external fault is detected by ANN2a and ANN2c. RPF output of the two modules changes from “1” to “-1” and EF output changes from “-1” to “1”. Fault recognition takes 12 ms.

Conclusion

A novel ANN-based directional distance protection technique for the HV double circuit transmission line protection is introduced. The protective scheme uses modular ANN of combined Kohonen/back-propagation structure. A modified concept of transverse directional protection, to detect internal faults, is introduced which can overcome the problems associated with conventional techniques. The proposed relay uses time-based voltage and current samples to avoid complex mathematical computations related to filtering algorithms. The relay was tested extensively by using validation data set of different fault types, fault inception angles, fault locations, pre-fault power flow conditions and fault resistances. Test results show that the relay is able to detect internal faults rapidly, classify faulted phases and provides selective pole tripping feature that can be used in conjunction with autoreclosures with backup protection feature for the external zones. Test results show that the proposed relay takes less than 5 ms to detect internal faults and initiate a tripping decision for the faulted phase(s) with circuit tripping discrimination. Results also show that power flow direction during normal operation and fault condition is correctly identified in less than one cycle. Generalization and robustness capabilities and adaptive nature of the relay make it able to process new situations and give correct decisions.

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