ADAPTIVE SINGLE-POLE AUTORECLOSURE SCHEME BASED ON STANDARD DEVIATION AND WAVE ENERGY

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Abstract: *Adaptive autoreclosures avoid reclosing unto permanent faults and reclose unto transient faults only after the secondary arc has extinguished. This paper presents an adaptive single-pole autoreclosure (AdSPAR) technique based on the standard deviation and percentage of energy in detailed coefficients of Daubechies db4 mother wavelet, and multilayer perceptron (MLP) artificial neural network (ANN). The proposed technique is able to distinguish between permanent and transient faults and in the case of the latter, predict optimal reclosure times.*

Key words: *Adaptive autoreclosure, Artificial neural networks, Autoreclosure, Signal processing, Stability and Transmission lines*

1. Introduction

The massive demand for electric power and difficulty in constructing new lines owing to cost and environmental pressures has led to the transmission of more power through existing transmission networks. This coupled with the high incidence of single-phase-to-ground faults threatens the stability of the power system [1] and thus making the use of autoreclosure schemes imperative. Notwithstanding, unsuccessful reclosure in conventional autoreclosure schemes using a fixed dead time may aggravate potential damage to system and equipment [2]. Adaptive autoreclosures adapt reclosure times and therefore present advantages such as: minimized unsuccessful reclosing, improvements in transient stability margins, high-speed response to sympathy trips and reduction in system and equipment shocks [3], [4].

Researchers, recognizing the numerous merits of the adaptive autoreclosure, have proposed a number of adaptive autoreclosure schemes. These include schemes which measure and compare the voltage of the tripped phase to that of the energized phases to initiate or prevent autoreclosing [5], [6], schemes which make use of various components of faulted voltage such as total harmonic distortion, dc component and rms value to achieve successful autoreclosing [7]-[11] and schemes which employ high frequency current and voltage signals [12]-[15]. One significant demerit of the aforementioned schemes is that the many causes of faults and the interplay of several factors such as line configuration, fault position, fault point on wave, prefault loading, source parameters, and atmospheric conditions which influence the actual waveforms of the secondary arc voltage, are likely to hinder their effectiveness [3]. They are also limited by their inability to cope with previously unencountered situations.

To overcome the above challenges, researchers are turning to ANNs which in recent years have clearly demonstrated their ability in solving some long standing problems in power systems where conventional techniques have difficulty. ANNs have the ability to learn from experience in the form of training and to recognize the hidden relationships that might exist in those training patterns. Patterns with noise superimposed on them may be recognized by a neural network that has been well trained [16]. A number of ANN-based autoreclosure schemes use artificial neural networks such as Recurrent, Multilayer perceptron (MLP) and Radial basis function (RBF)[2], [3], [17]-[23]. With the exception of the recurrent neural network-based scheme[23], the schemes employ signal processing tools such as Fourier transform[3], short-time fast Fourier transform[2], [17] and wavelet transform[18]-[22] to decompose voltage waveforms and extract vital features for adaptive autoreclosing. The signal processing is necessary to facilitate the decision making process of the ANN in the face of several factors given above that influence the fault voltage waveform.

The application of neural network to adaptive autoreclosure scheme generally consists of four basic tasks [3]: (i) collecting or producing sets of sample of faulted voltage waveforms:(ii) preprocessing the data and extracting the useful features; (iii) choosing and building the most appropriate neural network; and (iv) using the processed sample data to train the neural network and then testing it by simulated fault transient data. The adaptive single-pole ANN autoreclosure scheme presented in this paper employs Discrete Wavelet Transform (DWT) signal processing tool, which has been shown to be the most resilient to noise [18]. An ANN architecture is also developed to suit the signal processing tool. The scheme is simulated using the well proven and widely accepted Electro-Magnetics Transient Program (EMTP). The scheme is able to distinguish clearly between permanent and transient faults and in the case of the latter, predict optimal reclosure times at various fault points on wave and fault locations indicating its robustness.

2. Proposed adaptive single-pole autoreclosure scheme

A flow chart of the proposed DWT, ANN-based AdSPAR scheme is shown in figure 1. The scheme is activated by a start logic when the circuit breaker is tripped. The DWT processes the voltage signal of the faulted phase from one of the capacitors associated with a capacitor divider and extracts the standard deviations of detailed coefficients from one cycle(20ms) of the voltage waveform for the first neural network to make a decision as to whether the fault is permanent or transient.

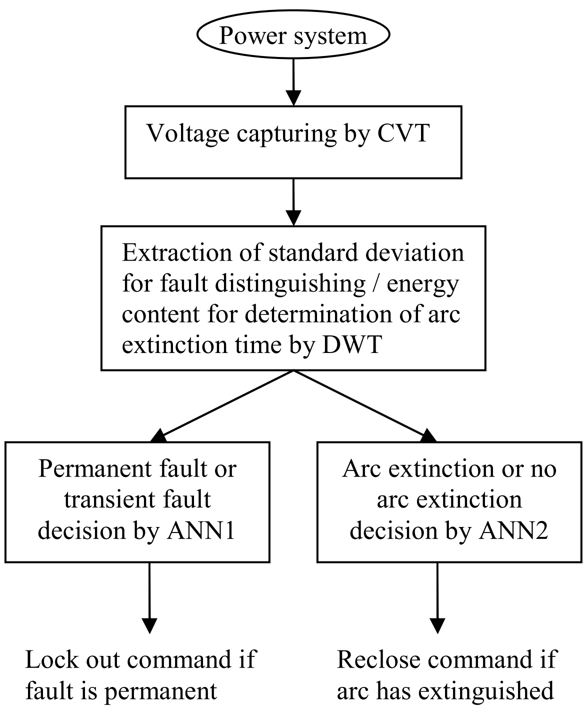

Fig 1: Block diagram of proposed scheme

If the fault is identified as transient, a signal is sent for the extraction of the percentage of wave energy in detailed coefficients from one cycle of the voltage waveform for a second neural network to determine whether or not the secondary arc has extinguished. Once the fault arc has extinguished, a signal is sent to reclose the breaker. However, if the fault is established to be permanent, a signal is sent to trip the other two healthy phase breakers immediately and lock out the single-pole autoreclosure.

3. Primary system simulation

A typical UK 400 kV uncompensated, single circuit, transmission line employed by many researchers to develop and test adaptive autoreclosure schemes [3], [18] is used for the study. The system is shown in figure 2. The frequency dependent parameters of the line were calculated via the inbuilt EMTP line constant program. The EMTP has no inbuilt transient arc model. The transient arc used for the study was modelled using the Transient Analysis of Control Systems(TACS) component of the EMTP based on the arc equations given in [24]. A 100Ω linear resistor was used to model permanent faults. Single phase-earth faults were simulated at various points along the line from the sending end. The fault point on wave was also varied. A sampling frequency of 6000Hz was used.

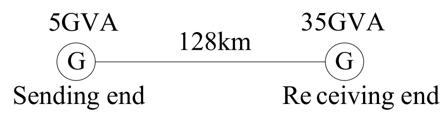

Fig 2: Studied system

4. Signal processing

Fault voltage waveform generated from the EMTP was converted into MATLAB files using a file converter. The waveform was then extracted every cycle for analysis.

Fault transients generated on a system contain a wide range of frequency components. It has been established from analysis that the most distinct characteristics of the waveforms are those associated with the variation of the frequency components over time [2]. It is also known from extensive studies that for each cycle, certain frequency bands can be used as potential features [3]. In order to distinguish between permanent and transient faults, the voltage waveform extracted every cycle was decomposed using the Daubechies db4 mother wavelet in MATLAB into 9 frequency bands(detailed coefficients): 3000-1500Hz, 1500-750Hz, 750-375Hz, 375-187Hz, ... Then the standard deviation (SD) of each frequency band was determined to identify the most significant bands. Analysis of the results revealed that the frequency ranges 750 – 375Hz(d3), 375 – 187.5Hz(d4) and 187.5 – 93.75Hz(d5) were the most significant. The standard deviations of these detailed coefficients formed the data for distinguishing between permanent and transient faults. The db4 was again employed to decompose the voltage waveform extracted each cycle into 5 frequency bands, and the percentages of energy of each band was determined. Analysis of the results showed that the percentages of energy in detailed coefficients 2 and

4 were the most significant. The extracted percentages of energy thus formed the arc extinction determination data.

5. ANN architecture and training

A three-layer feedforward-multilayer perceptron with no bias was used for this study. The choice was informed by the fast decision making capability of MLPs[8]. The number of nodes in the input layer equalled the number of input data (standard deviations or wave energies in detail coefficients). The networks had one node each in the output layer. The number of hidden layer neurons was varied. Figure 3 shows the architecture of a neural network with 3 neurons in the input layer, 4 neurons in the hidden layer and 1 neuron in the output layer. The ANNs had *purelin* as the input transfer function. Hidden layer and output neurons had *tansig* as the transfer function. The ANN for permanent and transient fault identification had three input neurons (standard deviations of d3, d4 and d5) while that for the determination of arc extinction time had 2 input neurons (percentages of energy of d2 and d4). Training of the networks was carried out using the Levenberg-Marquardt back-propagation technique for its fast and accurate training capabilities [25]. The neural networks were trained with a set of input-output pairs. The inputs for the ANN responsible for distinguishing between permanent and transient faults were the standard deviations of the detailed coefficients while the outputs were '1' for permanent faults and '0' for transient faults. The inputs to the ANN which determines the extinction time of secondary arcs were the percentages of energy. The outputs were '1' for secondary arc persistence and '0' for secondary arc extinction.

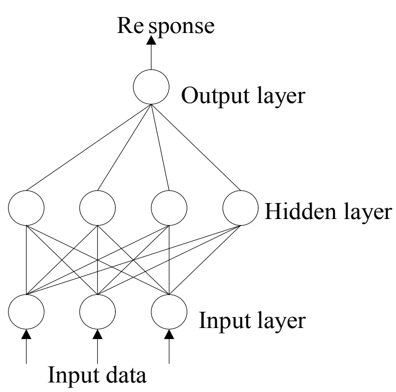

Fig 3: Neural network architecture

To test the robustness of the proposed scheme, both permanent and transient faults were simulated at various locations and for each location at voltage-zero and voltage-maximum. A credible AdSPAR scheme must be based on realistic transient fault arc model. Figures 4, 5, 6 and 7 show voltage waveforms of transient faults at 64km-voltage zero, 64km-voltage maximum, 120km-voltage zero and 120km-voltage maximum respectively. The waveforms, depicting the characteristics of a true faulted voltage waveform [24], show that the TACS-built transient arc model was very realistic. Voltage waveforms of permanent faults at voltage maximum at 64km and 120km respectively are shown in figures 8 and 9.

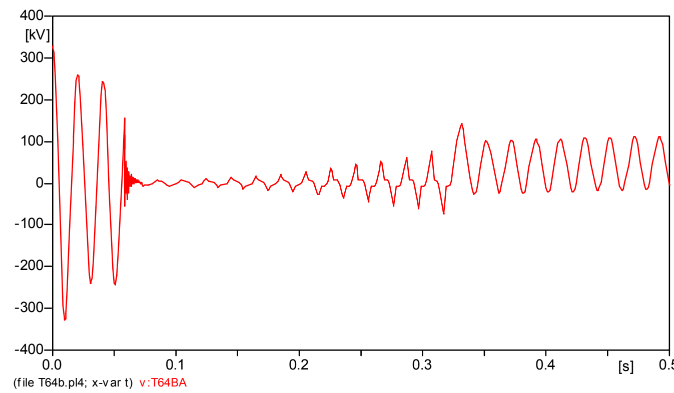

Fig 4: Transient fault at voltage zero at 64km

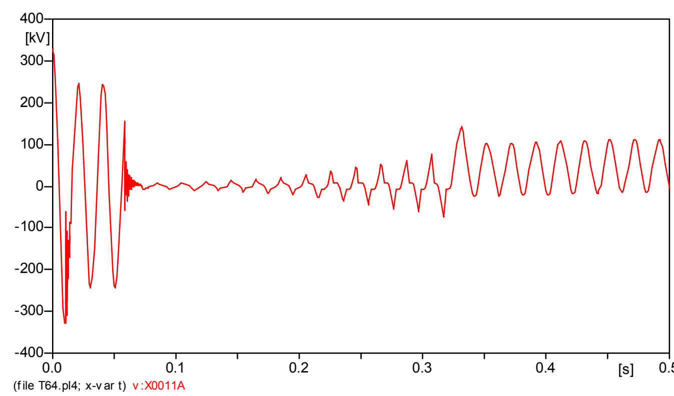

Fig 5: Transient fault at voltage maximum at 64km

6. Results and Discussion

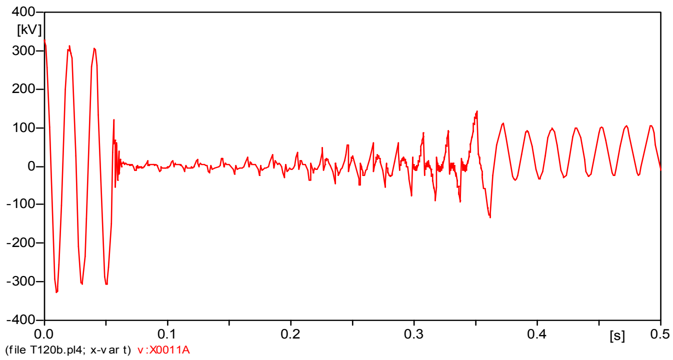

Fig 6: Transient fault at voltage zero at 120km

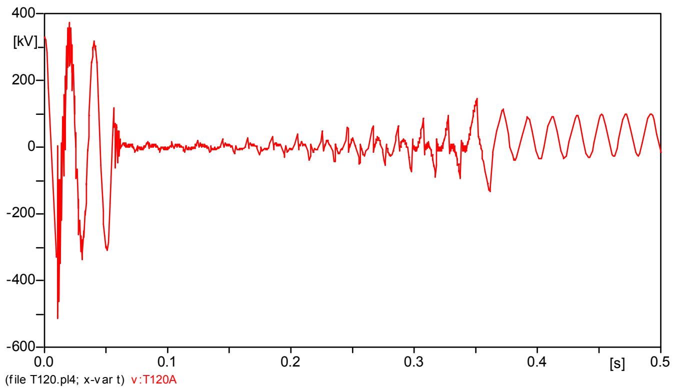

Fig 7: Transient fault at voltage maximum at 120km

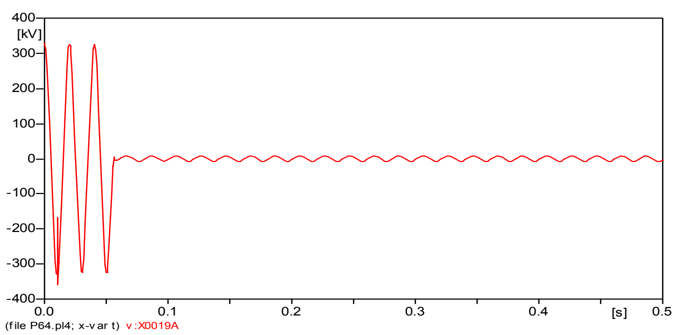

Fig 8: Permanent fault voltage maximum at 64km

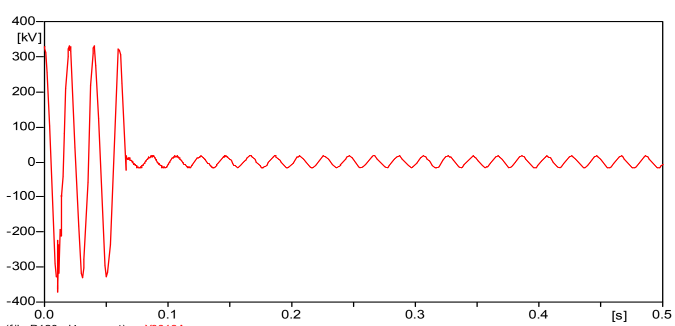

Fig 9: Permanent fault voltage maximum at 120km

Tables 1, 2, 3 and 4 show standard deviations for the detailed coefficients at 32km and 96km for permanent and transient faults which are representative of the results obtained.

Table 1: Standard deviations of detailed coefficients of permanent and transient faults at 32km, voltage- maximum

Cycle No.	Permanent fault			Transient fault		
	d3	d4	D5	d3	d4	d5
1	2.8459	1.1714	1.1952	9.1286	16.756	16.035
2	0.0936	0.1822	0.7909	0.2486	1.1061	1.4178
3	0.04	0.1752	0.7924	0.2534	1.2448	1.6453
4	0.0425	0.1764	0.7917	0.3423	1.4958	2.1764
5	0.0526	0.1764	0.7928	0.4813	1.6902	2.8769
6	0.0413	0.1755	0.7924	0.6294	1.7765	3.6937
7	0.0375	0.176	0.7907	0.8066	1.6853	5.0306
8	0.0427	0.1761	0.7907	1.0189	1.4134	7.3036
9	0.0431	0.1755	0.7912	1.0447	2.5816	9.4961
10	0.0406	0.1755	0.7907	1.2735	4.7381	10.639

Table 2: Standard deviations of detailed coefficients of permanent and transient faults at 32km, zero-crossing

Cycle No.	Permanent fault			Transient fault		
	d3	d4	D5	d3	d4	d5
1	2.9095	1.2515	1.2755	9.328	16.47	16.025
2	0.0432	0.1789	0.796	0.2451	1.1023	1.4191
3	0.0466	0.177	0.7963	0.261	1.248	1.6438
4	0.0411	0.1775	0.795	0.3372	1.4932	2.1774
5	0.044	0.177	0.796	0.4863	1.692	2.8754

Table 3: Standard deviations of detailed coefficients of permanent and transient faults at 96km, voltage- maximum

Cycle No.	Permanent fault			Transient fault		
	d3	d4	D5	d3	d4	d5
1	2.9019	1.2269	1.2635	9.1286	16.756	16.035
2	0.0489	0.1858	0.8126	0.2486	1.1061	1.4178
3	0.0616	0.18	0.8194	0.2534	1.2448	1.6453
4	0.0397	0.1831	0.8133	0.3423	1.4958	2.1764
5	0.0527	0.1809	0.8175	0.4813	1.6902	2.8769

Table 4: Standard deviations of detailed coefficients of permanent and transient faults at 96km, zero-crossing

Cycle No.	Permanent fault			Transient fault		
	d3	d4	d5	d3	d4	d5
1	2.9453	1.2278	1.2576	9.328	16.47	16.025
2	0.0450	0.1834	0.8163	0.2451	1.1023	1.4191
3	0.0470	0.1815	0.8165	0.261	1.248	1.6438
4	0.0423	0.182	0.8152	0.3372	1.4932	2.1774
5	0.0451	0.1815	0.8162	0.4863	1.692	2.8754

The tables show clear variations between the standard deviations of permanent and transient faults. These clear variations will make decision making by neural networks easy. The first cycle data are different from the others owing to high frequency transients that exist immediately after CB opening.

Tables 5 and 6 show percentage of energies of d2 and d4 for transient faults at 32km and 96km starting from the 3rd cycle – time when the algorithm will begin to determine arc extinction after a fault has been determined to be transient. .

Table 5: Percentage of energies of d2 and d4 for transient faults at 32km, voltage-zero and voltage-maximum

Cycle No.	32km Voltage-zero		32kmVoltage-max.	
	d2	d4	d2	d4
3	0.0179	1.9835	0.0136	2.0131
4	0.0128	2.0201	0.0146	2.049
5	0.0215	1.7309	0.0197	1.7298
6	0.0224	1.3023	0.0234	1.3043
7	0.0204	0.7546	0.0198	0.7522
8	0.0107	0.2881	0.0109	0.2879
9	0.0043	0.4875	0.0043	0.4864
10	0.0065	0.9183	0.0064	0.9167
11	0.0097	1.34	0.0097	1.3379
12	0.0114	1.4825	0.0114	1.4802
13	0.0127	0.6831	0.0127	0.6821
14	0.0045	0.2036	0.0045	0.2036
15	0.0069	0.1202	0.0069	0.1204
16	0.007	0.1403	0.007	0.1405
17	0.0075	0.1525	0.0076	0.1527
18	0.0079	0.1601	0.008	0.1603

Table 6: Percentage of energies of d2 and d4 for transient faults at 96km, voltage-zero and voltage-maximum

Cycle No.	96km Voltage-zero		96kmVoltage-max.	
	d2	d4	d2	d4
3	0.0179	1.9835	0.0136	2.0131
4	0.0128	2.0201	0.0146	2.049
5	0.0215	1.7309	0.0197	1.7298
6	0.0224	1.3023	0.0234	1.3043
7	0.0204	0.7546	0.0198	0.7522
8	0.0107	0.2881	0.0109	0.2879
9	0.0043	0.4875	0.0043	0.4864
10	0.0065	0.9183	0.0064	0.9167
11	0.0097	1.34	0.0097	1.3379
12	0.0114	1.4825	0.0114	1.4802
13	0.0127	0.6831	0.0127	0.6821
14	0.0042	0.1303	0.0042	0.1303
15	0.0039	0.0651	0.0039	0.0651
16	0.0029	0.0581	0.0029	0.0582
17	0.0028	0.0567	0.0028	0.0568
18	0.0028	0.0556	0.0028	0.0556

The responses of the neural network for fault distinguishing, to some test data are shown in tables 7, 8, 9 and 10.

Table 7: Neural network responses to transient and permanent faults at 32km voltage-zero

Cycle No.	Permanent fault		Transient fault	
	ANN response	Desired	ANN response	Desired
1	0.9981	1	0.0000138	0
2	0.9995	1	0.0003935	0
3	0.9995	1	-0.0000936	0
4	0.9995	1	0.000004	0
5	0.9995	1	0.0000136	0

Table 8: Neural network responses to transient and permanent faults at 32km voltage-maximum

Cycle No.	Permanent fault		Transient fault	
	ANN response	Desired	ANN response	Desired
1	0.9994	1	0.0000138	0
2	0.9996	1	0.0003634	0
3	0.9995	1	-0.0000927	0
4	0.9995	1	0.000004	0
5	0.9995	1	0.0000136	0

Table 9: Neural network responses to transient and permanent faults at 96km voltage-zero

Cycle No.	Permanent fault		Transient fault	
	ANN response	Desired	ANN response	Desired
1	0.999	1	0.0000138	0
2	0.9995	1	0.0003935	0
3	0.9995	1	-0.0000936	0
4	0.9995	1	0.000004	0
5	0.9995	1	0.0000136	0

Table 10: Neural network responses to transient and permanent faults at 96km voltage-maximum

Cycle No.	Permanent fault		Transient fault	
	ANN response	Desired	ANN response	Desired
1	0.9987	1	0.0000138	0
2	0.9995	1	0.0003934	0
3	0.9995	1	-0.0000936	0
4	0.9995	1	0.000004	0
5	0.9995	1	0.0000136	0

A comparison between the desired and obtained ANN outputs clearly shows that the results attained are satisfactory; ANN responses in most cases are very close to the ideal outputs of either '0' or '1'. The results show that fault distinguishing can be achieved within one cycle(20ms), with confirmation by the subsequent cycles.

Tables 11 and 12 show the responses of the neural network which determines the extinction time of transient fault arcs to test data.

Table 11: Neural network responses to transient faults at 32km

Cycle No.	32km, Voltage-zero		32km, voltage-maximum	
	ANN response	Desired	ANN response	Desired
3	0.9999	1	0.9999	1
4	0.9999	1	0.9999	1
5	0.9999	1	0.9999	1
6	0.9999	1	0.9999	1
7	0.9999	1	0.9999	1
8	0.9994	1	0.9994	1
9	1	1	1	1
10	0.9999	1	0.9999	1
11	0.9999	1	0.9999	1
12	0.9999	1	0.9999	1
13	1	1	1	1
14	0.0936	0	0.0933	0
15	0.00075127	0	0.00075988	0
16	0.0024	0	0.0025	0
17	0.0049	0	0.005	0
18	0.0076	0	0.0077	0

Table 15: Neural network responses to transient faults at 96km

Cycle No.	96km, Voltage-zero		96km, voltage-maximum	
	ANN response	Desired	ANN response	Desired
3	0.9999	1	0.9999	1
4	0.9999	1	0.9999	1
5	0.9999	1	0.9999	1
6	0.9999	1	0.9999	1
7	0.9999	1	0.9999	1
8	0.9994	1	0.9994	1
9	1	1	1	1
10	0.9999	1	0.9999	1
11	0.9999	1	0.9999	1
12	0.9999	1	0.9999	1
13	1	1	1	1
14	0.0014	0	0.0014	0
15	-0.00010554	0	-0.00010502	0
16	-0.00014839	0	-0.00014793	0
17	-0.00015689	0	-0.00015639	0
18	-0.00016407	0	-0.00016364	0

A comparison between the desired and obtained ANN outputs show satisfactory results; ANN responses in most cases are very close to the ideal outputs of either '0' or '1'. A change from near '1' to near '0' signifies the extinction of a transient fault arc and no change indicates the persistence of a transient fault arc. Additionally, the time at which the change occurs, gives the precise arc extinction time. Since there is always a deviation of the ANN output around '0' and '1', small threshold levels will have to be set.

7. Conclusion

An adaptive single-pole autoreclosure scheme based on Discrete wavelet analysis and multi-layer perceptron ANN is developed in this paper. The proposed technique uses standard deviations of detailed coefficients of Daubechies db4 in the frequency ranges: 750 – 375Hz, 375 –187.5Hz and 187.5 – 93.75Hz to distinguish between transient and permanent faults. The determination of arc extinction time for transient faults is achieved using the percentages of wave energy of detailed coefficients from db4 in the frequency ranges: 1500 – 750Hz and 375 –187.5Hz. The scheme can distinguish between transient and permanent faults within 20ms after circuit breaker opening and also determine secondary arc extinction times. The test results reveal that the standard deviation and energy content of detailed coefficients from db4 can be effectively used to detect and identify relevant permanent and transient fault features in EHV transmission systems.

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