USING FAULT INDUCED TRANSIENTS AND NEURAL NETWORK FOR T.L. ULTRA HIGH SPEED FAULT DETECTION AND CLASSIFICATION

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Abstract-This paper is concerned with a new approach for fault detection, direction discrimination, fault type classification and faulted phase selection, based on Artificial Neural Network (ANN), to be used for transmission line ultra-high speed (UHS) protection. The proposed approach is based on a 3-level hierarchical neural network structure, where the normalized fault induced transients in the instantaneous phase currents and/or voltages at the relaying point are to be fed. Compared to other architectures, this structure would have a high learning ability and accordingly a higher recall accuracy. The approach is tested using the Electromagnetic Transients Program (EMTP) to generate current and voltage samples at the relaying point for the study system. The training and testing results indicate the high speed and selectivity of the approach as well as the inherent adaptive feature.

Keywords: fault induced transients-directional protection - faulted phase selection - neural network.

I. INTRODUCTION

The interest in fault-initiated traveling wave-based protection is motivated by the consideration of modern bulk EHV/UHV transmission network with long lines [e.g. 1,9]. In these schemes the effect of load current and high frequency transients on the current and voltage accompanied with the fault are reduced to a minimum.

The conventional analytical-based protection approaches are expected to be affected by the system operating conditions. Moreover complete faulted phase selection can not be achieved through these conventional approaches [1]. The Artificial Neural Network (ANN) provides a viable alternative because they can handle most situations which are not defined sufficiently for deterministic algorithms to execute. Beside enjoying the advantages which are inherent in ANNs, (such as excellent noise immunity, robustness, etc. [3]), the protection scheme based on ANN would not be affected by changes in system operating conditions [4-7].

The objective of this paper is directed towards developing a new scheme based on ANN to be used for transmission lines fault detection, direction discrimination, fault classification and faulted phase selection, based on a narrow window of less than one fourth of the power frequency cycle. Instead of using the full values of voltages and currents as shown in [4-7], the proposed approach utilizes the normalized changes of the phase voltages and phase currents resulting from the fault induced transients. Compared to other schemes, this would lead to inherent adaptive feature for the proposed approach. Moreover, the use of the changes of currents and voltages would reduce the effect of fault resistance on the capability of the approach.

II. FAULT INDUCED TRANSIENTS-BASED DIRECTIONAL RELAYING SCHEME

The inception of a fault in a transmission line will cause the post fault voltage "v_R" and current "i_R" at the relaying point to deviate from the steady state prefault voltage and current "v^1_R" and "i^1_R" respectively, as shown in Fig. 1 (single-phase, lossless T.L.). With a fault at "F", the forward and backward traveling waves ($\Delta v(x,t)$ and $\Delta i(x,t)$) associated with the superimposed voltage and current quantities can be written as [1,9]

$$\Delta v(x,t) + Z\,\Delta i(x,t) = 2Z\, f_1\,(x-at) \tag{1}$$

$$\Delta v(x,t) - Z\,\Delta i(x,t) = -2Z\, f_2\,(x+at) \tag{2}$$

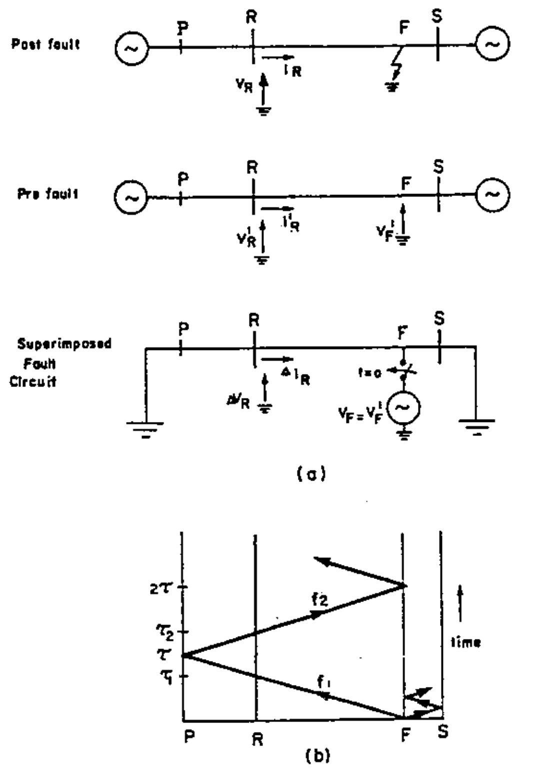


Fig. 1 a) Principle of Superposition
b) Traveling Wave Propagation for Forward Fault

where f_1 and f_2 are the foreword and backward traveling waves deviations resulting from fault inception as shown in Fig. 1.b, Z is the surge impedance and "a" is the propagation velocity.

Assume that the voltage and the line current changes produced by the fault at the fault point "F" are v_F and i_{FR}, we can write

$$v_F(t) + Z\, i_{FR}(t) = \Delta v_R(t+\tau_1) - Z\, \Delta\, i_R(t+\tau_1) \qquad (3)$$

where "τ" is the travel time between "F" and the point reflection "P", "τ_1" between "F" and "R" and "τ_2" for "F-R-P-R" as shown in Fig. 1.b. Assuming a prefault voltage at "F", v'_F, where

$$v'_F = V_{rms}\sqrt{2}\ \sin(\omega t + \phi) \qquad (4)$$

then, according to equation (3) the wave characteristic seen by substation "R" is

$$\Delta v_R(t+\tau_1) - Z\, \Delta\, i_R(t+\tau_1) = -V_{rms}\sqrt{2}\ \sin(\omega t + \phi) \qquad (5)$$

for $0 < t < 2\tau$.

This composite-termination-independent expression is observable at "R" from "τ_1" to "$2\tau+\tau_1$", (1st. incidence +1st. reflection + 2nd. incidence). However, after that time reflection from the fault location will change it.

It should be noted here that f_2 could be detected at "R" within the time span "τ_2" to "$2\tau+\tau_2$" from fault inception, i.e. after or within detecting f_1, and its value

$$f_2 = r_c f_1 , \qquad \text{for } t < 2\tau \qquad (6)$$

where r_c is a reflection coefficient.

A. Highly reliable discriminant function

The forward wave characteristics in equation (5) is independent of termination but it does depend on the fault inception angle ϕ. For $\phi = 0.0$ the characteristic magnitude becomes a ramp function $2V_{rms}/2 \sin(\omega t)$ which would be difficult to detect within the observable time span 2τ if $\tau \ll T$, where T is the period of the power frequency. The problem is avoided by using the the wave characteristic (5) in combination with its derivative to form the expression:

$$D_F = (\Delta v_R - Z\, \Delta\, i_R)^2 + 1/\omega^2 \left(d/dt\, ((\Delta v_R - Z\, \Delta\, i_R)^2\right) = 8\, V^2_{rms} \qquad (7)$$

for $\tau_1 < t < 2\tau + \tau_1$ and is independent of the angle of the fault inception. This signal D_F is observable at R from τ_1 to $\tau_1 + 2\tau$ and represents the traveling wave discriminant used to identify fault condition on the line. The magnitude of D_F is zero (except for noise) on a healthy line and is extremely high ($8\, V^2_{rms}$) on a faulted line in the interval $\tau_1 < t < 2\tau + \tau_1$.

Based on the previous analysis, the fault detection, direction discrimination, fault classification and faulted phase selection can be explicitly derived from information contained in fault induced transients of the three phase voltages and currents ({Δv_A, Δv_B, Δv_C} and {Δi_A, Δi_B, Δi_C}) [1]. These transients can be incorporated in two discriminate functions (D_F and D_B) based on the modal transform as shown by (8) and (9):

$$D_F^{(k)} = (\Delta v_R^{(k)} - z^k\, \Delta\, i_R^{(k)})^2 + \frac{1}{\omega^2}\left\{ \frac{d}{dt}(\Delta v_R^{(k)} - z^k\, \Delta\, i_R^{(k)}) \right\}^2 \qquad (8)$$

$$D_B^{(k)} = (\Delta v_R^{(k)} + z^k\, \Delta\, i_R^{(k)})^2 + \frac{1}{\omega^2}\left\{ \frac{d}{dt}(\Delta v_R^{(k)} + z^k\, \Delta\, i_R^{(k)}) \right\}^2 \qquad (9)$$

for mode-k, where z^k is the mode- k surge impedance, and $\Delta v_R^{(k)}$ and $\Delta\, i_R^{(k)}$ are the mode- k superimposing voltage and current respectively at the relay point.

These modal transform-based discriminant functions are incorporated in a way to achieve a directional relaying approach with a degree of fault classification and faulted-phase selection. This kind of pattern classification problem can be handled very well by ANNs.

III. ANN-BASED UHS RELAYING APPROACH

A- ANN - background

An ANN is made up of simple and highly interconnected elements, called neurons, which process information by its dynamic state response to external nodes. One of the operations that a neural network can be made to do is the pattern recognition and classification. This feature fits well with the problem of fault detection and diagnosis of power systems. The multi-layer perception (MLP) has been widely used for such application. The MLP identifies the type and location of faults with a given set of power system conditions, measurements, alarms, ..etc. However, it has been reported that simple applications of MLP still have difficulties in large-scale systems, without a sophisticated prefiltering technique [10].

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. Noisy patterns (those with desired segments missing and/or undesired segments added) may be recognized by a neural network that has been trained to recall the unnoisy patterns [4]. Therefore ANNs are able to extract signatures of fault existence, fault direction, different types of faults, as well as the faulted phase in power transmission lines with full resolution if they are properly trained.

B- Structure of the proposed ANN

The proposed ANN-based approach is to achieve, in a hierarchical mode, three protective relaying functions, namely:

1) Fault detection and direction discrimination
2) Fault type classification, and
3) Faulted phase selection.

Fig. 2 shows the proposed hierarchical structure comprising three levels of ANNs, where each level executes one of the previously mentioned functions. The first level ANN is responsible for detecting the fault and indicating its direction (forward or backward). The second level ANN is devoted for fault type classification. The third level provides faulted phase selection for each type of fault, if any. This third level consists of three separate ANNs, each of which selects the faultd phase(s) for L-G, LL-G, and L-L fault respectively. This new scheme would facilitate the training procedure and thus would improved learnability compared to other proposals.

Each of the used ANNs is a feedforward MLP with one hidden layer. Inputs to each ANN are to be the changes in the instantaneous values of the 3-phase voltages and 3-phase currents from prefault conditions (at the relaying point). This proposed structure would lead to a high learnability for each ANN. Moreover, it would lead to good performance for high impedance faults.

For the first level, the network has 60 neurons in the input layer, 30 neurons in the hidden layer and two neurons in the output layer. The firing of the output neuron represents the existence of the forward or the backward faults, respectively. For the second level, the network has the same inputs as those of the first level, 90 neurons in the hidden layer and four outputs. One output would be of value "1" for the corresponding fault type, while the others would be '0'. For the third level, each network has 60 inputs, 30 neurons in the hidden layer and three outputs. One output would be "1" for the corresponding faulted phase(s), while the others would be "0".

IV. TRAINING AND TESTING RESULTS

The EMTP program [8] is used for generating current and voltage samples at the relaying point for the system shown in Fig. 3: The process of feature extraction with training and testing procedure from the generated (or recorded) voltages and currents is shown in the flow diagram of Fig. 4. Since the classification is actually based on the superimposed transients and not on the power frequency components [1], no anti-aliasing low pass filter is considered.

Assuming a sampling frequency =3kHz, each voltage or current cycle could be sampled with 50 samples (power frequeny=60Hz). For UHS operation, equally spaced samples within less than one fourth of the cycle will only be

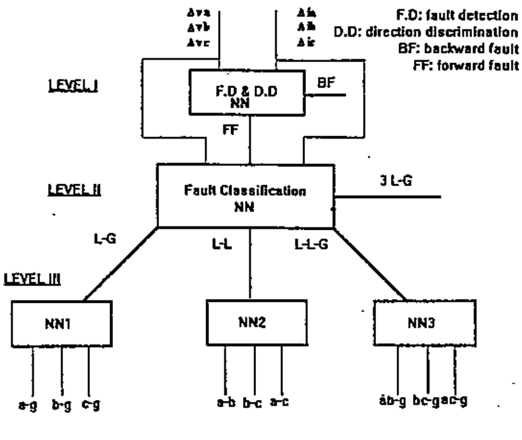


Fig. 2 The Proposed Hierarchical Structure of the Developed ANN Protection Scheme

considered. Therefore, each input in the first, second, and third level represents the first 10 equally spaced samples of normalized changes in 3-phase voltages and currents out of the available 50 samples per cycle. Fig. 4 shows the 3-phase voltage and current waveforms for a L-G fault at 60% distance from the relay.

A- First level: Fault direction discrimination

The network in the first level is trained using the most common and the most severe faults (3 phase to ground and line to ground faults respectively). The data used is extracted from different locations of the fault occurrence (0%, 40%, 80%, 100% for the forward fault and 40% , 80% for the backward fault). Testing of the network is performed for all types of faults at 20% and 60% for the forward faults and at the same two locations for the backward fault as those used in training. The maximum recorded error for the training of the network is found to be 0.00031 for node 1 and 0.00018 for node 2. The maximum recorded error for testing is found to be 0.1736 and 0.18489 for the two nodes respectively.

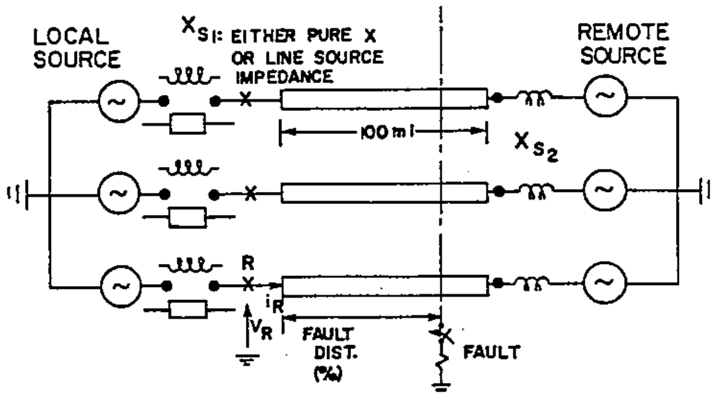


Fig. 3 A Single Circuit 500kV Study System

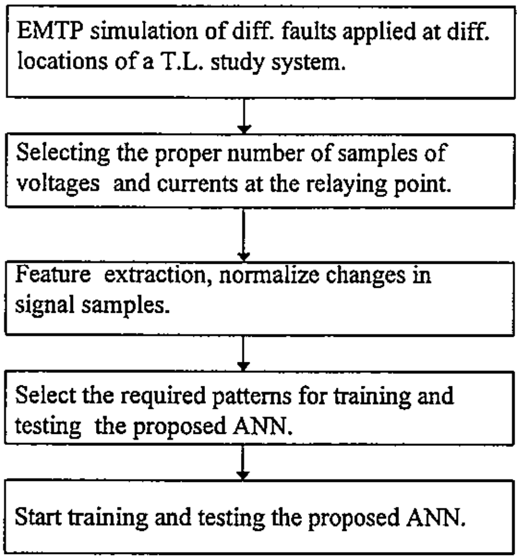


Fig. 4 A Flowchart for the Process of Generating Pattern

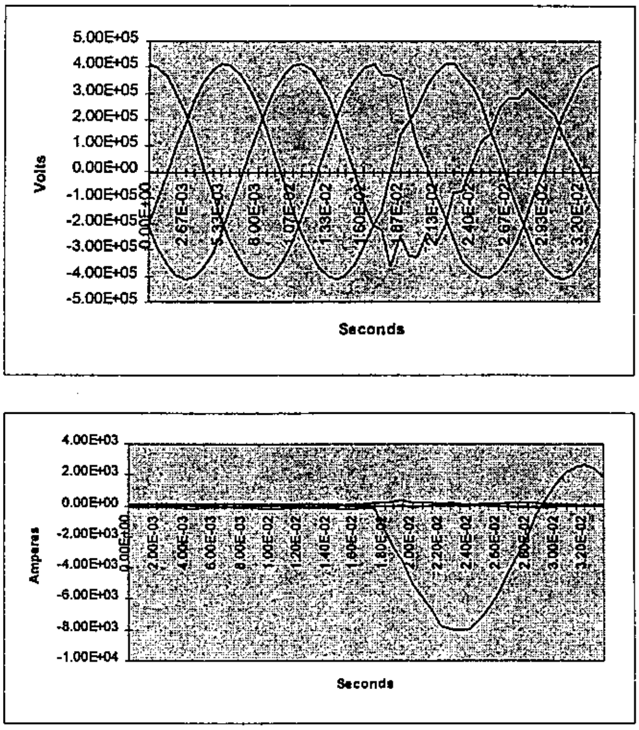


Fig. 5 3-Phase Votage and Current Waveforms for a L-G Fault at 60% Distance

Fig. 6 and Fig. 7 show the training and testing rms errors for the detection of forward and backward faults respectively. Fig. 8 shows the training and learning rates for the fault detection level.

B- Level 2: Fault classification:

The outputs in the second level represent the four types of faults: 3LG, LG, LLG and LL respectively. The data used for training the ANN is extracted from the fault at 40% and

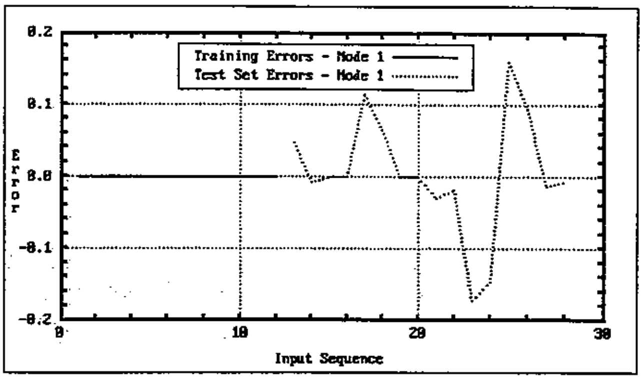


Fig. 6 Training and Testing RMS Error for Node 1 (Level 1)

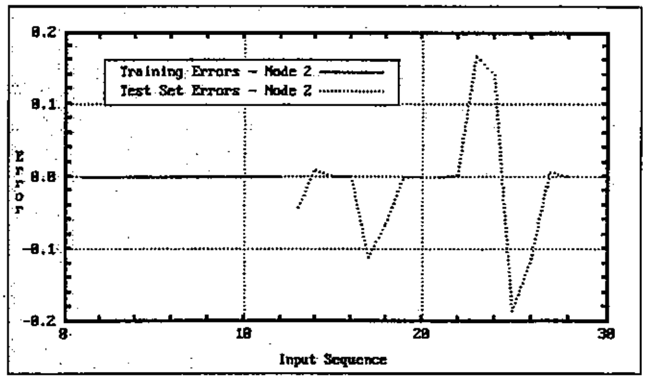


Fig. 7 Training and Testing RMS Error for Node 2 (Level 1)

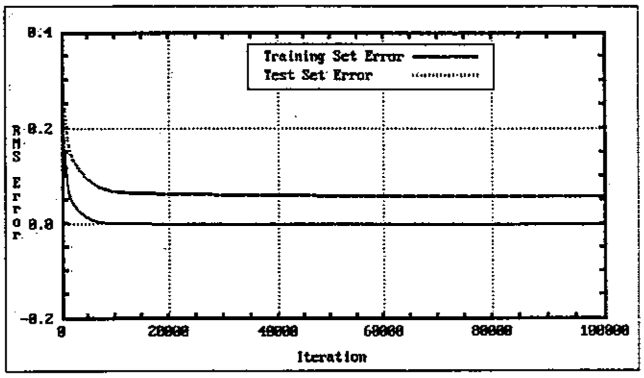
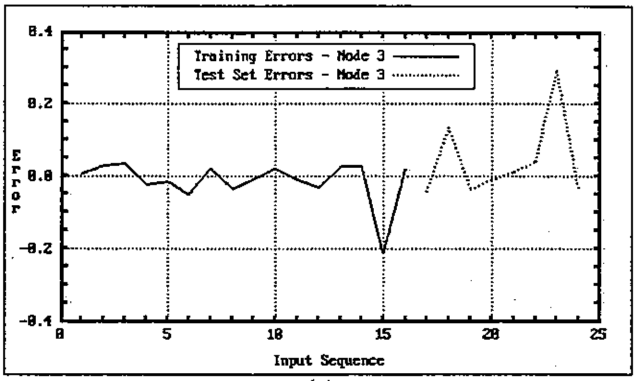
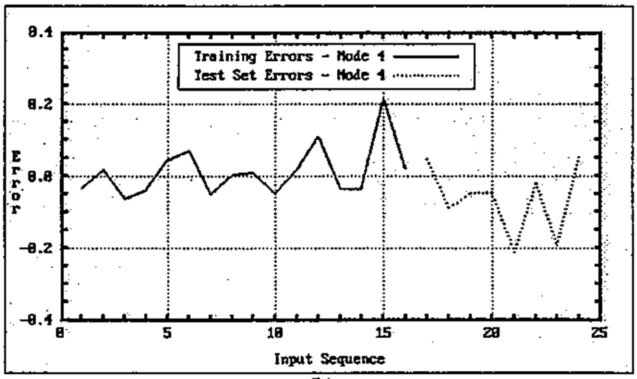


Fig. 8 Training and Learning Rates for level 2 (Fault Detection)

60% distance from the source, while the data used for testing is extracted using the same fault type at 0%, 20% , and 80% distance. Table (1) shows the results for one of the training and testing case studies. Fig. 9 shows the training and testing rms errors for nodes 3 and 4 of the output patterns,



(a)



(b)

Fig. 9 Training and Testing RMS Error (level 2)
a) Node # 3
b) Node # 4

for a different case study. In the latter case, the used training patterns are for fault locations at 0%, 40% and 100%, while the related testing is conducted for faults at 80%. It is generally seen from the results that the accuracy is practically accepted.

C- Level 3: Faulted phase selection:

The outputs in the third level represent faulted phase combinations (a, b, c), (ab, bc, ca) or (abg-bcg-cag), for line-ground, line-line and line-line-ground respectively. The data used for training is extracted from the fault at 20% distance from the source, while the data used for testing is extracted from the 40% location. Table (2) shows the results for the three cases.

The output testing results for each level show small fluctuations in the actual ANN outputs around one and zero (in the range of 0.2 or less) which can't be practically avoided. A small threshold level can be built in the ANN algorithm in order to minimize the degree of uncertainty.

Table(1): Training and Testing Results for level 2 (Fault Classification).

Fault Type	Training at 40%		Training at 60%		Testing at 20%	
	-et	Output	Target	Output	Target	Output
3LG	1	1.00001	1	0.9999	1	1.12239
3LG	0	0.00001	0	-.00001	0	-.01313
3LG	0	0.00001	0	-.00002	0	-.05924
3LG	0	0.00002	0	-.00002	0	-.07668
LG	0	0.00001	0	-.00002	0	0.00268
LG	1	1.00001	1	0.99997	1	1.13704
LG	0	0.00001	0	-.00002	0	0.10105
LG	0	0.00001	0	-.00002	0	-0.1586
LLG	0	0.00002	0	-.00002	0	0.00224
LLG	0	0.00003	0	-000001	0	-.01843
LLG	1	1.00002	1	0.99998	1	1.02442
LLG	0	0.00002	0	-.00001	0	0.00631
LL	0	-.00008	0	0.00008	0	0.00481
LL	0	-.00011	0	0.00012	0	0.01887
LL	0	-.00009	0	0.00009	0	0.00163
LL	1	0.9992	1	1.00009	1	0.97882

Table(2): Training and Testing Results for level 3 (Faulted Phase Selection)

Faulted Phase(s)	Training at 20%		Testing at 40%	
	Target	Output	Target	Output
a-g	1	0.99996	1	1.0215
b-g	0	0.00002	0	-0.02075
c-g	0	0.00003	0	-0.01241
a-g	0	0.00002	0	0.0325
b-g	0	0.00002	0	-0.1334
c-g	1	0.99993	1	0.99514
a-g	0	0.00003	0	0.08086
b-g	1	0.99996	1	0.99894
c-g	0	0.00004	0	-0.03017
a-b-g	1	0.99997	1	0.86967
b-c-g	0	0.00003	0	0.04866
c-a-g	0	0.00003	0	0.05296
a-b-g	0	0.00004	0	0.04538
b-c-g	0	0.00004	0	0.04809
c-a-g	1	0.99998	1	0.8851
a-b-g	0	0	0	0.05896
b-c-g	1	0.99994	1	0.87224
c-a-g	0	-0.00001	0	0.06034
a-b	1	0.99995	1	0.87915
b-c	0	-0.00001	0	0.05686
c-a	0	-0.00001	0	0.05316
a-b	0	0.00003	0	0.06219
b-c	0	0.00003	0	0.05657
c-a	1	0.99999	1	0.86868
a-b	0	0.00001	0	0.06294
b-c	1	0.99998	1	0.86529
c-a	0	0.00001	0	0.05773

V. CONCLUSION

An ANN model for directional relaying scheme-based on fault induced transients has been developed and tested in this paper. The developed scheme comprised 3-level hierarchical NN structure for fault detection, direction discrimination, and faulted phase selection. The adoption of the normalized signals of the fault induced transients instead of the the full values preserves the approach adaptivity. Simulation results using the EMTP program have proved the validity of the proposed scheme. Excellent training convergence, extremely fast recall and reasonable accuracy represent some features of the proposed technique.

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