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PCA based protection algorithm for transformer internal faults

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Abstract

In this paper a new protection scheme is introduced to detect and identify transformer winding faults. The new approach is based on artificial neural networks (ANNs) using radial basis functions (RBFs) and the principal component analysis (PCA). The nonlinear system's input and output data is manipulated without considering any model of the system. This approach is used to detect and identify internal short circuit faults of a three phase custom built transformer. The suggested technique is also able to distinguish between the fault and magnetizing inrush current. The test studies carried out shows that the proposed method leads to satisfactory results in terms of detecting and isolating parameter faults taking place in non-linear dynamical systems.

Key Words: *Protection, internal faults, transformers, PCA, ANN, RBF.*

1. Introduction

The continuity of transformer operation is of vital importance to maintaining the reliability of a power network. Any unscheduled repair work, especially replacement of a faulty transformer is very expensive and time consuming. Major damage following a fault may require shipping the transformer to a manufacturing site for extensive repair, which results in an extended outage period. If the faulted condition can be detected before a major damage occurs, the necessary repairs can often be made more quickly [1].

In a power transformer two types of faults can be considered. These are internal, and incipient short circuit.

Internal short circuit faults are generally turn to turn short circuits or turn to earth short circuits in the transformer windings.

This type of fault occurs suddenly and usually requires fast action by the protective relay to disconnect the transformer from the electric power system. Statistical surveys show that 70%–80% of transformer failures result from inter-turn/internal faults. Internal fault phenomenon is one of the transient conditions in a power transformer and begins with a small discharge inside the transformer tank. As the short circuit current continues to flow, it causes further damage by accelerating the insulation breakdown and leading to more serious permanent faults.

Incipient transformer faults usually develop slowly, often in the form of gradual deterioration of insulation. They are also called 'high impedance' faults and it is usually very difficult to distinguish this type of faults from normal operation conditions. When the condition of system equipment degrades because of some electrical, thermal or chemical effects, intermittent incipient faults begin to persist in the system and may lead to serious failure [2, 3].

Traditionally, a Fast Fourier Transform (FFT) or a wavelet technique (WT) is used for analyzing dynamic and transient signals such as transformer incipient faults. However, this procedure has some drawbacks in analyzing transient signals taken from power systems [4]. These techniques rely on the fault current including second and fifth harmonic components. The most familiar of these problems is the current offset. DC offset currents can cause increased flux density in the current transformers and this can result in saturation. Saturated current transformers are the cause of a variety of relay mal-operations. Traditionally harmonic restraint algorithms are used to overcome this problem [5, 6]. They compare the peak values of the second harmonic and fundamental frequency components of the differential currents. If a second harmonic component exceeds a pre-specified percent of the fundamental frequency component, the algorithm classifies the situation as magnetizing inrush. All the past algorithms may be affected by current transformer saturation.

In [7], the discrimination method is based on the time interval of the peak value of the current waveform, and no explicit discrimination algorithm is given in wavelet-based discrimination between a magnetizing inrush and a fault. Additionally, in the study of analysis using the DWT of magnetizing inrush currents and fault currents inside a transformer, spikes in detail coefficients have been pointed out, but no accurate detection algorithm has been indicated. Since the DWT method uses only the current waveform, the detection speed is inevitably degraded. To obtain more satisfactory results, wavelet filters having longer length and more levels of wavelet decomposition must be employed or wavelet coefficients must be interpreted by an expert system. Consequently, more processing time is required, which is a drawback for protection relays.

It is observed that an internal fault current unlike magnetizing inrush current primarily has mainly the fundamental component of power system frequency. Therefore the use of FFT or wavelet based techniques for identifying internal faults may not be suitable due to the low magnitude of harmonic component currents. However, a high-speed online detection method of magnetizing inrush current, internal fault current, and load current was investigated in the proposed paper.

PCA is one of the multivariate statistical techniques, which can reduce the dimension of the data. The original idea was reviewed by J. J. Edward [8] to solve fault detection and identification (FDI) problems. The similar methods based on malfunction detection might lead to difficulties in the fault identification stage. There are also several existing diagnostic tools based on PCA. Process monitoring and fault diagnosis using PCA have been studied intensively and applied to industrial processes. In the literature, linear PCA and its various extensions such as multi-scale PCA, neural PCA, model based PCA or multiple local PCA have been applied to a variety of dynamic and static systems to diagnose system faults [9]. Many other approaches have also been suggested to extend the monitoring capabilities of PCA using different methods such as support vector machine [10] and genetic programming [11].

In [12], an algorithm for transformer differential protection based on pattern recognition of the differential current is described. The algorithm uses PCA to preprocess data from the power system in order to eliminate unnecessary information and increase unknown pattern in differential current to discriminate between internal faults from inrush and over-excitation conditions. The algorithm was proven using PSCAD/EMTDC simulations in a three-phase power system considering critical fault cases.

In [13], a protection algorithm for single phase distribution transformers is proposed. The proposed protection algorithm is based on PCA uses both primary and secondary currents for feature (residual) extraction. After analyzing both currents, two residuals, $\Re_1$ and $\Re_2$, are obtained and compared a threshold value to see if there is a fault in the protection region. Then fault detection and identification is achieved by a simple rule set of low and high of the residuals.

In [14], a monitoring system for distribution transformer based on PCA is proposed. The use of the historical data of distribution transformers to evaluate distribution transformer's optimal operation is preprocessed by PCA. Many indices of the operational parameters from huge historical loading data are calculated to evaluate distribution transformer's optimal operation. PCA is used for reducing the dimension of the indices through matrix conversion.

Similarly in [15], a condition monitoring of power transformers is presented based on partial discharges. Partial discharges obtained by remote radiometric measurements from a power transformer with a known internal defect are analyzed. Investigation based on Euclidian and Mahalanobis distance measures and Ward and Average linkage algorithms were performed on partial discharge data pre-processed by PCA. A clear separation of partial discharges emanating from the transformer and discharges emanating from its surrounding is achieved.

In this study a new on-line protection algorithm is presented. The proposed algorithm uses only rms value of the phase currents and it is not rely on the current harmonic components. It consists of two stages: Residual generation with dynamic PCA and fault isolation with an RBF based diagnoser. The RBF network is a universal approximator which can approximate arbitrarily well any multivariate function given a sufficiently large number of hidden units. The term dynamic comes from the employed data manipulation technique. The suggested protection scheme is also sensitive to magnetizing inrush conditions and load changes. The two RBF networks are also used for discriminating magnetizing inrush and load change cases. Rule based reasoning approach is then used for interpreting the outputs of the RBF networks.

As an extended version of the referenced paper [13 and 16], this paper presents a complete protection scheme including magnetizing inrush phenomenon, multiple and external faults studies. The paper has the principles of the PCA fault detection and RBF fault identification in the first and second sections, respectively. Experimental results using faults induced on a laboratory transformer are then presented to demonstrate the performance of the proposed protection scheme compared with traditional FFT based schemes. Finally, conclusions and future work are given in the last section.

2. Principal Component Analysis (PCA)

For PCA the discrete time linear system is assumed to be in the form of

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k + B_f f_k \\ y_k &= Cx_k + Du_k + D_f f_k \end{aligned} \tag{1}$$

where x_k, u_k and y_k denote the state, the known input applied to the system and the system output at time k respectively [7], [8]. f_k is the unknown fault input and the matrices B_f and D_f determine which part of the system (actuators or sensors) will be affected by the different faults.

If the data are collected dynamically, i.e. $Y = (y_{k-l+1}^T ... y_k^T)^T$, the output signal Y_k can be formulated as

$$Y_{k,s,N} = \Gamma X_{s,N} + HU_{k,s,N} + GF_{k,s,N}. \tag{2}$$

The sequences u_k and f_k are stored in a similar way in the matrices $U_{k,s,N}$ and $F_{k,s,N}$. This representation is called the parity space model. A residual to be used for fault detection and diagnosis can be defined, if there is no actuator and sensor fault as

$$r = W^T(Y_{k,s,N} - HU_{k,s,N}) = W^T GF_{k,s,N}, \tag{3}$$

where $W^T\Gamma$ should be chosen as zero. However, the parity space model can be used if a nonlinear system's linearised model is utilized or a state space model is obtained from the data. However, a nonlinear system may not easily be linearised every time. Hence, a PCA based fault detection method can be a solution to determine faults in nonlinear complex systems since it only uses measured data. It is not necessary to construct a state space model for the system.

A principal component is defined as a linear transformation of the original variables, which are normally correlated, into a new set of variables that are orthogonal to each other. The basic goal in PCA is to reduce the dimension of the data. This is done in the mean square sense. Such a reduction in dimension decreases the computation time and removes the effects of the noise.

Consider a data matrix $Y \in R^{m\times n}$ consisting of m sample rows and n variable columns that are normalized to zero mean and unit variance. The matrix $\mathbf{Y}$ can be decomposed into a score matrix $T = [t_1, t_2, ..., t_n]$ as

$$T = YV, \tag{4}$$

where matrix $V = [v_1, v_2, ..., v_n]$ is a loading matrix whose columns are the right singular vectors of $\mathbf{Y}$. PCA decomposes $\mathbf{Y}$ as follows:

$$Y = T_r V_r^T + R = T_r V_r^T + \hat{T}_r \hat{V}_r^T = \sum_{i=1}^{k} t_i v_i + \sum_{i=k+1}^{n} t_i v_i, \tag{5}$$

where $R = \hat{T}_r \hat{V}_r^T$ is the residual (error) matrix, V_r, $V_r \in R^{n\times k}, k\langle n$, are the first k principal component loading, T_r, $T_r \in R^{m\times k}$ are corresponding scores. Matrices $\hat{V}_r$ and $\hat{T}_r$ consist of the last $n-k$ column vectors of loadings and row vectors of scores, respectively. The decomposition of data matrix $\mathbf{Y}$ in equation (5) can be implemented by SVD of covariance matrix Y_{cov} as

$$Y_{cov} = Y^T Y = V\Omega^{1/2} V^T, \tag{6}$$

where $V = [\ V_r \quad \hat{V}_r\ ], V\Omega^{1/2} = [\ T_r \quad \hat{T}_r\ ]$, the elements of diagonal matrix Ω are the positive square roots of the eigenvalues $\lambda_i (i = 1, ..n)$ of the matrix Y_{cov} called the singular values.

3. A new protection algorithm

The architectural structure of the proposed protection scheme is given in Figure 1. It consists of three RBF networks (ANN1, ANN2 and a diagnoser), PCA and a decision making unit. The PCA unit is used to produce residuals R using the line currents of I_A, I_B and I_C. Residuals are applied to ANN1, ANN2 and diagnoser in order to produce a binary number to diagnose faults. ANN1 and ANN2 have an input layer with 1 neuron, a hidden layer with 8 neurons and an output shown in red seen Fig.2. The nodes in the adjacent layers are fully connected to these networks. The outputs of the ANN1 and ANN2 are binary numbers and denoted via magnetizing inrush (MI) and load change (LC), respectively. If any of these outputs becomes binary 1, it indicates a 'magnetizing inrush' or 'load change' condition.

The outputs of the ANN1 and ANN2 are applied to the decision making unit. The decision making unit activates the diagnoser unit according to the rule set given in subsection 3.3. The diagnoser discriminate the fault type and define the percentage of the winding get involved.

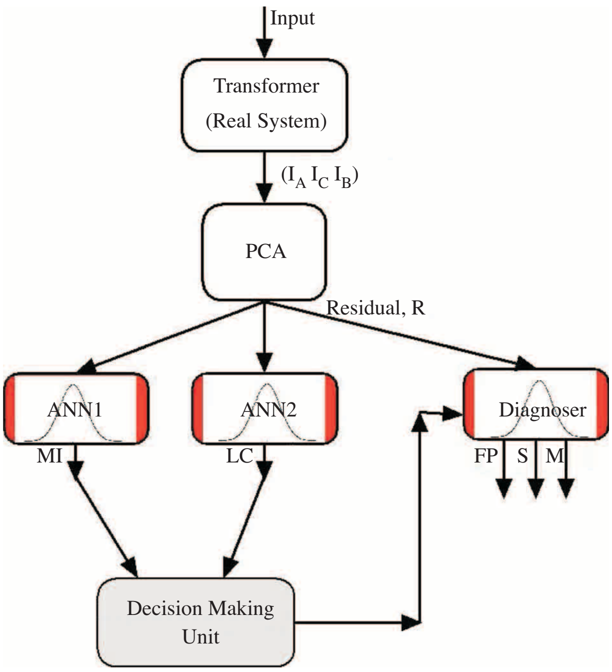

Figure 1. The overall structure of protection scheme.

The proposed method can be expressed step by step as follows.

3.1. Residual generation with PCA

There are three steps in the PCA based fault detection approach. These are data manipulation, off-line procedure and on-line fault detection.

(a) The data manipulation stage: The data matrix Y can be constructed in a dynamic way. The matrix Y is constructed under normal operating conditions from the samples of the system inputs $(u(k))$ and/or outputs $(y(k))$ as

$$Y = [y_{k-l+1}^T y_{k-l+2}^T, ..., y_k^T]^T, \tag{7}$$

where l denotes the system order and y contains inputs and/or outputs data of length k.

(b) Off Line Procedure: In the off-line procedure the data matrix Y's mean and variances are firstly calculated. It is also auto scaled (i.e., zero mean, unity variance) using mean and variances calculated before constructing the correlation matrix (covariance). Then the covariance matrix of data matrix Y is calculated by using equation (6). Then, matrices $\hat{V}_r$ and $\hat{T}_r$ are calculated for online fault detection procedure.

(c) On-line Fault Detection Procedure: In the on-line fault monitoring stage, each new observation vector is auto scaled using the means and variances obtained in the off-line stage and projected onto the principal component sub-space. For a new sample Y_m, the residual (R) is given by

$$R = \left\|Y_m - T_r V_r^T\right\|^2 = \left\|Y_m - Y_m V_r V_r^T\right\|^2 = \left\|Y_m(I - V_r V_r^T)\right\|^2 = \left\|Y_m \hat{V}_r \hat{V}_r^T\right\|^2 \tag{8}$$

If the residual exceeds a predefined threshold value, it is assumed that a fault has occurred in the system. Immediately after detection of the fault, a fault isolation technique is required. Threshold based fault isolation techniques may not work well in the PCA based FDI. Hence, a classification technique or a reasoning based fault isolation method should be used.

In order to indicate probable faults, an RBF network similar to a fuzzy reasoning method including a fuzzy rule-base based on expert knowledge has been used in the identification unit. The residual vector R is then applied to the RBF network as an input.

3.2. The structure of the diagnoser, ANN1 and ANN2

RBF networks are used in the online fault isolation procedure and to detect magnetizing inrush and load changes.

The basic architecture of the diagnoser based on RBF networks is shown in Figure 2. The diagnoser gives the decision about the type and degree of fault such as "single fault" or "multiple faults." The corresponding fault probabilities are also made available in the diagnoser. FP, S and M are respectively indicate the fault percentage, the decision of a single phase fault and the decision of multiple phase fault.

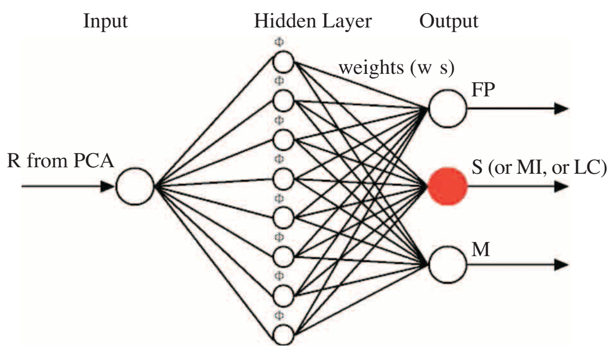

Figure 2. The structure of the RBF network type diagnoser, ANN1 and ANN2.

As is seen in Figure 3, the suggested RBF network type diagnoser has an input layer with 1 neuron (i.e. coming from the PCA algorithm), a hidden layer with 8 neurons and an output layer with 3 neurons. In this network, the nodes in adjacent layers are fully connected. All of the three RBF networks, ANN1, ANN2 and diagnoser can be represented by the parametric model [12]

$$f(R_k) = \sum_{i=1}^{n} w_i \Phi_i(\|R_k - c_i\|, \sigma_i), \tag{9}$$

where

- R_k is the k^{th} input,
- $\Phi(\cdot)$ is a given function, known as the *radial basis function*,
- c_i is the center of the i^{th} RBF,
- σ_i is the width of the i^{th} RBF,
- $||$ denotes the Euclidean norm, and
- w_i is the linking weight between the i node in the hidden layer and the output layer.

Radial Basis Function (RBF) neural networks are simply a weighted linear combination of a set of basis functions (normally Gaussian). The basis functions in the hidden layer produce a localized response to the input and typically use hidden layer neurons with Gaussian response functions. In that case, the activation levels Φ_i of hidden unit i are calculated by as:

$$\Phi_i = \exp\left[-\frac{\|R - c_i\|^2}{\sigma_i^2}\right]. \tag{10}$$

Off-line RBF Network Training: To obtain the training set the suggested ANNs based on RBFs a number of laboratory experiments have been done. These experiments cover 'normal operating conditions with load loads', 'turn to turn faults' and 'turn to earth faults' in both primary and secondary sides of the transformer. True rms values of the primary currents are pre-processed by the PCA to extract feature vectors used in the network training. The training vectors (TV) in kth discrete time have been constructed as:

$$TV = [R_k FP_k S_k M_k LC_k MI_k]_{40x6}, \tag{11}$$

where k=1,2, .. 40, R_k is the output of the PCA algorithm, FP_k is the fault percentage vector, S_k is the single phase fault indicator, M_k is the multiple phases fault indicator, LC_k is the load changing indicator, and finally MI_k is the magnetizing inrush current indicator. TV set is a matrix with a dimension of 40×6.

Approximately 70 training and validating tests concerning RBF network are carried out. The training and validating procedure are performed for not only a single phase but also for the other two phases. For example, if RBF network is trained for internal fault scenario in phase A (in primary or secondary side), the validating test outputs are obtained from phase B and/or phase C. This approach is also valid for multiple fault scenarios. In the training procedure, RBF network parameters are chosen as; learning coefficient for weights is

0.09, learning coefficient for centers is 0.08, learning coefficient for widths is 0.07, iteration is 100 and the sum of squares error is 3.45.

After training the ANN networks, the calculated R vector in real time is applied to the trained networks as an input. The suggested network type is similar to fuzzy based fault identifier and its learning algorithm is 'gradient descent'.

3.3. Decision making unit

The decision making unit allows the diagnoser unit to work or not. If the decision making unit detects a magnetizing inrush (MI) or load change condition (LC), it produces a signal to block the diagnoser. The rule set for decision making unit is:

IF LC **OR** MI is 1 **THEN** diagnoser unit will not work **ELSE** diagnoser unit will work.

3.4. Generalization of the protection method

After the explanation of all steps forming the protection method the generalization of the suggested technique can be summarized as follows:

i. Three-phase instantaneous currents are taken from a real-time system and sampled with a frequency of 2 kHz using a NI-DAQ PCI 16MIO-E series data acquisition board. A general-purpose DAQ board can be used for field tests.

ii. True rms values of the phase currents are calculated using following:

$$I_{\mathrm{rms}} = \sqrt{\left(\frac{1}{N}\right) * \sum_{n=0}^{N-1} (i_n)^2}, \tag{12}$$

where N is number of the samples per cycle and i_n is the sampled value of the instantaneous current at the sampling instant of n.

This procedure causes 20 ms delay (for 50 Hz power frequency) for the initialization. After calculating the first true rms values of the phase currents, a sliding window algorithm is used for calculating rms values yielding to 0.5 ms time delay only.

iii. Principal component analysis (PCA) is used for feature extraction. PCA algorithm uses the rated measured input-output values of the protected device in the background. The technique works both for no-load and loaded condition in the transformers. The transformer data was obtained from the manufacturer data sheet.

iv. The residual vector R is the input of the RBF based ANN units. Two RBF based ANNs are used for MI and LC units. The training vectors for these units are obtained from laboratory experiments. They are related to the rated values of the input -output currents of the transformer. The outputs of these units are the binary numbers which are used as the input of the 'decision making unit'.

v. The diagnoser unit deals with the fault conditions and has the outputs of S, M and FP. This unit produces its decisions within 3 to 6 sampling intervals.

4. Real time test studies

Real time test studies have been carried out by using a custom-built transformer in the laboratory. The rated values of the transformer are given in Table 1. The custom-built transformer has been equipped with various taps placed on both primary and secondary windings so that internal faults could be performed by connecting two taps. A combination of an electromechanical relay and a start switch is used for connecting two taps manually. In order to have more realistic fault studies a fault resistance of 1 Ω in the primary and secondary side of the transformer is used for limiting incipient short circuit currents in the laboratory environment.

Table 1. Transformer Specifications.

Rated-Power	1000 VA
Input-Output Voltage Ratio	380/220 V
Winding Ratio	525/265
Rated-Frequency	50 Hz
Type of the transformer	Three phase Shell form

The diagram of the real-time test model is shown in Figure 3. The Signal Conditioning Unit includes residual generation, the RBF based ANNs and Decision Making unit. As soon as the 'S' or 'M' parameter in diagnoser unit receives a logic 1 in the diagnoser unit, a trip signal will be initiated, then the transformer will be switched off.

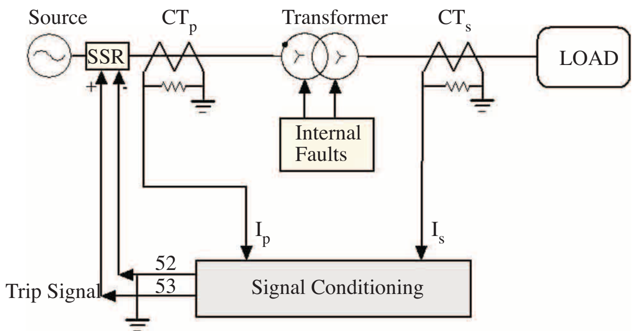

Figure 3. Real-Time Test System.

A number of tests are performed to check the FDI algorithm performance in the laboratory environment. As a primary voltage source, a variable auto-transformer is used and manually controlled. In all real time experiments the time step was 0.5 ms which corresponds to 40 samples per cycle of the supply frequency. When an internal fault occurs on the primary of the transformer, the primary current will increase a bit and secondary current doesn't change much. However, a very large magnitude of circulating current flows trough the shorted turns. For a 10 turn short circuit in the transformer primary winding the circulating current is measured as around 10 A. As stated before, a fault resistance of R_F is used to limit the circulating current. Short circuits have been performed manually using an electromechanical relay such that the duration of the fault last 3 to 6 periods of system frequency.

(a) Test studies for transformer energizing

Figure 4 shows the instantaneous value of the primary current during energizing the transformer. It is clearly seen from the Figure that the MI condition ends within 250 ms; however the variation of the second harmonic current is still over 35–40% due to the CT saturation. This may cause mal-operation of a traditional protection algorithms based on FFT.

Figure 5 shows the true rms values of the primary currents of the transformer and the related PCA output vector during the magnetizing inrush. It is seen that as the effect of MI decreases the PCA output drops zero suddenly. As seen in Figure 5, the feature vector (the output of the PCA algorithm) becomes a zero within 250 ms and the proposed algorithm detects the MI condition within 40 ms only. The MI unit produces binary

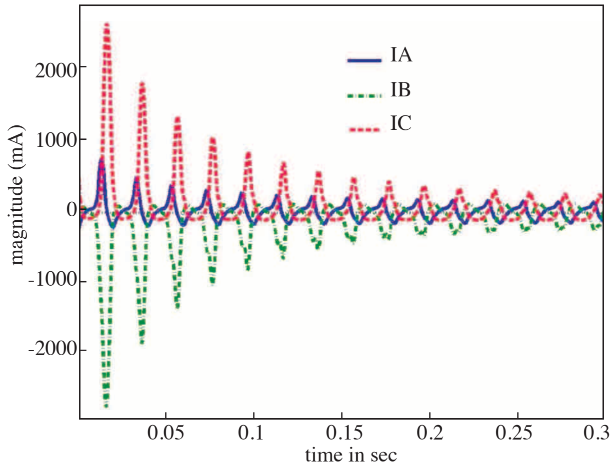

Figure 4. Primary currents of the transformer during MI condition.

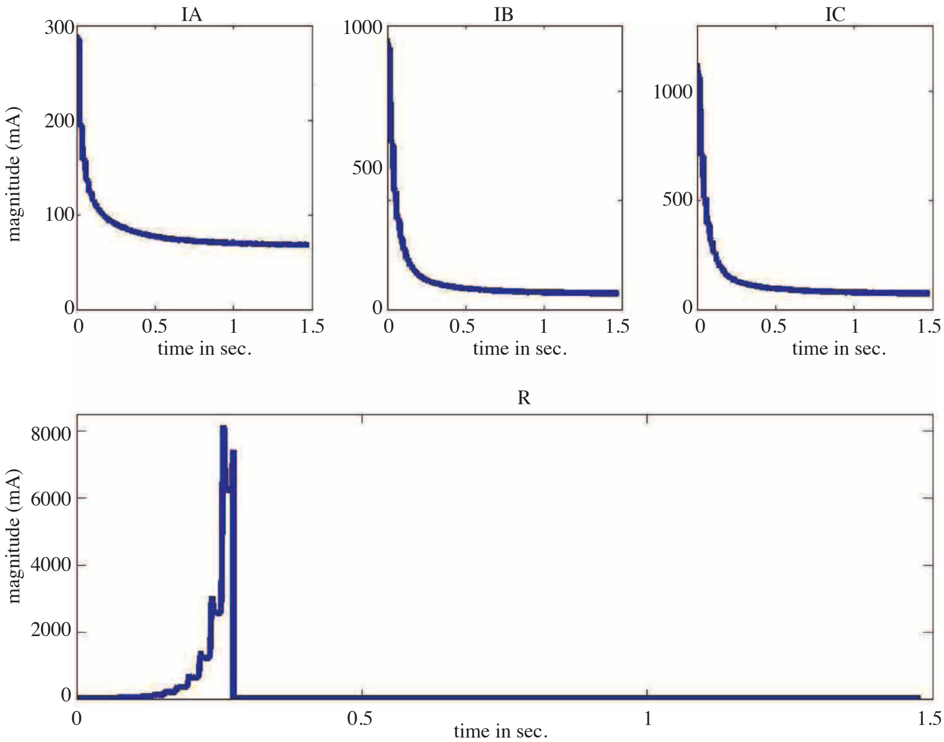

Figure 5. Line currents and related PCA output R during magnetizing inrush condition.

decision 1 immediately after detection of the magnetizing inrush. In this case, the decision making unit does not produce a trip signal.

As seen in Figure 6, the MI unit detects magnetizing inrush condition because the RBF output (dotted line) exceeds the MI pointer. If RBF output reaches the value of 0.97 or above, the MI unit interprets it as "MI inrush detection." The other outputs related with LC, FP, S, and M are zero. The decision making unit

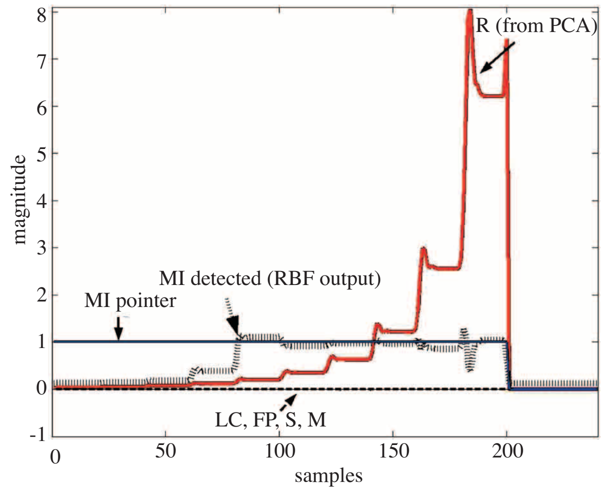

Figure 6. The output of the MI unit during magnetizing inrush condition.

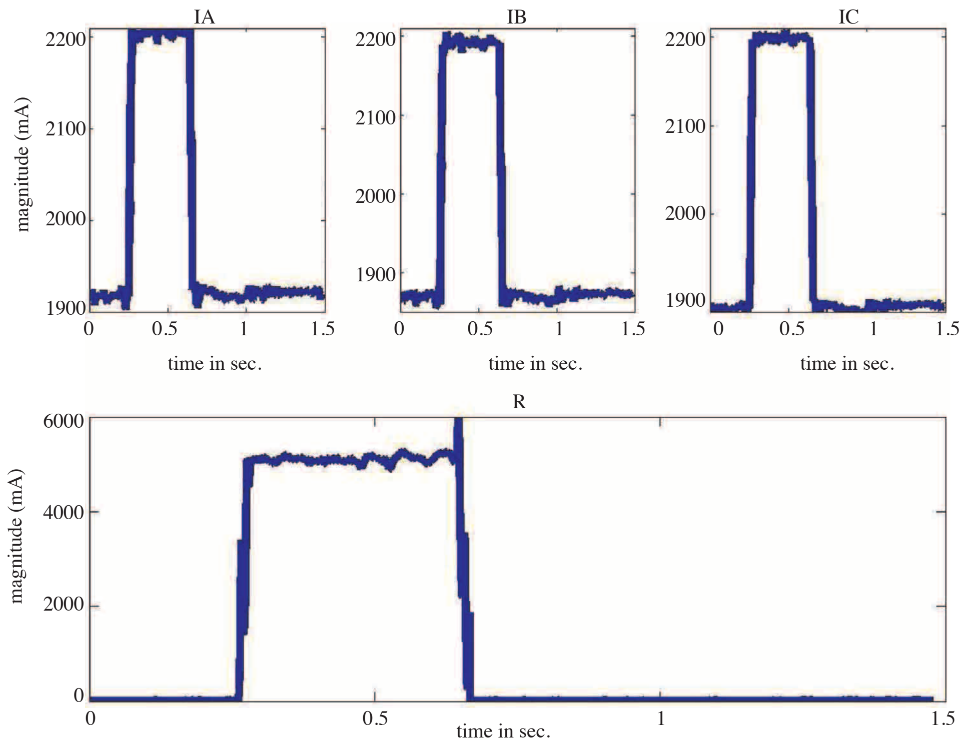

Figure 7. Line currents and related PCA output R during a load changing condition.

interprets this situation as energizing of the transformer and produces binary 1, and does not produce a trip signal.

(b) Test studies for load changes

Figure 7 shows the response of the proposed algorithm to a steady state load change condition. In this particular test the test transformer is full loaded for a moment. LC unit produces binary decision as 1 immediately after the load change. However the fuzzy reasoning unit does not permit the diagnoser unit to initiate a trip signal.

As is seen from Figure 8(a), the LC unit (dotted line) detects the load changing condition, and the other outputs related with MI, FP, S, and M are zero. Decision making unit interprets this situation as a load change and does not initiate a trip signal. This is valid for all level of load changes conditions. Figure 8(b) illustrates the detailed representation for the case seen in Figure 8(a). The LC unit out put exceeds preset value of 0.97 and this indicates a load change condition.

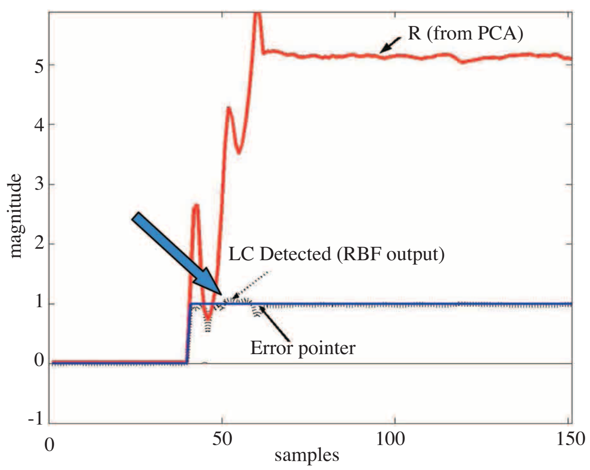

Figure 8(a). The output of the LC unit during a load changing condition.

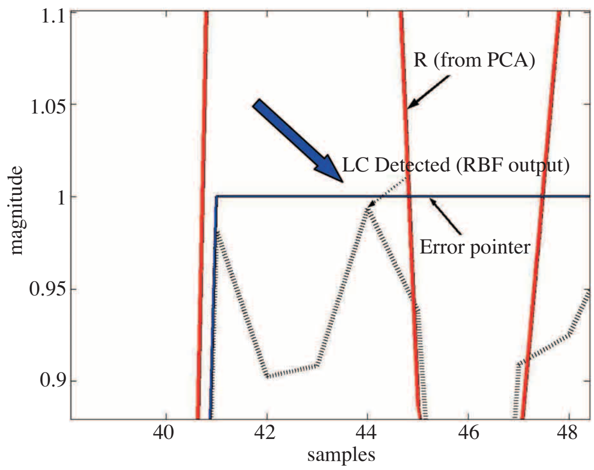

Figure 8(b). A detailed representation of Figure 8(a).

(c) Faulted transformer test studies

The following examples are related to internal fault scenarios. In case of 'no fault' condition, the magnitude of the R vector is relatively small as in seen in Figure 9. The decision making unit interprets this situation as "no fault" and does not produce a trip signal.

Single-Phase Fault Condition A: An internal fault is created in the primary phase winding side between the turns 151 and 156. The fault duration is initiated at 380 ms and ended at 500 ms. The test transformer is loaded with an R-L load before the fault is initiated. Figure 10(a) shows the instantaneous values of phase currents (IA, IB, and IC) before, during and after the fault. As it is seen since this is high impedance turn to turn fault, hence the phase currents do not change in a detectable amount. Figure 10(b) shows the primary currents and the related PCA output R.

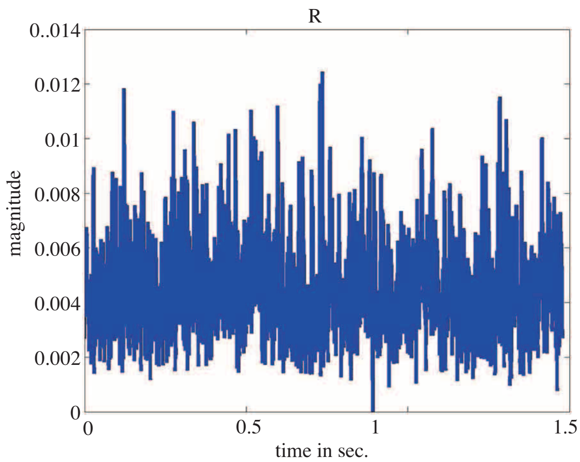

Figure 9. The output of the PCA during a no-fault condition.

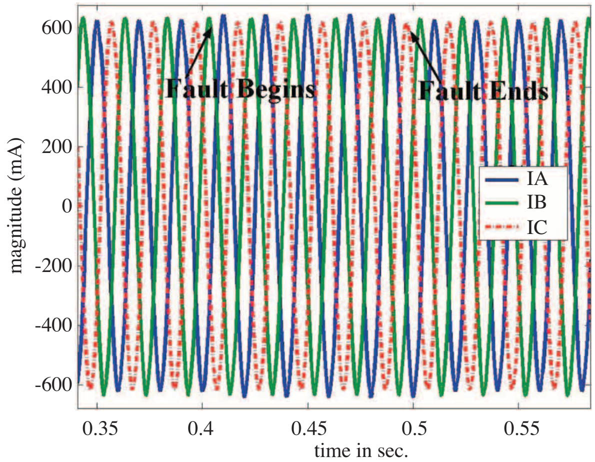

Figure 10(a). Instantaneous values of primary phase currents during a turn to turn fault in the phase A of primary winding.

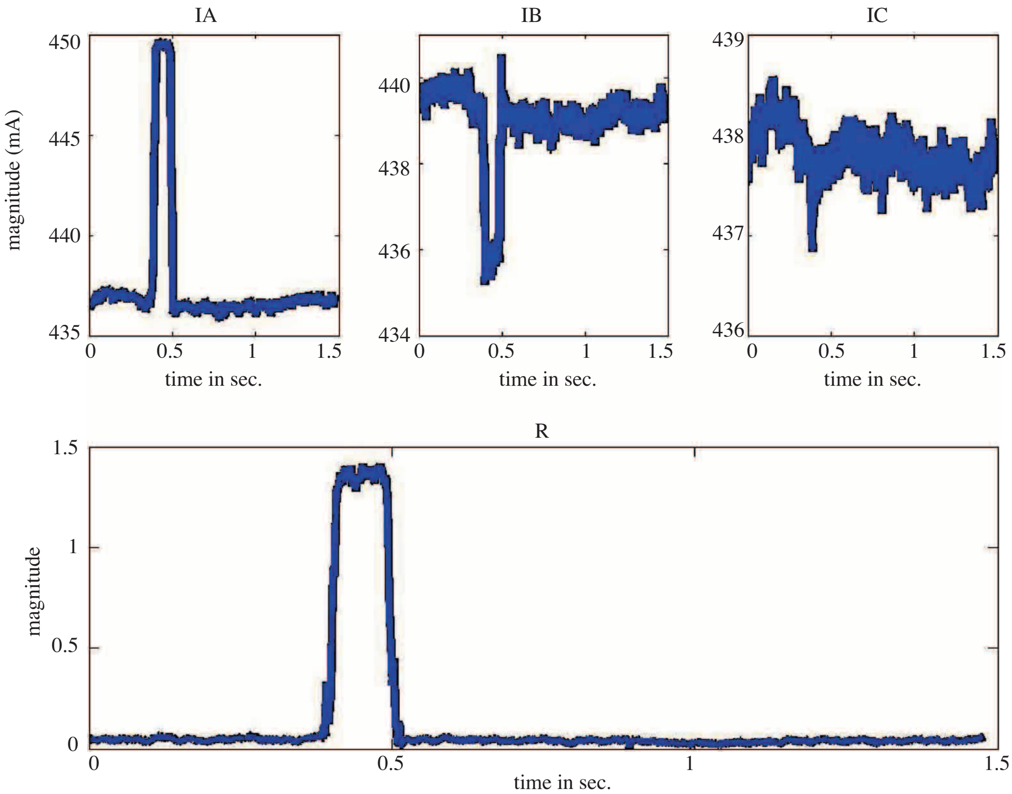

Figure 10(b). An internal fault in primary side of the transformer and related PCA output R.

Figure 10(c) gives more information about the response of the algorithm to the same fault condition such as the output of the ANN based on RBF. The proposed algorithm produces trip signal within a quarter of a power system frequency cycle.

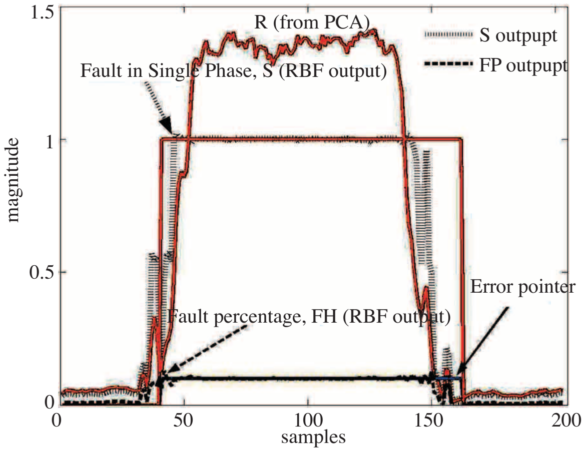

Figure 10(c). A single phase fault and its related network outputs.

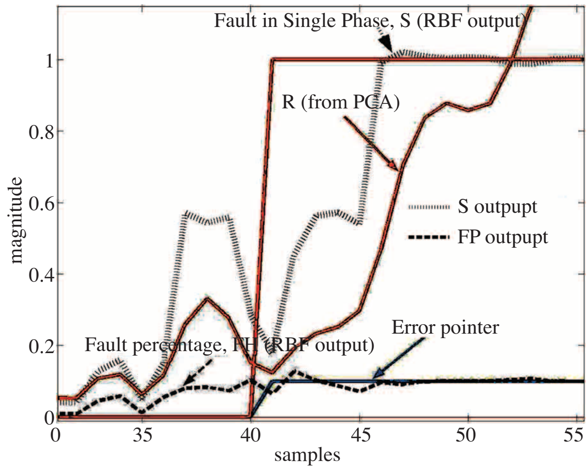

Figure 10(d). More details of the algorithm response to the same fault.

The response of a traditional FFT based protection algorithm to the same fault condition can be estimated using Figure 11. It is seen that variation of the 2^{nd} harmonic component in the phase currents during an internal fault. (The horizontal axis shows ratio of the 2^{nd} harmonic current to the fundamental component in percent). Figure shows that the second harmonic component of the current present at the beginning and at the end of the fault instants. These peaks can also occur during load switching and capacitor switching conditions. Hence traditional algorithm based on second harmonics current can not detect this condition.

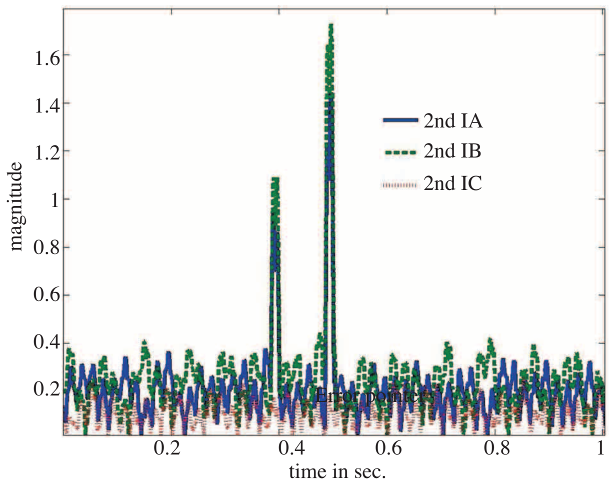

Figure 11. The variation of the 2^{nd} harmonic component currents during a turn to turn fault.

Single-Phase Fault Condition B: Similarly an internal fault is created in phase C of the secondary winding of the test transformer (between turns 194 and 199). Figure 12 shows primary phase currents of the transformer and the feature vector (R and PCA outputs) during the fault. The fault begins at 360 ms and ends at 500 ms. The proposed method produces trip signal within a quarter of a power system frequency cycle.

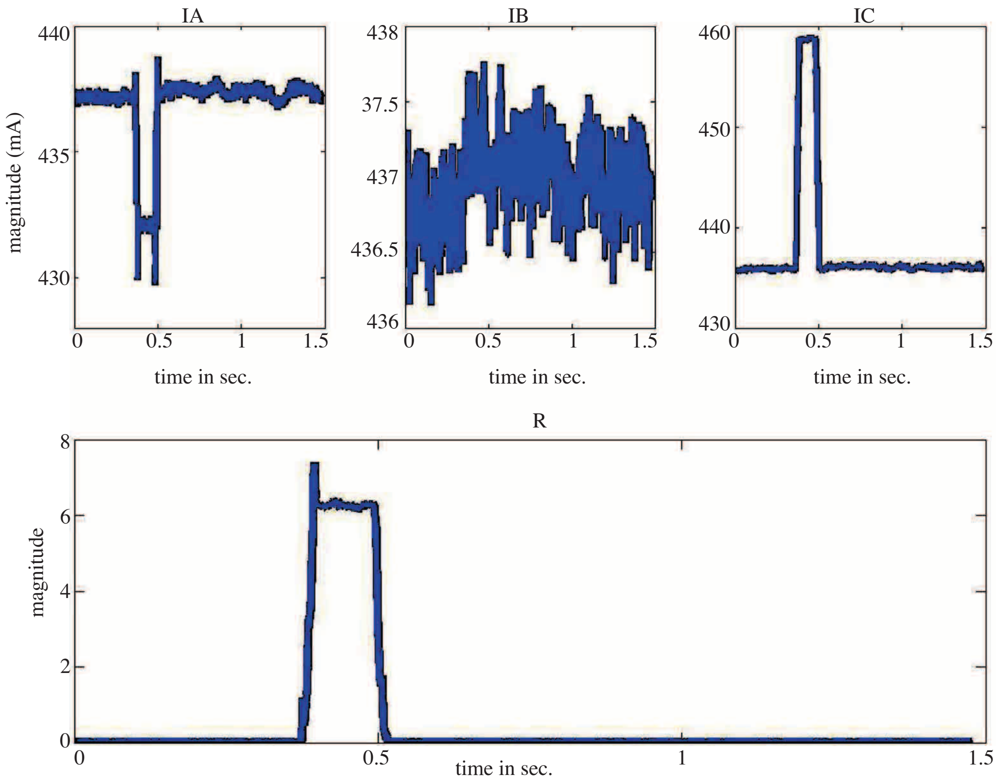

Figure 12. An internal fault in secondary side of the transformer and related PCA output, R.

Figure 13 shows the output of the RBF based ANN for the same fault condition seen in Figure 12.

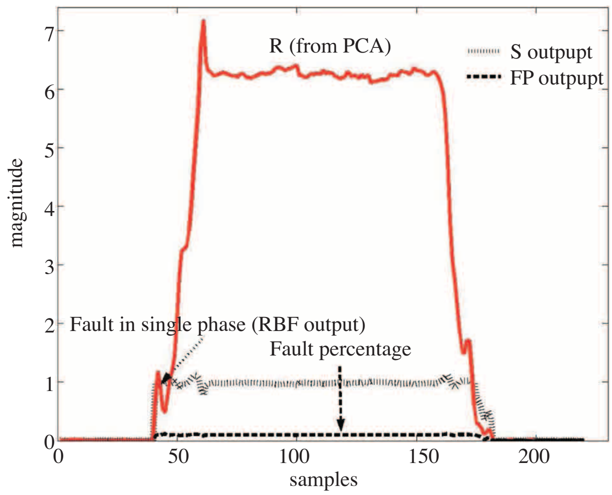

Figure 13. A single phase fault in secondary side (phase C) and its related network outputs.

Multiple Phase Fault Conditions: In this scenario multiple faults are created involving phase B and phase C between turns 100 and 105, and turns 194 and 199 at the same time. Figure 14 shows the primary currents and the related PCA output during a multiple fault conditions in the primary side. The fault begins at 340 ms and ends at 490 ms. The transformer is loaded with an R-L load prior to the fault conditions.

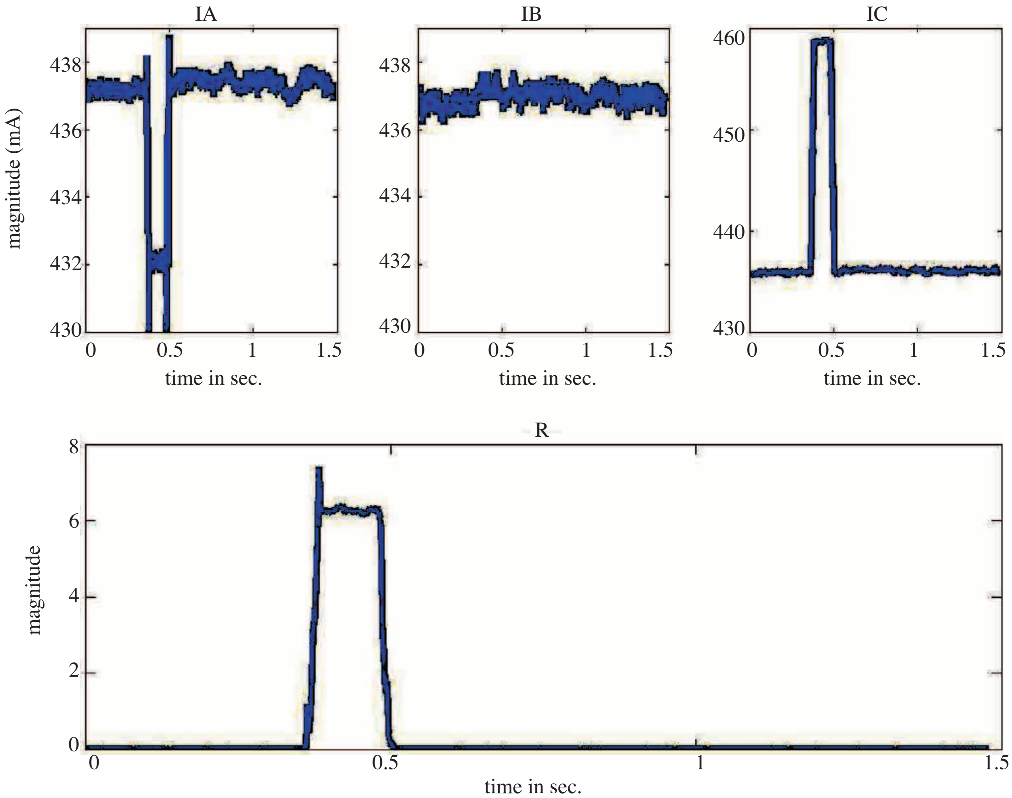

Figure 14. An internal fault both in phase B and C in the primary side of the transformer and related PCA output.

Figure 15 shows the output of the ANN based on RBF for the fault and the proposed protection scheme initiates a trip signal within a quarter of a power system frequency cycle.

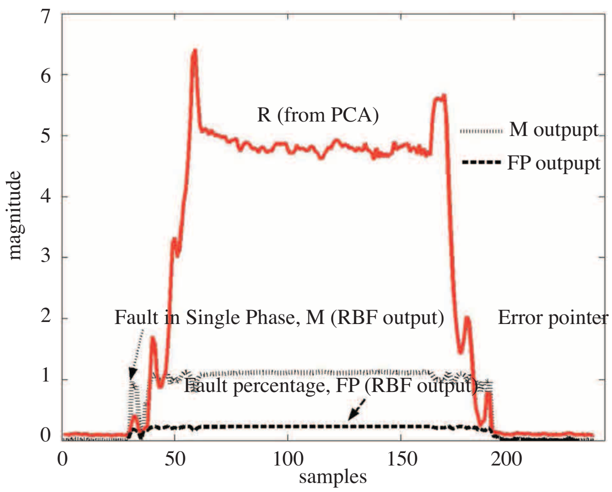

Figure 15. Internal fault in multiple phases and its related network outputs.

5. Conclusion

In this paper, a new relaying method is introduced to provide protection against transformer internal fault conditions. The proposed scheme includes a new approach for discrimination between normal operating current and internal fault current. A PCA algorithm is used to generate residuals by using the true rms values of the transformer primary currents. An ANN algorithm based on RBFs produces the decisions of three main outputs to distinguish the internal fault conditions from the magnetizing inrush current' and 'load changing' conditions.

Real-time test studies indicate that:

1. The proposed protection scheme provides protection against transformer internal fault conditions which may not be detected using traditional protection algorithms. Also, the fault conditions initiated with a small number of winding turns can also be properly detected using the new protection scheme.

2. The protection scheme detects the load change and magnetization inrush current conditions but it does not produce a trip signal and remains stable for those conditions. The suggested protection algorithm is immune to CT saturation such as MI phenomena. It does not need any further algorithm to correct the CT secondary current.

3. Since the fault current is mainly the fundamental component of power system frequency for high impedance faults, traditional FFT or wavelet based techniques do not give distinctive features. Therefore, the performance of the proposed technique for these types of faults is relatively better than the traditional techniques.

The proposed protection scheme can easily be implemented in a microprocessor based protection relay environment due to its computational simplicity. And it can be modified to provide protection for faults taking place within generator or motor windings.

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