

Research Article

A New Approach in Power Transformer Differential Protection

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Abstract

This paper proposed a new classification method based on Slantlet Transform (ST) combined with an automated classification mechanism based on Artificial Neural Network (ANN) for power transformer protection to discriminate between internal faults and no fault conditions (normal, inrush condition, over excitation and external faults with current transformer saturation) in three phase power transformers. Slantlet Transform has been regarded as a contemporary development in the field of multi-resolution analysis, which is proposed as an improvement over the discrete wavelet transform (DWT). For the evaluation of the developed algorithm, transformer modeling and simulation of fault and no fault condition are carried out in power system computer-aided designing PSCAD/EMTDC. For each candidate internal fault or no fault conditions current waveform suitable features are extracted by employing ST. Then, a successfully trained Artificial Neural Network based classifier, developed utilizing inputs comprising the features extracted from a training set of waveforms, is implemented for a testing set of sample waveforms. The simulation results obtained show that the method is faster, more reliable and accurate when compared with some of published research works in the area. The proposed scheme could achieve nearly 100% classification accuracy in the testing phase.

Keywords: power transformer, differential protection, Slantlet transform, Artificial Neural network.

1. Introduction

Power transformers are very expensive and vital components of electric power system. The continuous monitoring of power transformer can provide early warning of electrical failure and could prevent catastrophic losses. It minimizes the damages and provides uninterrupted power supply. Accordingly, high expectations are imposed on power transformer protective relays. Expectations from protective relays include dependability (no missing operations), security (no false tripping) and speed of operation (short fault clearing time). Whenever, there is large and sudden change in the input terminal voltage of transformer, either due to switching-in or due to recovery from external fault getting, a large current is drawn by the transformer from the supply that this current is usually ten times that of the full load current. It persists only for a very short duration and decays very quickly, which is very high magnitude causes the relay to operate falsely. This phenomenon is known as magnetizing inrush, it looks like an internal fault to the differential relay and ends up as spill current and the relay mal-operates. Distinguishing inrush current from an internal fault current is one of the most challenging power system problems. To overcome this drawback, percentage differential relay was implemented. But still percentage differential relay tend to mal-operate for inrush currents.

One way to combat this problem is to desensitize the relay for a brief period of time, just after switching on. However, this is not desirable, since the probability of insulation failure just after

Switching on is quite high and the desensitized relay would be blind to faults taking place at that crucial time. Earlier, Harmonic restraint techniques were used which discriminates inrush current from internal fault using second harmonic component (M.A. Rahman al, 1988). This method based on the second harmonic content with respect to fundamental one was introduced as an identification criterion (H.k.Verma al, 1990), which improved security and dependability was appreciated. However, sometimes, the second harmonic component may be generated in the case of internal faults in the power transformer and this is due to current transformer (CT) saturation or presence of a shunt capacitor or the distributive capacitance in a long extra high voltage transmission line to which the transformer may be connected (T.S. Sidhu al, 1992) and (P.Bastard al, 1995). Inrush current will have dominant second harmonic component compared to internal fault. However, with improvement in transformer design, this second harmonic component is highly reduced and it was complex to discriminate using harmonic restraint techniques (P.Liu al, 1992).

To enhance the reliability of differential protection, and for the above foregoing problem, several methods have utilized voltage signals as well as current signals (K. Inagaki al, 1998). In (K.Yabe, 1997), differential power

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method has been proposed to recognize fault from inrush current. The proposed method in (T. S. Sidhu al, 1992) is based on modal transform of voltage and current wave forms. Disadvantages of these methods include the need to use voltage transformers and increased protective algorithm calculation cost.

In other methods, fault conditions are recognized by the distortion characteristic of differential current wave form. One of these methods operates via measuring of intervals between two successive peaks of differential current wave form (G. D. Rockefeller, 1969). The operation criterion in another method is the duration in which differential current wave form remains near zero (A. Giuliante al, 1991). Delayed fault detection is the disadvantage of this group of algorithms. Various methods such as wave comparison and error estimation method (B.He al, 2006), fuzzy logic based techniques (M.c.Shin al, 2003), principle component analysis method (E. Vazquez al, 2008), and correlation analysis method (X. N. Lin al, 2002) to discriminate internal fault condition from non-fault condition have been proposed. In (Z. Moravej, 2003), (K. Inagaki al, 1998) and (K.Yabe , 1997), differential current harmonics were used as input to train neural network. Few works which investigate the feasibility of using ANN for power transformer differential protection has also been reported (L. Yongli al, 1995) and (Z. Moravej, 2005). The problem associate with these methods is the need to design neural networks or fuzzy lows, which require a huge number of training patterns produced by simulations of various cases (M. E. Hamehani Golshan al, 2004). To overcome the above limitations, wavelet transform is required. Wavelet transform is a powerful tool in the analysis of the transient phenomena of power transformers because of its ability to extract information from the transient simultaneously in both the time and frequency domain unlike Fourier transform, which can give the information the frequency domain only. Wavelet transforms have been extensively used for analyzing the transient phenomena in a power transformer for distinguishing internal fault current from no fault condition (O. Okan al, 2004). The discrete wavelet transform (DWT) is particularly useful for signal/ image processing (A.A. Hossam Eldin al, 2011). In fields of denoising, compression, estimation etc. In (P.L.Mao al, 2000) and (O.A.S.Youssef, 2003) authors have used discrete wavelet transform for differential protection. In (H.Monsef al, 2007) and (Okan Ozgonenel, 2006) have utilized wavelet transform for feature extraction and ANFIS (adaptive neuron fuzzy inference system).

However, it cannot yield an optimal discrete-time basis, from the point of view of time localization. To overcome these limitations, very recently, an improved variant of DWT, namely, Slantlet transform (ST) has been widely used as a feature extracting tool, which can provide better time localization (I.W. Selesnick, 1999). ST has been derived from DWT, wherein the filter bank structure is implemented in a parallel form, employing different filters for each scale (I.W. Selesnick, 1999). ST can be implemented employing filters of shorter supports and yet ST can maintain the desirable characteristics like

orthogonally and an octave – band characteristic, with two zero moments. A new classification method for discriminating between internal fault currents and no fault conditions (normal, inrush condition, over excitation and external faults with current transformer saturation) are presented in this paper by combining Slantlet transform (ST) and artificial neural network (ANN) in three phased power transformers.

The proposed algorithm has been realized through two different ANN architectures. One is used as an internal fault detector (IFD) and the other one detects and discriminates the other operating conditions like normal, inrush, over excitation, and CT saturation due to external faults. The developed ANN architectures are trained by using RBF algorithm. ST has been regarded as a contemporary development in the field of multi resolution analysis, which proposed as an improvement over the discrete wavelet transform (DWT). Extensive simulation studies have been conducted using PSCAD/EMTDC software to verify the feasibility of the proposed protection scheme for inrush current at different voltage closing angles, various types of internal faults such as signal phase to ground faults, double phase to ground faults, three phase to ground faults, two phase fault and three phase faults, various over excitation case and various external faults, for each candidate internal fault or no fault conditions current wave form, suitable features are extracted by employing ST. Then, a successfully trained ANN based classifier, developed utilizing inputs comprising the features extracted from a training set of wave forms, is implemented for a testing set of sample wave forms. The performance of the proposed method is evaluated in terms of accuracy and speed and encouraging results have been obtained. A comparison between ST-RBFN and Slantlet transform feed-forward back propagation (FFBP) has also been made. The simulation results obtained show that the method is faster, more reliable and accurate when compared with some of published research works and ST-FFBP in the area. The proposed scheme could achieve nearly 100% classification accuracy in the testing phase and could be performed in $1/8^{\text{th}}$ of a cycle.

The rest of the paper has been structured as follows: section 2 and section 3 give an overview of the Slantlet Transform (ST) and radial basis function neural network (RBFNN), respectively. Section 4 briefly presents the simulation of various operating condition of power transformer. Feature extraction of the test cases are discussed in section 5.

In section 6, implementation of proposed algorithm and results of the test cases are discussed and, section 7 concludes the paper.

2. Slantlet transforms (ST)

Slantlet transform is an orthonormal transform that defines a continuous function over L^2 space with shorter support and retains the same level of vanishing moment (I.W. Selesnick, 1999). This is achieved by employing a filter bank approach than the traditional tree based approach,

with filters of different lengths at different scales. The methodology gives it more Flexibility in designing filters that target different data features, in the spirit of an equivalent form of the DWT implementation, where the filter bank is implemented in form of a parallel structure. Figure 1 shows an equivalent form of the two scale orthogonal DWT iterated filter bank with two zero moments, called D_2 (proposed by Daubechies) and the corresponding filter bank realized using ST. This ST filter bank maintains desirable properties of orthogonality and two vanishing moments (I.W. Selesnick, 1999).

Here different filters are implemented for each scale. For the case in Figure 1, the iterated D_2 filters are of length 10 and 4, while the corresponding Slantlet filters are of length 8 and 4, respectively. To present a detailed perspective, in Figure 1(a), for the implementation of DWT, we have two branches implementing product form of filters: the branch with the $H(z)H(z^2)$ filter and the branch with the $H(z)F(z^2)$ filter. Each of these two filter branches is of length 10. The other two branches for DWT implement the $F(z)$ filter and the $z^{-2} F(z)$ filter, i.e. a shifted version of the $F(z)$ filter. Each of these two filter branches is of length 4. For the implementation of ST, as shown in Figure 1(b), we also have four branches. Two of these branches for ST implement the $G_1(z)$ filter and the $z^{-3} G_1(1/z)$ filter, i.e. a shifted time-reversed version of the $G_1(z)$ filter.

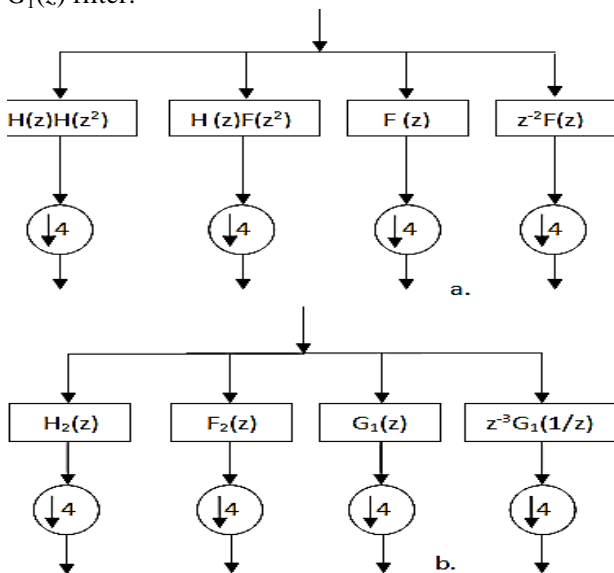


Figure 1. (a) Two-scale iterated D_2 filterbank and (b) corresponding two-scale Slantlet filterbank

Each of these two filter branches is of length 4. The two remaining branches implement the $H_2(z)$ filter and the $F_2(z)$ filter. Each of these two filter branches is of length 8. Hence, while $G_1(z)$ and $z^{-3} G_1(1/z)$ filters are of the same length as $F(z)$ and $z^{-2} F(z)$ filters, each of $H_2(z)$ and $F_2(z)$ filters in ST achieves a reduction of two samples, compared to the product filters in the iterated DWT, i.e. $H(z)H(z^2)$ and $H(z)F(z^2)$ filters. Similarly, a comparison of the three-scale iterated D_2 filter bank and the three-scale ST filter bank shows that each of these filter banks employs six parallel branches. In case of the three-scale D_2

filter bank, two filter branches implement filters each of length 22, two filter branches implement filters each of length 10 and the remaining two filter branches implement filters each of length 4. In the case of the three-scale ST filter bank, filter bank, two filter branches implemented filters each of length 16, two filter branches implemented filters each of length 8 and the remaining two filter branches implemented filters each of length 4. Hence, compared to the two-scale case, the three-scale ST filter bank achieved greater reduction in filter support compared to the three-scale D_2 filter bank. As we increased the number of scales (and subsequently the number of the parallel branches), the difference in the number of supports kept growing. While iterated D_2 filters required $(3 \cdot 2^i - 2)$ supports at the i th scale, the corresponding Slantlet filters required $2i+1$ supports. Hence Slantlet filters were implemented with shorter and shorter supports and yet they maintained all desirable, characteristic features of the iterated DWT filter banks. However, due to the shorter supports of component filters, ST provided a filter bank which was less frequency selective than DWT, although ST provided better time-localization compared to DWT. In the case of Slantlet analysis, the desirable feature is shorter support, which gives it the improved time frequency localization upon the Haar wavelet counterpart. The filter banks in the Slantlet analysis is determined by solving variables (parameters) in (1):

$$g_i(n) = \begin{cases} a_{0,0} + a_{0,1}n, & \text{for } n = 0, \dots, 2^i - 1 \\ a_{1,0} + a_{1,1}n, & \text{for } n = 2^i, \dots, 2^{i+1} - 1 \end{cases} \quad (1)$$

$$h_i(n) = \begin{cases} b_{0,0} + b_{0,1}n, & \text{for } n = 0, \dots, 2^i - 1 \\ b_{1,0} + b_{1,1}n, & \text{for } n = 2^i, \dots, 2^{i+1} - 1 \end{cases}$$

$$f_i(n) = \begin{cases} c_{0,0} + c_{0,1}n, & \text{for } n = 0, \dots, 2^i - 1 \\ c_{1,0} + c_{1,1}n, & \text{for } n = 2^i, \dots, 2^{i+1} - 1 \end{cases}$$

The solution to (1) is solved by subjecting (1) to several constraints. All three functions need to satisfy the unit form condition and orthogonality to their shifted time reverse condition. Both $g_i(n)$ and $f_i(n)$ functions need to annihilates linear discrete time polynomials (I.W. Selesnick, 1999).

3. RBF neural network for pattern classification

A RBF network is a three-layer supervised feed forward neural network, which has a faster rate of convergence than back propagation neural network for pattern recognition. It is being extensively used for on- and off-linear adaptive modeling and control applications.

Moreover, RBF neural network can model random nonlinearity through practice and the problem of local minimum is avoided effectively.

RBF nets belong to the group of kernel function nets that utilize simple kernel functions, distributed in different neighborhoods of the input space, whose responses are essentially local in nature. The architecture consists of one hidden and one output layer. This shallow architecture has great advantage in terms of computing speed compared to

multiple hidden layer nets. Each hidden node in an RBF net represents one of the kernel functions. An output node simply computes the weighted sum of the hidden node outputs. A kernel function is a local function and the range of its effect is determined by its center and width. Its output is high when the input is close to the center and it decreases rapidly to zero as the input's distance from the center increases. Different types of radial basis functions are in use, but the most common is the one, using Gaussian function which can provide very fast convergence in the training phase, provided the system can support the memory requirement as showed in as Figure 2. Normally, this method is suitable when the system is required to train a maximum of a few hundred free parameters.

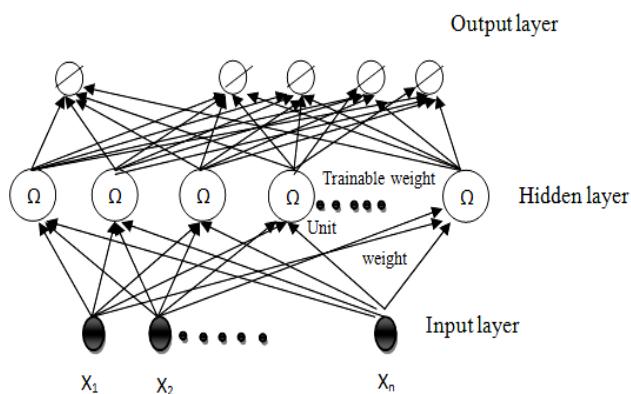


Figure2. radial basic function neural network

The mapping from input-layer to hidden-layer is nonlinear, and from hidden-layer to output-layer is linear. The output of the i th hidden-layer can be formulated as:

$$q_i = \sum_{k=1}^n w_{ki} q_i - \theta_k = R(\|x - c_i\|) \tag{2}$$

Where, x is the input vector, c_i is the center of hidden neuron, q_i is the output of the i th hidden neuron, $\|\bullet\|$ is Euclidean norm, $R(\bullet)$ is RBF function. The output y_k of the k th output neuron can be formulated as the linear combination of the output of the hidden neuron:

$$y_k = \sum_{i=1}^n w_{ki} q_i - \theta_k \tag{3}$$

Where, w_{ki} is the weigh between the i th hidden neuron and the k th output neuron, θ_k is the threshold quantity of the k th output neuron, threshold quantity of the i th output neuron (Zhang MG al, 2006).

The design and training of an RBF net consists of

- (1) Determining how many kernel functions to use;
- (2) Finding their centers and width;
- (3) Finding the weights that connect them to the output node.

The parameters of the RBF units are determined in three steps of the training activity. First, the unit centers are determined by some form of clustering algorithm. Then, the widths are determined by a nearest-neighbor method.

Finally weights connecting the RBF units are calculated using multiple linear regression techniques.

4. Simulation and training case

Power transformer operating conditions may be classified as:

- Normal condition
- Magnetizing inrush /sympathetic inrush condition
- Over excitation condition
- Internal fault condition
- External fault condition with CT saturation.

In the normal condition, rated or less flow through the transformer, in this condition normalized differential current is almost Zero (only no load component of current).

Whenever, there is large and sudden change in the input terminal voltage of transformer, either due to switching-in or due to recovery from external fault getting, a large current is drawn by the transformer from the supply. As a result, the core of transformer gets saturated. This phenomenon is known as magnetizing inrush or in other words, inrush can be described by a condition of large differential current occurring when transformer is energized in parallel with another transformer that is already in service, it is known as sympathetic inrush condition. Among the various faults in transformer, phase to ground, fault occurs most frequently on the basis of fault current, phase to ground fault, for protective device operation view point may be further classified as:

- 1) Heavy faults,
- 2) Medium level fault and
- 3) Low level fault.

In all above cases, the nature of abnormality is almost same but magnitudes of current resulting due to the fault are quite different. If the level of fault can be detected in time and corresponding protective actions are initiated, than the major damage to the protected element can be prevented.

PSCAD/EMTDC simulation software is used to obtain the required current Signals under different operating condition of transformer that are fault type, fault condition, source impedance, remnant flux, fault inception time and other parameters are changed to obtain training patterns covering a wide range of different power system conditions for investigation of the proposed algorithm. For this, a power system consisting of a 400kv source, three phase 200 MVA, 400/230 KV, 50Hz , Y/D. Transformer connected to a 220 KV transmission line connected to an infinite busbar is modeled and simulated as shown in the Figure 3.

For internal fault, the required current signals are done be simulating various types of internal faults such as signal phase to ground faults, double phase to ground faults, three phase to ground faults, two phase fault and three phase faults. Two CT's are installed on the primary and secondary side of the transformer with a ratio of 300:1 and 500:1, respectively. The fundamental frequency of current is 50Hz. The current waveforms generated using PSCAD

software has a sampling frequency of 2.5 kHz. There are 50 samples/cycle.

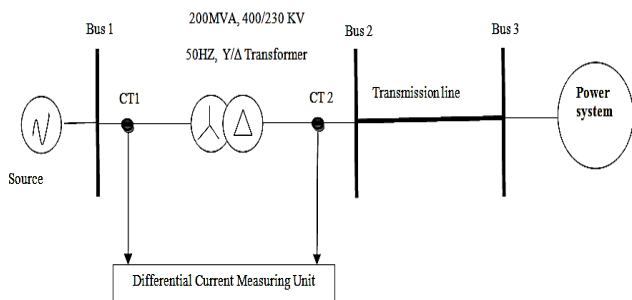


Figure3. Simulated power system.

5. Feature extraction

The test signals so obtained by simulation various operating conditions of transformer are shown in figure 4-8. All the components of each Signal are normalized with respect to the fundamental component Generally the Signatures of signals are different. Hence, it is possible to classify the different events by extracting the dissimilar features of the representative current signals, which can, then, serve as the input to the classifier.

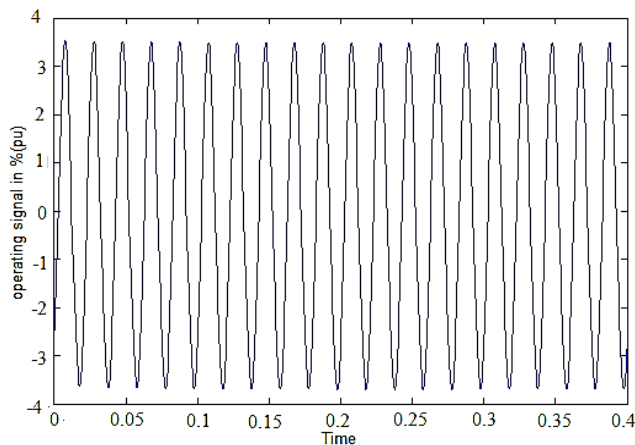


Figure 4. Typical differential current waveform for normal operation

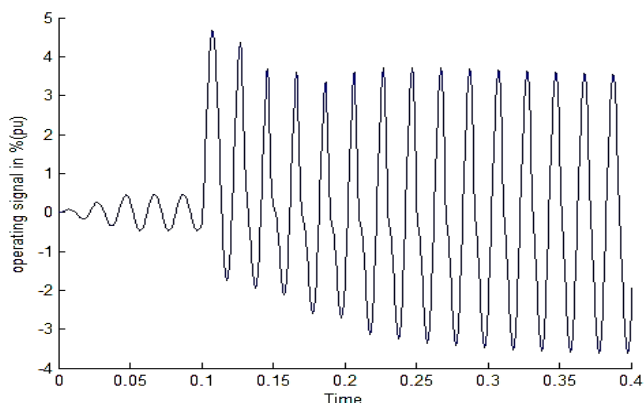


Figure 5. Typical differential current waveform for internal fault.

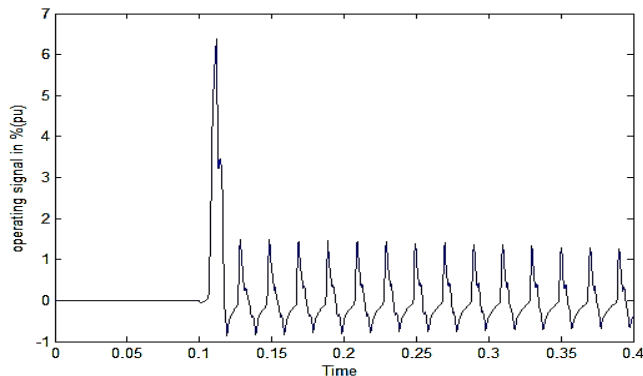


Figure 6. Typical differential current waveform for magnetizing inrush.

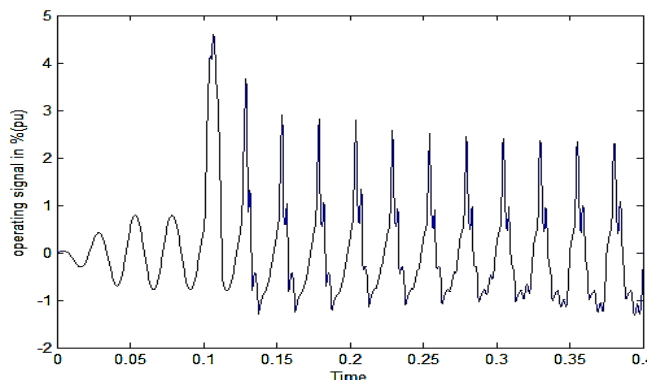


Figure 7. Typical differential current waveform for over-excitation.

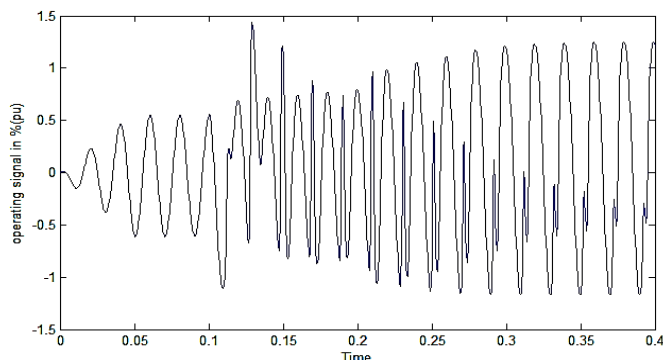


Figure 8. Typical differential current waveform for CT saturation (due to external fault).

An effective feature extraction scheme reduces the curse of dimensionality, i.e., it reduces the dimension of data to be handled by classifier by order of magnitude. So, it is obvious that a good feature extraction mechanism should be able to infer meaningful features in an automated way along with determining less number of relevant features to characterize the complete system, so that the subsequent computational burden of the classifier to be developed can be kept reasonably light.

Applications of the proposed Slantlet transform (ST), for the extraction of features (based on the suggested formulation) can be summarized as the following step by step algorithm:

Step 1) At first the current and voltage signals are obtained from the three phase transformer using PSCAD/EMTDC software for different types of fault and no fault conditions.

Step 2) The differential currents of the transformer are calculated.

Step 3) Slantlet transform of the three phase differential current are obtained using MATLAB software. Each signal can be characterized as a finite length one-dimensional signal; its ST output can be computed, by periodizing the signal of size (I.W. Selesnick, 1999).

Step 4) l is defined based on the problem under consideration and the outputs of the g filters and their respective shifted time reversed versions are computed for $i = 1, 2, \dots, (l - 1)$ scales. In this part, l plays main rule in characterizing size of signal (I.W. Selesnick, 1999).

Step 5) $y(n)$ is produced by scales i , where $y(n)$ produces the ST output corresponding to the n th spatial position (I.W. Selesnick, 1999). For example, for scale $i=1$, the corresponding ST outputs, as computed utilizing the g_1 filter channel and its adjacent channel comprising the shifted time-reversed version of filter, are produced as ST outputs. Similarly for other scales, the corresponding adjacent g filter channels produce ST outputs.

Step 6) To keep a smaller length of feature vectors we have considered two extreme values of y as the representative ST outputs for each scale. Hence, for each signal, we have chosen two y as the representative ST outputs for each scale.

Step 7) each signal is characterized by features vector from y . Namely, for $l = 4$, we created a six-dimensional feature vector each signal, similarly we can create another feature vector for different l 's.

Step 8) feature vectors of fault and no fault currents are fed to ANN and trained.

Step 9) ST based relay distinguishes internal fault current from no fault currents.

Note: In this method, is used from $l=4$ (since $2^4=16$) Thus, for each category of fault conditions and no fault conditions (normal, CT Saturation due to extranet fault, over excitation and inrush current), we have obtained ST outputs and then we created a six-dimensional feature vector for each signal. Flow chart of the STNN based relay algorithm is shown in figure 9.

6. Implementation of ST-RBFNN based algorithm and result

Neural networks have proved to be very efficient in the field of classification. Thought in recent times support vector machines (SVMs) (A. Karami al, 2008) have emerged as a strong competitor for binary classification, yet Different types of artificial neural networks are in use, but the most common is the one, using Gaussian function which can provide very fast convergence in the training phase, provided the system can support the memory requirement which have shown wide ranged useful applications as multi-class classifiers. In this study,

Gaussian function is used for classifying internal fault current from no fault currents in the transformer. The RBF

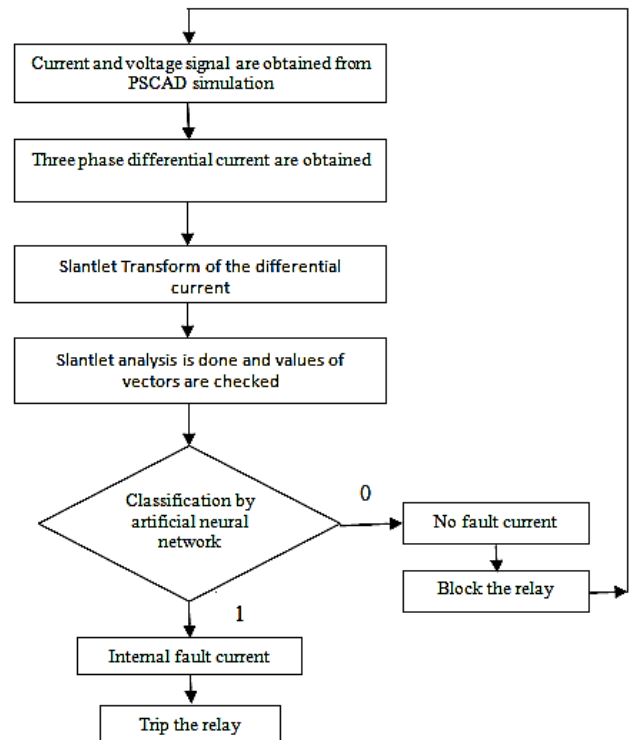


Figure 9. Flow chart of the ST-RBFNN based relay algorithm

based classifier is developed as a six-input one output system, there six inputs for the RBFNN correspond to the six features extracted from each signal. We have assumed that fault has already occurred. For analysis purpose only first cycle of signals; namely, fault condition and no fault condition wave forms, has been considered. Our objective lies in demonstrating the usefulness of our algorithm in classifying signals based on data acquired for one cycle only. With a fundamental of 50Hz. Hence, the sampling of the signals results in 50 possible instantaneous $p.u.$ current amplitudes in each case. These $p.u.$ current amplitudes are computed assuming the amplitude of the fundamental to be 1 $p.u.$ in each case. Therefore, each one cycle event can be considered as a finite length one dimensional signal, of Size 16 (which is in power of 2), and is perfectly amenable for analysis by ST. Once the ST outputs are computed for each signal, we create a data set of $M \times 7$ of size, where M rows correspond to the number of exemplars in the data set i.e. a total of M Signals under consideration (Amitava Chatterjee al, 2009). The 7 columns indicate that in the dataset, for each Signal, we have 6 input features (extracted by applying ST) and 1 corresponding output class label (chosen as 1 for fault current and 0 for no fault currents). This dataset is then divided into two Subsets: a training dataset and a testing dataset. For a given h and p (design parameter) RBFN is trained using 250 sets of data out of 500 data sets and the remaining 250 sets are used to test the network's generalization ability. In this work, we have used 50% of

input signals to form each of the training and testing datasets, Hence, out of 500 signals generated under worst case scenario (i.e. the signals generated in the worst affected phase with highest current amplitude) for each of the events, 250 signals per event are used for training the neural network and the remaining 250 Signals are used for testing purpose .The mean square difference between the target outputs and the predicted output is the error associated with the testing sets. The mean square error over all the testing sets is the error estimate for the given RBFN. This procedure is repeated several times with different values of h and p to obtain the optimum network structure with the minimum mean square error. Various architectures and combinations of input sets have been attempted to arrive to the final configuration with a goal of maximum accuracy. Many algorithms are available to find the optimal values of the centers and spread of the RBF (D. Devaraj al, 2011), (Kabir Chakraborty al, 2012) and (M. Tripathy, 2010). In this paper, the center is found by using “k-means” clustering algorithm. Then, the width is determined by a nearest-neighbor. Finally, weights connecting the RBF units and the output units are calculated using multiple linear regression techniques. A network with 12 neurons has been found suitable for this work. Hence the final architecture consists of 6 input nodes, the hidden layer with 12 neurons and five outputs. The outputs of the network have a unique set (e.g. 10000 = normal, 01000 = inrush, 00100 = over excitation, 00010=external fault currents and 00001 internal fault currents). This network i.e., with five outputs indicates all the phenomena occurring in the power transformer and it issues the trip signal only under internal fault condition i.e., when output is 00001.

The network training starts with the clustering algorithm. The nature of the network is such that the numbers of epochs are same as the number of clusters. 422 training epochs were found suitable for this work, in contrast to the said network the ST- FFBP model with same input and 12 neurons in the hidden layer requires 356 iterations as shown in figure 10 and the training error has been reduced to 0.00496. Therefore FFBP is faster in training as compared to RBF but prediction time in RBF is faster than another one.

A ST-FFBPNN model has been developed to compare the performance of ST-RBFNN model. Based on the training and testing result, the model, for this problem showed superior performance when the number of hidden nodes was equal to 12. Both the network performed well in the detecting and classifying the desired target. The training time for the ST-RBFNN model is much less than that for the ST-FFBP model.

The parameters in ST-RBFN can be independently controlled and hence the training is easier and faster compared to ST-FFBP. The error is taken as the performance measure to compare the proposed network with the ST-FFBP. To find the optimal network structure of RBF (i.e., design parameters h and p), a set of RBFNN models was trained. In this simulation the number of RBF units (h) varied from 2 to 89 and the overlap parameter (p) varied from 0.067 to 2. After the training of network the net has been tested with different sets of data and the network respond adequately performing the discrimination and classification of normal, inrush, over-excitation and internal fault currents correctly for all the cases. Table 1,2,3 show the performance of two model and their corresponding errors.

Table 1. Internal fault detector using ST-FFBPNN

Operating conditions	ANN architecture	Output for the training of developed ANN architectures			Output for the testing of developed ANN architectures		
		Actual(A)	Target (T)	Error	Actual(A)	Target (T)	Error
Normal	6-6-1	0.0017	0	-0.0017	0.00120	0	-0.00120
	6-10-1	0.0024	0	- 0.0024	0.00200	0	-0.00200
	6-12-1	0.0011	0	-0.0011	0.00009	0	-0.00009
Inrush	6-6-1	0.0037	0	-0.0037	0.00230	0	-0.00230
	6-10-1	0.0034	0	-0.0034	0.00180	0	-0.00180
	6-12-1	0.0022	0	-0.0022	0.00130	0	-0.00130
Over excitation	6-6-1	0.0023	0	-0.0023	0.00220	0	-0.00220
	6-10-1	0.0023	0	-0.0023	0.00290	0	-0.00290
	6-12-1	0.0016	0	-0.0016	0.00110	0	-0.00110
CT saturation (due to external fault).	6-6-1	0.0038	0	-0.0038	0.00340	0	-0.00340
	6-10-1	0.0041	0	-0.0041	0.00371	0	-0.00371
	6-12-1	0.0024	0	-0.0024	0.00204	0	-0.00204
Internal fault	6-6-1	0.9842	1	-0.0158	0.98510	1	-0.01490
	6-10-1	0.9886	1	-0.0114	0.98820	1	-0.01180
	6-12-1	0.9911	1	-0.0089	0.99040	1	-0.00960

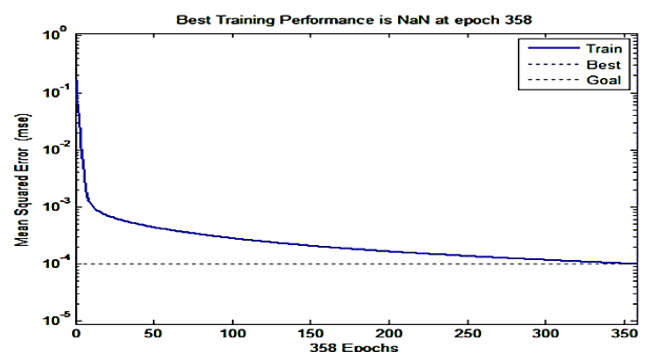
Table 2. Internal fault detector using ST-RBFNN

Operating conditions	ANN architecture	Output for the training of developed ANN architectures			Output for the testing of developed ANN architectures		
		Actual(A)	Target (T)	Error	Actual(A)	Target (T)	Error
Normal	6-6-1	0.0000	0	0.0000	0.0000	0	0.0000
	6-10-1	0.0000	0	0.0000	0.0000	0	0.0000
	6-12-1	0.0000	0	0.0000	0.0000	0	0.0000
Inrush	6-6-1	0.00050	0	-0.00050	0.00041	0	0.00041
	6-10-1	0.00076	0	-0.00076	0.00068	0	0.00068
	6-12-1	0.00067	0	-0.00067	0.00061	0	0.00061
Over excitation	6-6-1	0.00032	0	-0.00032	0.00023	0	0.00023
	6-10-1	0.00040	0	-0.00040	0.00042	0	0.00042
	6-12-1	0.00036	0	-0.00036	0.00032	0	0.00032
CT saturation (due to external fault).	6-6-1	0.00016	0	-0.00016	0.00012	0	0.00012
	6-10-1	0.00036	0	-0.00036	0.00032	0	0.00032
	6-12-1	0.00035	0	-0.00035	0.00034	0	0.00034
Internal fault	6-6-1	0.9984	1	-0.0016	0.9983	1	-0.0017
	6-10-1	0.9963	1	-0.0037	0.9965	1	-0.0035
	6-12-1	0.9968	1	-0.0032	0.9971	1	-0.0029

Table 3. Performance comparisons of ST-RBFNN and ST-FFBPNN training

Parameters	ST-FFBPNN	ST-RBFNN
Convergence	358	422
Time taken for simulation (s)	4	4
Mean average error	0.00283	0.000126
Accuracy (%)	99.72	99.9874

Three different architectures (6-6-1, 6-10-1,6-12-1) and for condition monitoring three different architectures (6-6-4, 6-10-4, 6-12-4) were developed .After enough experimentation, it was inferred that the architecture (i.e. 6-12-1) was giving optimum results for internal fault detector (IFD). And architecture (6-12-4) was selected for condition monitoring .The detailed simulated results for ST-FFBPNN training of IFD and ST-RBFN and their conditions monitoring architectures and accuracy in classification are given Table 4, 5.



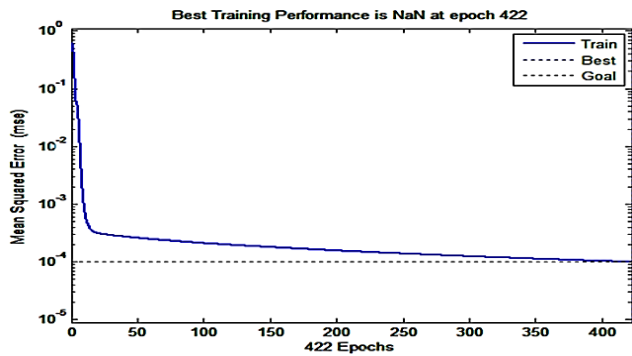


Figure 10. Best training performance in ST-RBFNN and ST-FFBPN

Proposed relay has been tested off line using the simulated data of 200 MVA, 400/230 KV, 50HZ, Y/D power transformer. Both the ANN models classified and recognized the fault in all cases and gave the trip signal output within 1/8th cycle of the fault occurrence. ST-RBF the models took approximately 12 ms to recognize the fault once it trained but ST-FFBP took up to 15 ms. In view of other added advantages of RBFN over FFBN already mentioned, RBF model has been selected for this work.

ST-RBFNN has good generalization capability to distinguish between fault conditions and no fault condition of power transformer. In order to show the effectiveness

Table 4. Condition monitor using ST-FFBPNN

		Output during training and testing of ANN architectures							
Operating conditions	ANN architecture	normal		inrush		Over excitation		External fault	
		A	T	A	T	A	T	A	T
Normal	6-6-1	0.9814	1	0.00430	0	0.0048	0	0.00260	0
	6-10-1	0.9822	1	0.00307	0	0.0023	0	0.002410	0
	6-12-1	0.9841	1	0.00312	0	0.0018	0	0.001903	0
Inrush	6-6-1	0.00214	0	0.9693	1	0.00340	0	0.0028	0
	6-10-1	0.00207	0	0.9756	1	0.00280	0	0.0017	0
	6-12-1	0.0072	0	0.9787	1	0.00203	0	0.0017	0
Over excitation	6-6-1	0.00460	0	0.0022	0	0.9841	1	0.0042	0
	6-10-1	0.00362	0	0.0020	0	0.9832	1	0.0038	0
	6-12-1	0.00340	0	0.0012	0	0.9862	1	0.0031	0
Ct saturation (due to external fault).	6-6-1	0.00110	0	0.00325	0	0.0028	0	0.9869	1
	6-10-1	0.00304	0	0.00256	0	0.0033	0	0.9873	1
	6-12-1	0.00220	0	0.00176	0	0.0018	0	0.9882	1

Table 5. Condition monitor using ST-RBFNN

Operating conditions	ANN architecture	Output during training and testing of ANN architectures							
		normal		inrush		Over excitation		External fault	
		A	T	A	T	A	T	A	T
Normal	6-6-1	1	1	0.0000	0	0.0000	0	0.0000	0
	6-10-1	1	1	0.0000	0	0.0000	0	0.0000	0
	6-12-1	1	1	0.0000	0	0.0000	0	0.0000	0
Inrush	6-6-1	0.00017	0	0.9923	1	0.00024	0	0.00018	0
	6-10-1	0.00022	0	0.9903	1	0.00021	0	0.000241	0
	6-12-1	0.00024	0	0.9914	1	0.00032	0	0.000209	0
Over excitation	6-6-1	0.000460	0	0.000220	0	0.9946	1	0.000562	0
	6-10-1	0.000372	0	0.000261	0	0.9935	1	0.000423	0
	6-12-1	0.000690	0	0.000190	0	0.9928	1	0.000411	0
Ct saturation (due to external fault).	6-6-1	0.000110	0	0.000256	0	0.000309	0	0.99690	1
	6-10-1	0.000142	0	0.000221	0	0.000468	0	0.99432	1
	6-12-1	0.000209	0	0.000262	0	0.000254	0	0.99261	1

Table 6. Performance Comparisons of ST-RBFNN and other methods

Parameter method	Training Time	Mean average error	No. of epochs	Detection time (cycle)	Accuracy (%)
M. Tripathy 2010	11 Sec	0	1000	15 ms	100
M. Tripathy 2010	11 Sec	0.0271	1000	13.33 ms	97.29
M. Tripathy 2010	11 Sec	0.0136	1000	13.33 ms	98.64
M. Gethanjal al,2008	4 Sec	0	520	-----	100
S. Sudha al, 2008	17.9 Sec	-----	79	1/8 th of Cycle	100
S. Sudha al, 2008	281 Sec	0.00429	190	1 Cycle	99
S. Sudha al, 2009	----	0	2000	1/8 th of Cycle	100
Proposed method (ST-RBFNN)	4	0.000126	422	12 ms	99.9874

of the proposed approach to protect of three power transformer problems, it is compared with some of published research works in the area that is shown in Table 6. From the results and above discussions, it is clear that the ST-RBFNN has better detection accuracy than the conventional ANNs.

The detection time is less or comparable with the conventional ANNs. Tremendous capability of ST-RBFNN for classification problems shows suitability for digital differential relaying protection scheme. It is free from the setting of threshold value. It is also immune from the different harmonics contained in operating signals which makes it simpler and robust than the conventional digital filtering algorithms. All tests of this paper were carried out on a simple personal computer IV at 2.13GHZ with 512 MB RAM using the MATLAB software package.

Conclusion

This paper presents a novel approach based on Slantlet transform (ST) combined with an automated classification mechanism based on artificial neural network (ANN) for three phase transformer is proposed and its performance is compared with some of the most recently published research works in the area. Slantlet transform is an improved variant of DWT that can be implemented effectively for feature extraction procedure. The performance of ST as a feature extracting tool followed by BPNN as a supervised binary classifier satisfy the challenge posed by the problem. The mentioned comparisons reveal the efficiency and robustness of the developed approach. The relay also provides high sensitivity for internal fault currents and no fault conditions. In addition, the proposed scheme shows classification accuracy nearly as high as 100%. The presented neural network model issues tripping signal in the event of internal fault within 12 ms of fault.

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