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An Intelligent Protection Algorithm for Unsymmetrical Phase Shifting Transformers

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Abstract: ***This abstract illustrates differential protection philosophy for indirect unsymmetrical phase shifting transformer (IUPST) by using combined wavelet transform principal component analysis (PCA) and support vector machine (SVM). Discrimination between interval fault and magnetizing inrush condition is a very challenging task in IUPST differential protection scheme. Therefore, discrete wavelet transform is used to extract the feature from the relaying signal (i.e. differential current) and the features of the relaying signal is used to train and test the SVM. The IUPST is modelled in PSCAD/EMTDC software to obtain the relaying under different operating conditions. The proposed algorithm is evaluated in MATLAB under forward and backward mode of PST operation and the tested data is simulated in PSCAD/EMTDC by varying inception angle, fault position, tap positions, loading conditions of IUPST. Results shows that the proposed algorithm is stable, reliable and selective under different operating conditions of IUPST.***

Keywords: Indirect Unsymmetrical Phase Shifting Transformer, IUPST, Principal Component Analysis, PCA, Support Vector Machine, SVM

1. Introduction

PSTs are devices that require continuous monitoring and fast protection because they are essential to the electrical power systems to improve reliability. In PST 70% of faults are caused by short-circuits in its windings. In case of magnetizing inrush and sympathetic inrush large current flows in the source side. This large current from the source results in large differential current, which in turn causes the relay to operate undesirably. Owing to this reason, conventional differential relays are blocked for few initial cycles of energization which makes the relay operation delayed on switching-in of the PST on faults. Therefore, discrimination between magnetizing inrush and internal fault condition is the key to improve the security of the differential protection scheme. Traditionally, two types of approaches are used for this purpose, that is, harmonic restraint (HR) and waveform identification (WI) concepts. The HR is based on the fact that the second harmonic (sometimes the fifth) component of the magnetizing inrush current is considerably larger than that in a typical fault current. The literature reveals the extensive use of the HR method. However, the HR-based method fails to prevent false tripping of relays because high second harmonic components during internal faults and low second harmonic components are generated during magnetizing inrush for transformers having modern core material. Therefore, the techniques based on detection of second/fifth harmonic component are not useful to discriminate between the magnetizing inrush and internal fault condition of modern power transformers.

The second method consists of distinguishing magnetizing inrush and over-excitation condition from internal fault condition on the basis of WI concept. The development of advanced digital signal-processing techniques and recently introduced support vector machine (SVM) provide an opportunity to improve the conventional WI technique and facilitate faster, secured and dependable protection for phase shifting transformers.

1.1 Power transmission line

The essential parts of any electrical distribution system are transmission lines because they allow electricity to be transferred from generation to load. Transmission lines are meant to be closely interconnected and operate at voltages ranging from 69 to 765 kV.

The simple single line diagram of the model to be studied is shown in Fig.1. Three generators, nine buses, three loads, and six transmission lines are included.

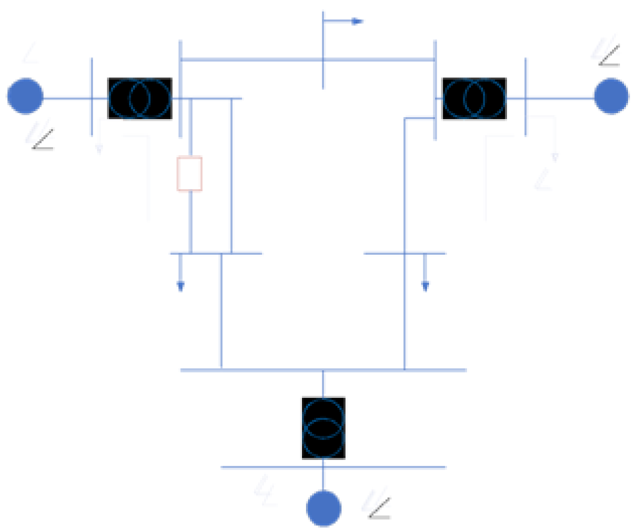

Figure 1: 500kV Single line model to be studied with phase shifting transformer in 9 bus system Operating Conditions of PST

This section will describe briefly the various operating situations of power transmission line safety. This condition of affairs can be classified as follows:

Normal operating condition: In this situation rated or less rated current will flow in PST and differential current in this case is nearly zero for (87P and 87S) and in case of 87T differential current is present and it vary with every tap position.

External fault is the one which occur outside of the protection zone of the relay. It could be LG, LL, LLG, LLL or LLLG fault. In this case huge amount of current above rated current flows in the power system.

Internal fault is the one when transmission line gets braked and falls in ground or whenever arc induces between two phases of the line. The types of internal fault are LG, LL, LLG, LLL, LLLG and TT fault. In this case huge amount of current above rated current flows in the power system.

Over excitation: whenever large reactive load is removed from system then voltage gets increased this phenomenon is over excitation. In this situation v/f ratio increases from normal one. Due to over excitation differential current occurs due to current imbalance in PST and this differential current has odd harmonics component. 3rd harmonic current is cancelled due to delta connection. So, 5th harmonic component is use for discrimination purpose [4].

Magnetizing Inrush: Whenever large sudden changes in input voltage of PST occur, magnitude of the current in input side increases, due to large magnitude of current core of the PST get saturated this is a magnetizing inrush phenomenon. Input voltage increases during switching-in of PST when energized, and when external fault is recovered and when state of fault is changed like LL to LLG. In this situation differential current occur [4]. Power swings are oscillations in active and reactive power caused by load variation, clearing of faults and generator disconnection [3].

Sympathetic Inrush: When another transformer is connected in parallel with already energized PST then sympathetic inrush will flow in first one (PST). Due to DC decaying component present in inrush of parallel transformer. The DC component flow in PST which is responsible to saturate the core of PST, this phenomenon happens. Sympathetic inrush also depends on switching-in and when external fault is recovered. 2nd harmonic current present in this case is very low. In this case differential current occurs.

Differential Relay

Differential current relay is mainly two types:

- Simple differential relay
- Percentage differential relay

Percentage differential relay without restraining coil is considered as a simple differential relay.

Number of turns in restraining coil and operating coil decides the slope of the differential relay. Slope of the differential relay is in between differential current vs. restraining current (biased current).

When compare restraining torque with operating torque the final equation will be

$$I_1 - I_2 = \frac{I_1 + I_2}{2} + T_0 \qquad (1)$$

Where,

$$T = \frac{Nr}{No}$$

N_r is the number of turns in restraining coil
N_o is the number of turns in operating coil
I_1 is the current obtained from one of the CT
I_2 is the current obtained from another one of the CT
T_0 is the minimum pick up value of differential relay

Number of turns in restraining coil number of turns in operating coil current obtained from one of the CT current obtained from another one of the CT minimum pick up value of differential relay.

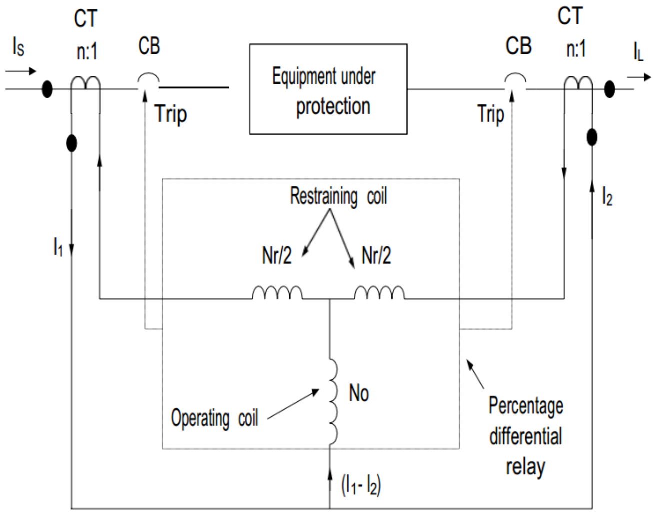

Figure 2: Percentage differential relay

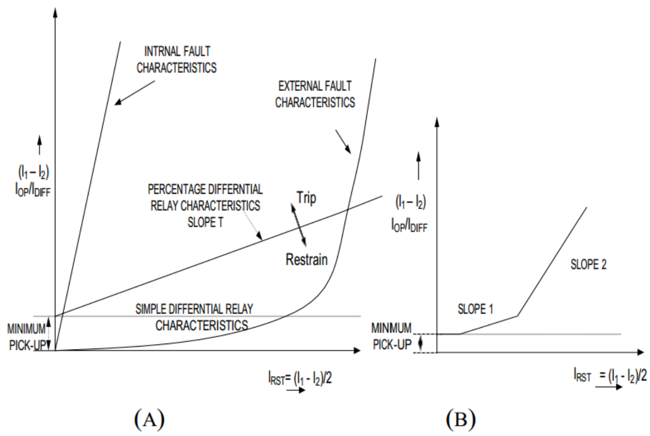

Figure 3: (A) Percentage differential relay, (B) Dual slope percentage differential relay

From above figure 3: (B) the percentage differential relay can be made more immune to mal-operation on 'external fault' by increasing the slope of the characteristic. That’s why we go for dual slope percentage differential current slope1 gives high sensitivity for internal faults and slope2 gives high security against external fault magnitude of slope2 is greater than slope1 knee point of dual slope differential current is decided where saturation of CT is started. In the

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literature mainly differential protection scheme is used for the protection of PST. Mainly two types of protection schemes have been discussed till now in the literatures for PST. Where primary differential relay (87P) is use to protect primary winding of the exciting and series unit and secondary differential relay (87S) is use to protect secondary winding of the exciting and series unit. These 87P and 87S combine protects the PST [5]. Other than these differential relays there exist overall differential relay (87T) to protect primary and secondary winding of the series and exciting unit combined [6].

2. Discrete Wavelet Transform (DWT)

Whenever fault occurs there are always transients present. This transient contains different frequency component of current at different time. The strength of different frequency depends on different operating current. Like in case of inrush 2nd harmonic current are higher than the fundamental current [14].

Different signal processing techniques are available to study the different frequency component present in the differential current. One of the techniques is Discrete Fourier Transform DFT. It is used only for stationary signal and it gives only about frequency information and its losses about time information. So, this technique is not suitable for this purpose because differential current contains transients. Another technique is the discrete time Short Time Fourier Transform STFT. It gives information about frequency as well as time but limited precision. It increases the frequency information by varying window then time information is reducing. So, to overcome the above problem DWT is introduced, it gives information about frequency as well as time at very high precision and it gives information like at what time what frequency component is present which is very useful for analysis of transient in fault current [10].

Discrete signal is comprised by using scaling and wavelet function is:

$$x[n] = \frac{1}{\sqrt{M}} \sum_{k} U_{\Omega}[l_0, k] \Omega_{l_0,k}[n] + \frac{1}{\sqrt{M}} \sum_{l=l_0}^{\infty} \sum_{k} U_{\beta}[\,l, k] \beta_{l,k}[n] \qquad (2)$$

Where,

$\Omega_{l_0,}[n]$ is scaling function

$\beta_{l,}[n]$ is wavelet function

$U_{\Omega}[l_0, k]$ is approximate coefficient

$U_{\beta}[\,, k]$ is detailed coefficient

l_0 is shifting parameter

k is shifting parameter

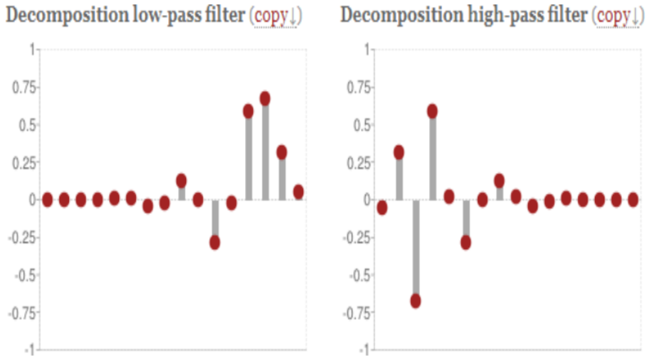

Figure 4: Decomposition LPF and HPF

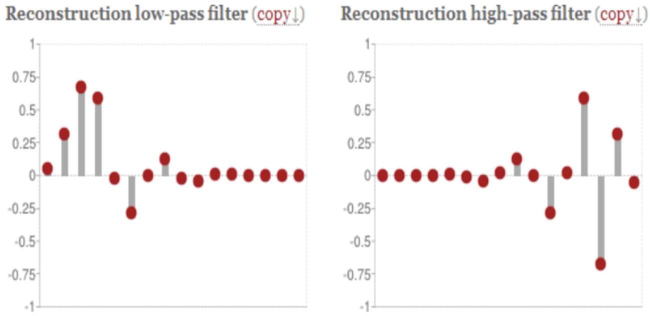

Figure 5: Reconstruction LPF and HPF

Approximate (3) and detailed (4) coefficients are:

$$U_{\Omega}[l_0, k] = \frac{1}{\sqrt{M}} \sum_{k} x[n] \Omega_{l_0,k}[n] \qquad (3)$$

$$U_{\beta}[\,l, k] = \frac{1}{\sqrt{M}} \sum_{k} x[n] \beta_{l,k}[n] \quad l \geq l_0 \quad (4)$$

There are many kinds of mother wavelets, like Harr, Daubichies, Coiflet and Symmlet wavelets. Smoothness of db8 (Daubichies) wavelet is same like power signal (differential current). So, it gives vary good result to extract higher harmonics present in differential current. Discrete db8 filter is shown in figure 4.

As from figure 6. differential current is first sampled with sampling frequency fs ($f \geq 2f$, f =fundamental frequency) then passes through LPF and HPF parallel. half of lower frequency band is passed through LPF and half of higher frequency band is pass through HPF, the total number of samples after filtering is+ $l - 1$, here L is length of input signal, l is length of FIR of filter, it means number of samples is getting increased after passing again output of LPF through HPF and LPH, so that to make less calculation and memory efficient, number of samples stored by reduce to half of the total sample by taking only even number of samples. This process is called down sampling. Output of LPF is called approximate coefficient and output of HPF is called detailed coefficient. Reconstruction of signal is done by first padding zero in odd places of signal (up sampling) and then pass-through opposite of the filter that is used before for filtering purposes.

Frequency band of detailed and approximate coefficient after m-level of decomposition are:

$$f_{approximate_c} = [0, \frac{f_s}{2^{m+1}}]$$

$$f_{detail_c} = [\frac{f_s}{2^{m+1}}, \frac{f_s}{2^m}]$$

In this process decompose the signal into 5 level means get detailed coefficient from d1 to d5 and approximate coefficient A5, and waveform of d4 is clearly different for inrush and all types of internal faults so that coefficient of d4 component is use for classification purpose. To obtain waveform of different level of decomposition coefficient reconstruction filter is used which is mentioned in figure 5.

Table for frequency band of various detailed coefficient are:

Table 1: Frequency content in different detailed coefficient

Detailed Coefficient	Frequency Band (Hz)
d1	[2500, 5000]
d2	[1250, 2500]
d3	[625, 1250]
d4	[312.5, 625]
d5	[156.25, 312.5]

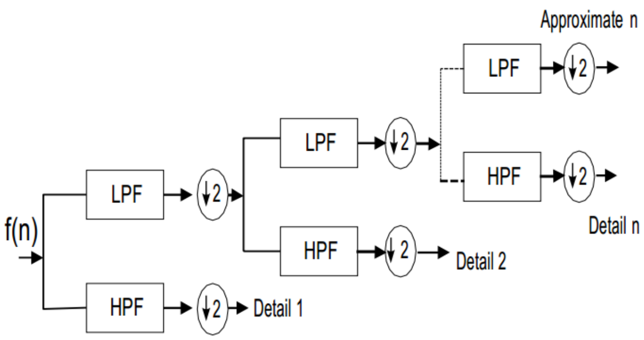

Figure 6: Decomposition filtering block diagram

Principal Component Analysis

Here the basic application of principal component analysis is to reduce the dimension of the input vector that goes to the SVM for classification purpose so that the classification accuracy of the SVM increases.

PCA finds a new set of dimensions such that all the dimensions are orthogonal and ranked according to the variance of data among them [7]. It means more important principal axis occurs first.

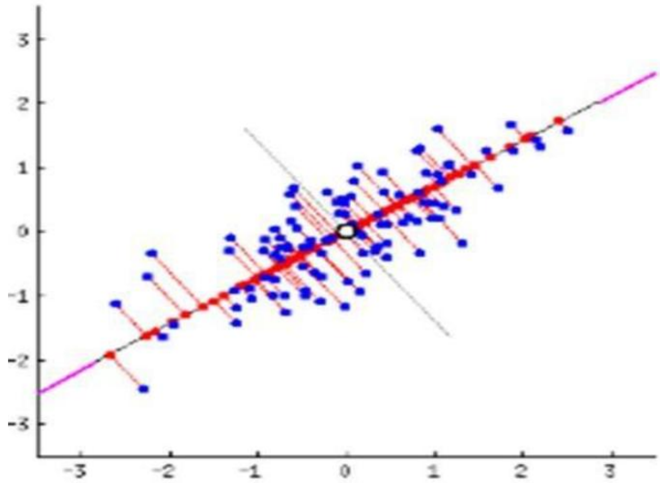

Figure 7: Mapping of data from 2- dimensional to 1-dimensional in the red line axis

PCA works as follows:

- It first calculates the covariance matrix of 'n' dimensional input data sets.
- Calculate Eigen vectors and corresponding Eigen values.
- Arrange the Eigen vectors according to their Eigen values in decreasing order.
- Select first 'm' Eigen vectors and that will be the new 'm' dimensions.
- Transform the original n-dimensional data points into 'm' dimensions.

3. Support Vector Machines

Support vector machines are supervised learning model with associated learning algorithm that analyses set of data for classification or regression purposes. Here SVM is used for classification purposes. SVM as a classifier takes training data sets of two categories (class1 and class2) after that it builds the model that assigns new data set into either class 1 or class 2.

SVMs are based on the idea of finding a hyper-plane that best divides a dataset into two class, in case of two-dimensional data points the hyper-plane would be a line (one dimension less than the dimension of the input data). A good separation is achieved by the hyper-plane that has the largest distance to the nearest training-data point of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier [15]. Figure .8. shows three hyper-plane H1, H2 and H3, where H1 clearly does not classify the input data sets, but H2 and H3 both are able to classify. Due to the fact that H3 has high functional margin than the H2 hyper-plane, H3 would be the best hyper-plane that would lead to the minimum generalization error.

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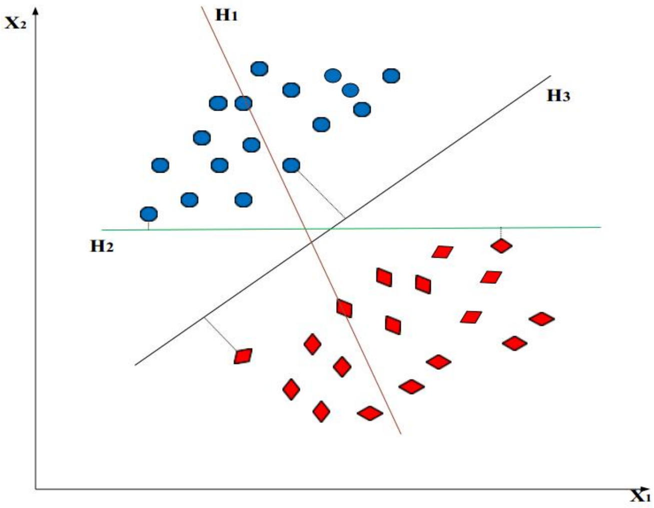

Figure 8: Choosing proper hyper-plane to classify two types of data sets

SVMs are a group of learning machines for solving pattern recognition problems efficiently. SVMs try to find the hyper-plane, which separates optimally the training patterns according to their classes (i.e., hyper-plane with maximum boundary margin). They have a good generalization performance over traditional approaches, since their training is based on the principle of structural risk minimization (SRM) (i.e., minimizing the upper bound on the expected risk), while the training traditional approaches is based on empirical risk minimization (i.e., minimizing the number of the training error). SVMs have a high computational efficiency in terms of speed and complexity [11]. They are also more preferable when dealing with high dimensional data as they are more robust than traditional approaches which may over-fit the data. The description of SVMs classification can be explained as follows:

Linearly Separable Data

Let us consider a linear classification problem aiming to find optimal separating hyper-plane with maximum margin [15]. Assuming that for the set of n training data:

$$T = \{(\vec{x}_i, y_i);\ \vec{x}_i \epsilon \mathrm{R}^d, y_i \epsilon \{1, -1\}\} \qquad (5)$$

Where,

i=1, 2, 3…. n;
$\vec{x}_i$ is a d-dimensional input vector
y_i indicate class 1 or -1 for the corresponding $\vec{x}_i$

For this $\vec{x}_i$ it is possible to find a maximum margin hyper-plane that linearly separates the appropriate class as shown in the figure 8. In such case hyper-plane can be described by the formula $\vec{w} . \vec{x}_i - b = 0$; where $\vec{w}$ is a weight vector and b is a bias. Additionally, it is possible to find two hyper-planes with no points between them one is $\vec{w} . \vec{x}_i - b = 1$ and another one is $\vec{w} . \vec{x}_i - b = -1$, then a distance between these two hyper-plane is called margin= $\frac{2}{\|\vec{w}\|}$.

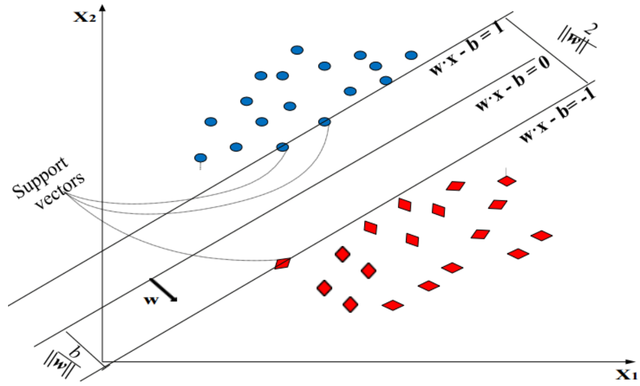

Figure 9: Hard margin classifier

Then class 1 (1) and class 2 (-1) for the input vector is depicted by the following formula.

$$\vec{w} . \vec{x}_i - b > 1 \text{ , if } y_i = 1 \qquad (6)$$

Or

$$\vec{w} . \vec{x}_i - b < -1 \text{ , if } y_i = -1 \qquad (7)$$

For better SVM classifier this margin should be maximum, it means the $\|\vec{w}\|$ should be minimum. This finding $\vec{w}$ and b can be done by several optimization techniques [12]. But this optimization problem is solved by introducing Lagrange multipliers and then class of the unknown data x may be determined as follows:

$$Class(x) = sign(\vec{w} . x - b) \quad (8)$$

Where

$$\vec{w} = \sum_{i=1}^{N_{sv}} \alpha_i y_i \vec{x}_i \qquad (9)$$

Where,

x is a input vector to be classify?

$\vec{x}_i$ is a support vector

y_i is a class of given support vector

α_i is a Lagrange multiplier

N_{sv} is a number of support vector

b is a bias value (calculated during training process)

Linearly Non- separable Data

In case when training data can't be able to get separated by linear hyper-plane then these input vector gets mapped into the one higher dimension feature space in such a way so that the mapped data gets separated by linear hyper-plane [15].

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For this purpose, nonlinear function ø is used. Then the class of unknown data x may be expressed as follows;

$$Class(x) = sign\Big(\sum_{i=1}^{N_{sv}} \alpha_i y_i \phi(\vec{x}_i).\phi(x) - b\Big) \quad (10)$$

$$K(\vec{x}_i, x) = \phi(\vec{x}_i).\phi(x) \quad (11)$$

Then the decision function of SVM is:

$$Class(x) = sign\Big(\sum_{i=1}^{N_{sv}} \alpha_i y_i K(\vec{x}_i, x) - b\Big) \quad (12)$$

The most common kernel functions are:

- Linear: $k(\vec{x}_i, x) = (\vec{x}_i \cdot x)^d$
- Polynomial: $k(\vec{x}_i, x) = (\vec{x}_i \cdot x + 1)^d$
- Gaussian radial basis function: $k(\vec{x}_i, x) = \exp(-\gamma\|\vec{x}_i - x\|^2)$, for $\gamma > 0$
- Hyperbolic tangent: $k(\vec{x}_i, x) = \tanh(k\vec{x}_i \cdot x + c)$, for some (not every) $k > 0$ and $c > 0$

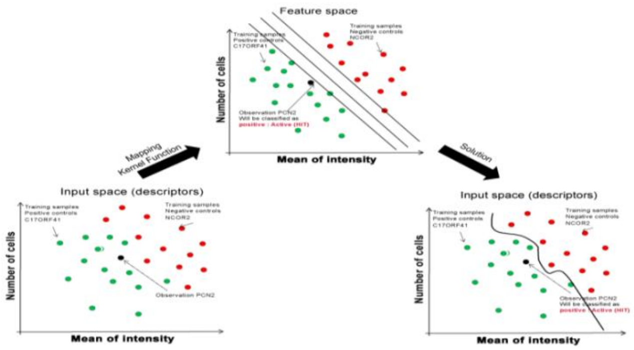

Figure 10: Non-linear based SVM classification

Soft Margin

It may happen that even in new feature space it is impossible to split this space into two classes. Then, soft margin method may be employed to moderate optimization constraints. Soft margin method allows the classifier to misclassify some examples, what is illustrated in figure. This method introduces two parameters (used in training process) [15].

ξ_i is a slack variable that allow patterns to be in the margin $(0 \le \xi_i \le 1$, margin errors) or to be misclassified $(\xi_i > 1)$.

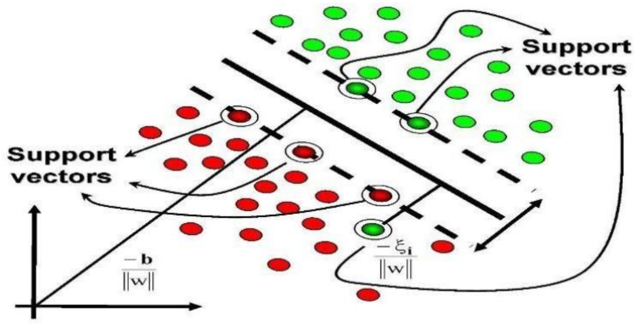

Figure 11: Soft margin classifier

General Feature

Support vector machine is considered as a promising method for classification due to;

- Solid mathematical foundations,
- Fast optimization algorithms,
- No local optima, unlike in neural networks,
- SVMs maximize the margin, which corresponds to maximizing the generalization performance,
- SVMs deal with nonlinear classification efficiently (employing the kernel trick),
- Good generalization performance even in case of high-dimensional input vector and a small set of training data.

The following algorithm provides the phase shifting transformer protection:

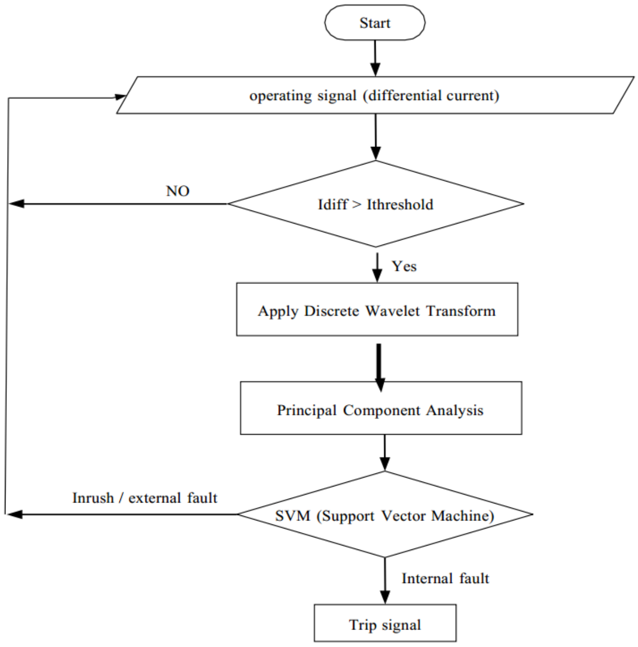

Figure 12: DWT and SVM based phase shifting transformer in 9 bus system

5. Modeling, Simulation and Results

The rating of IUPST for overall and based on exciting and secondary unit and current transformer are listed below [5], [3].

Rating of PST:
Voltage- 500kV / 547kV

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Phase shift- ±24°
Frequency- 60 Hz

Exciting unit:
Voltage- 288.68/kV / 115.47 kV (at full tap position) taping present in lower voltage side
MVA- 289 MVA (3Ph)

Series unit:
Voltage- 128.53kV / 200kV
MVA- 316.5 MVA (3Ph)

CT rating of source side and load side is [8]:
Current ratio- 3600A / 1A
Burden- R=1.0 ohm

Simulation of PST is done in PSCAD/EMTDC and all the operating signals are generated. When generating internal fault current three things are considered. First is fault percentage of winding, at what phase angle fault (time of fault) occurs and tap position of exciting unit. In case of Ph-G percentage of fault winding is 20%, 50% and 80% from the neutral point, and fault inception angel is varied from 0° to 330° in the interval of 30° and tap of exciting unit is also varied from -0.3 to 0.5 (-8° to+12°) of full tap. Same is done for Ph-G fault in exciting primary series primary and secondary winding and also for turn-to-turn fault. For finding operating signal for remaining fault percentage of winding is different and other things are same as Ph-G fault condition. Model of IUPST for above condition is shown in figure 15.

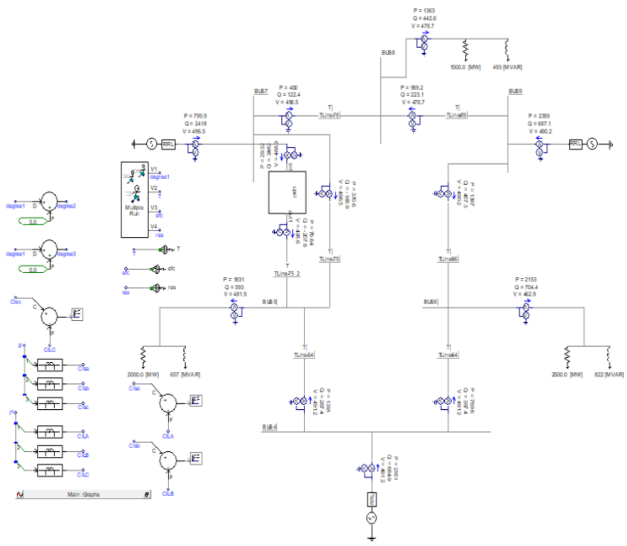

Figure 13: PSACD model for series primary fault

In case of inrush four things are considered first is the residual flux, second is the switching angle and third is the tap position of exciting unit and last is the load condition. In this case switching angle is varied from 30° to 330° in the interval of 30° and residual flux is varied from 20% to 80% of rated flux in the interval of 20%. The total number of 6696 testing and training signal are generated. Model of IUPST for above condition is shown in figure 16.

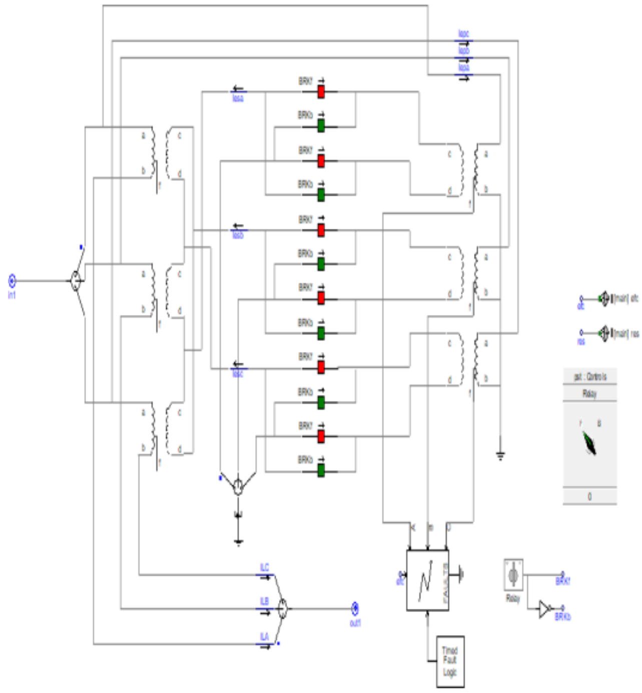

Figure 14: PSACD model for Exciting primary fault

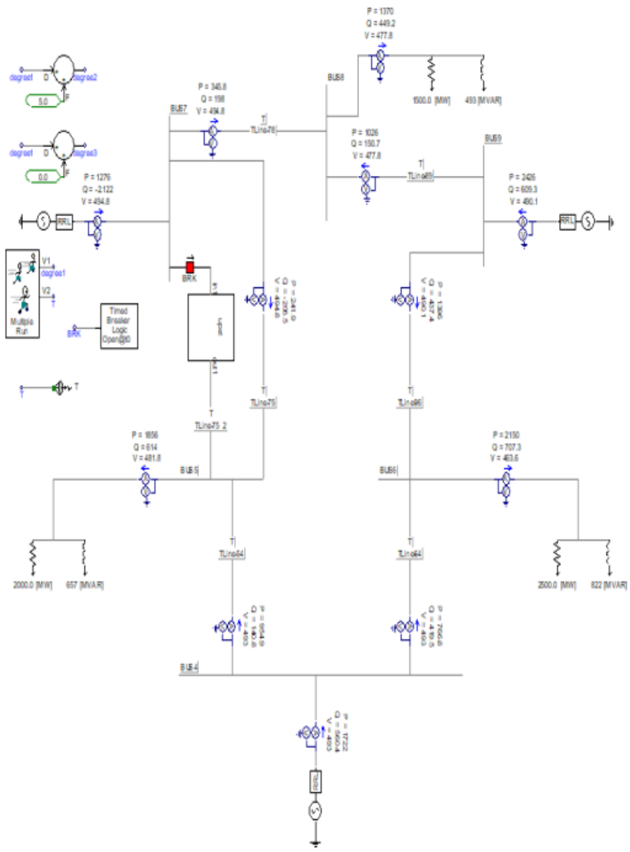

Figure 15: PSACD model for Inrush with load

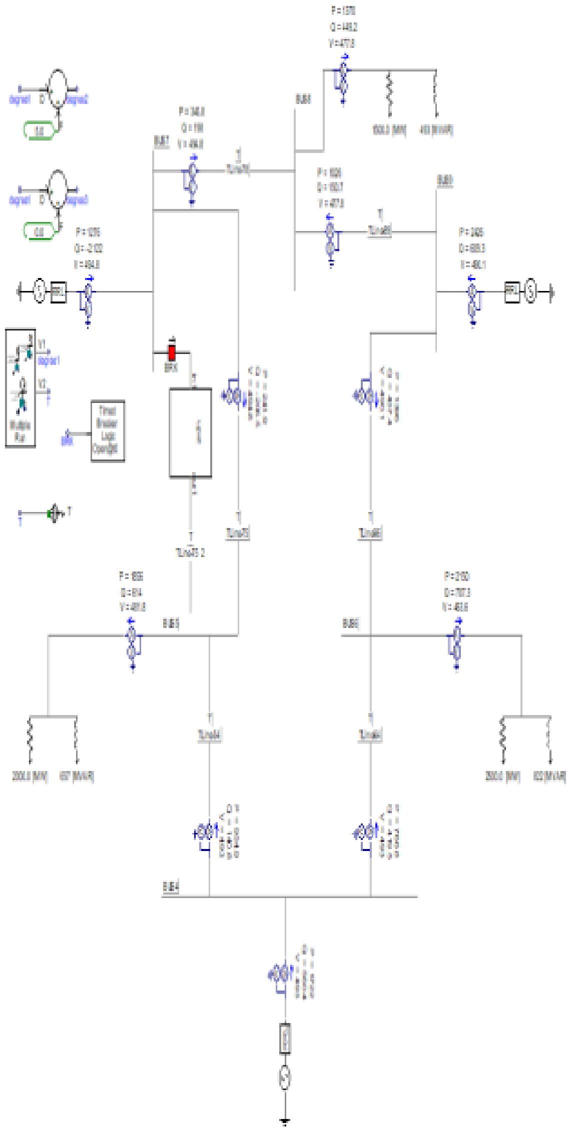

Figure 16: PSACD model for Inrush with no load

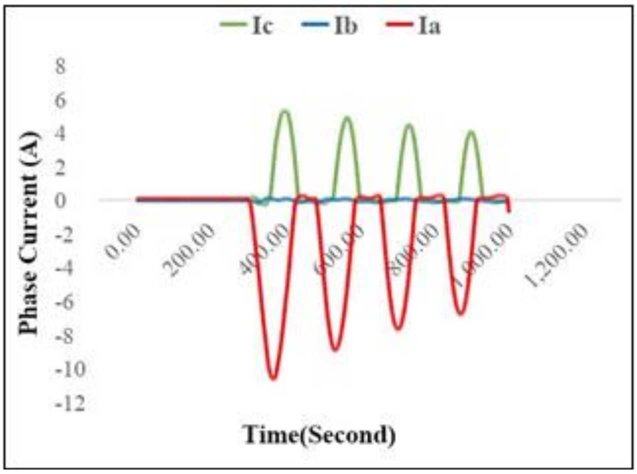

Figure 17: Differential current of magnetizing inrush on no during 80% residual flux

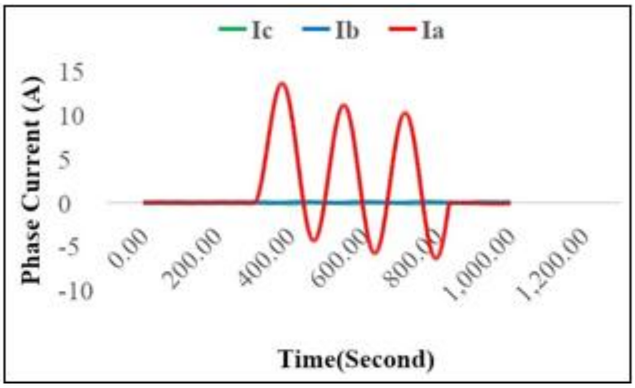

Figure 18: Differential current during L-G fault on the exciting primary with forward phase shift

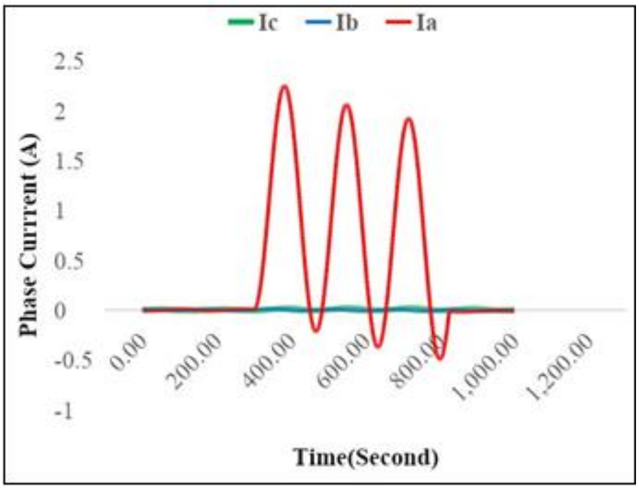

Figure 19: Differential current during L-G fault on the exciting secondary with backward phase shift

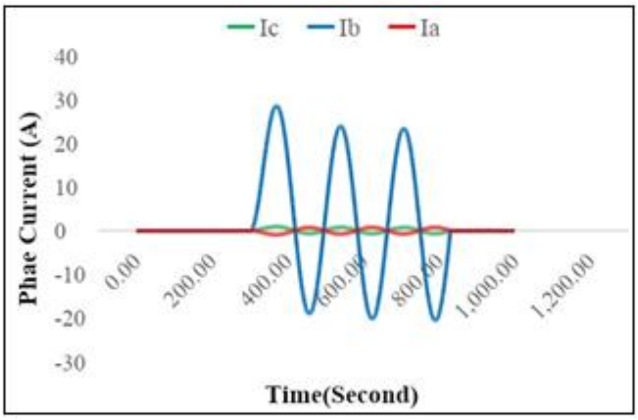

Figure 20: Differential current during L-G fault on the series primary with backward phase shift

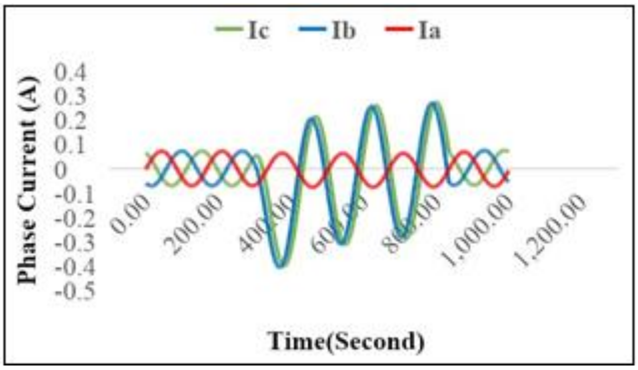

Figure 21: Differential current during L-G fault on the series secondary with forward phase shift

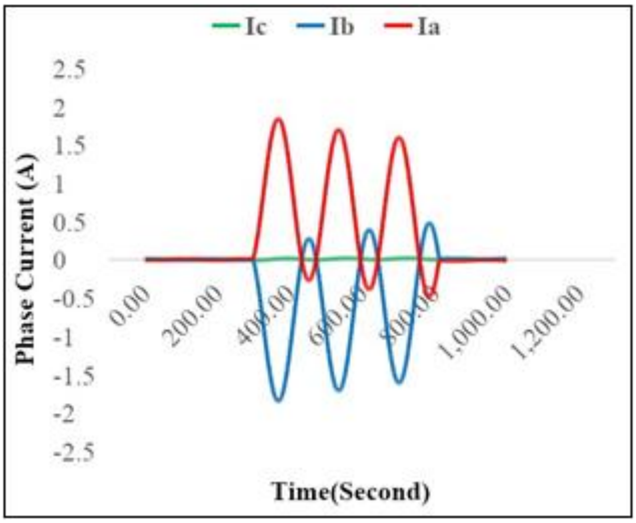

Figure 22: Differential current during L-L fault on the exciting secondary with backward phase shift

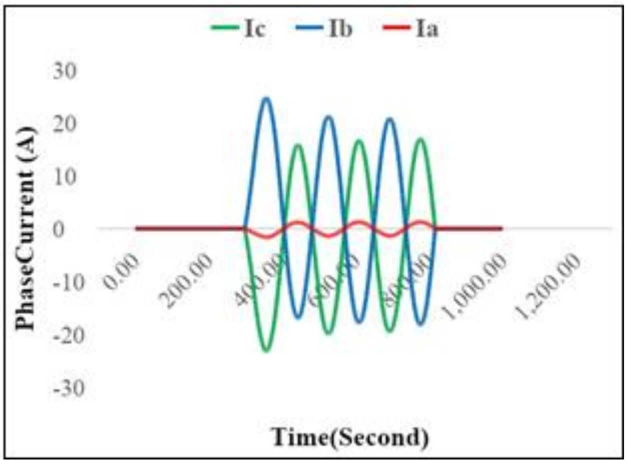

Figure 23: Differential current during L-L fault on the series primary with backward phase shift

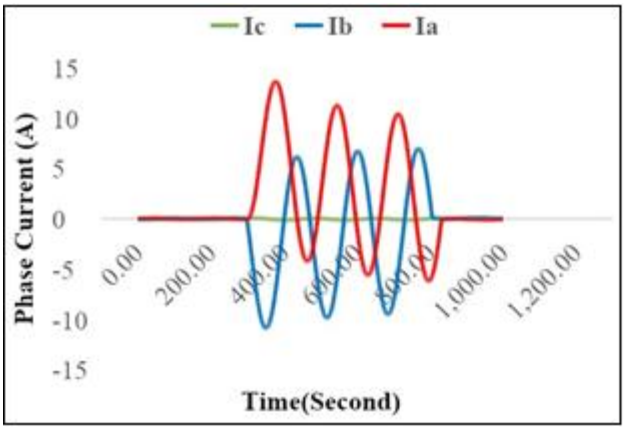

Figure 24: Differential current during LLG fault on the exciting primary with forward phase shift

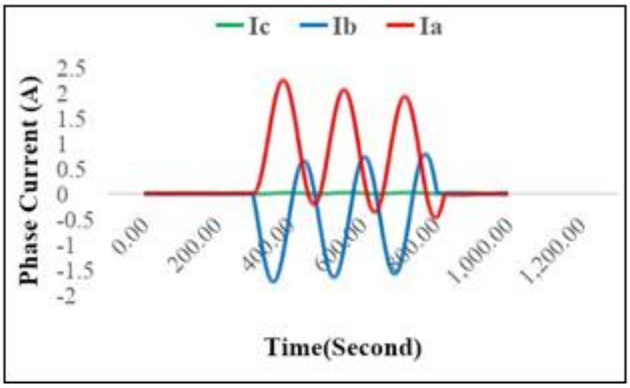

Figure 25: Differential current during LLG fault on the exciting secondary with backward phase shift

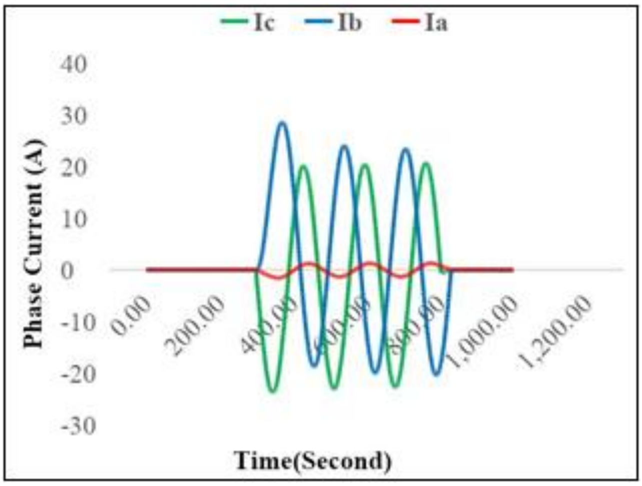

Figure 26: Differential current during LLG fault on the series primary with backward phase shift

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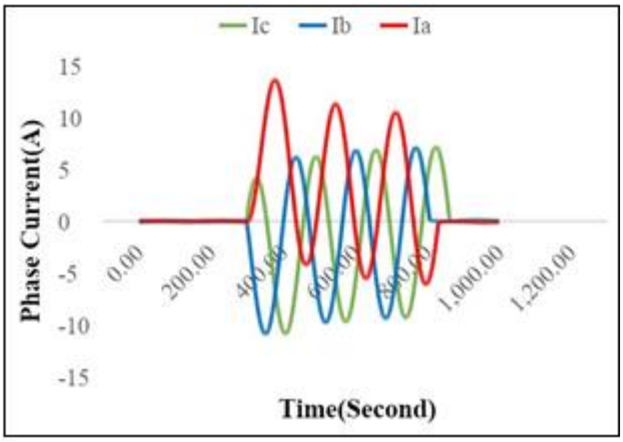

Figure 27: Differential current during LLLG fault on the exciting primary with forward phase shift

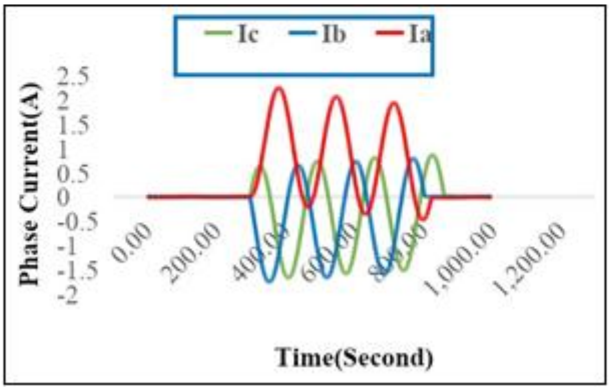

Figure 28: Differential current during LLLG fault on the exciting secondary with backward phase shift

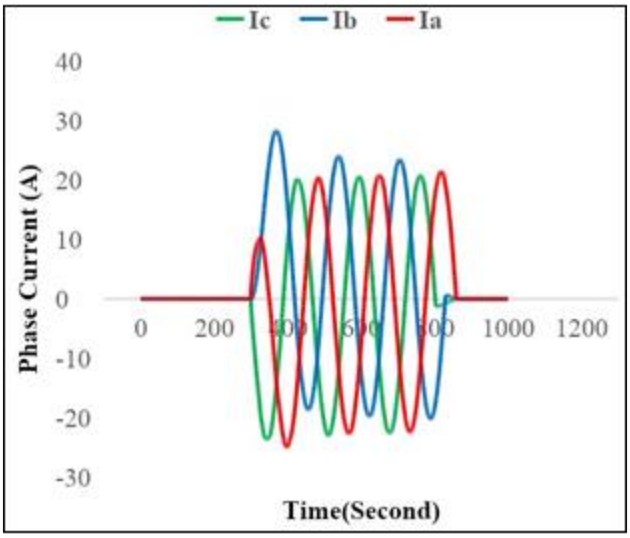

Figure 29: Differential current during LLLG fault on the series primary with backward phase shift

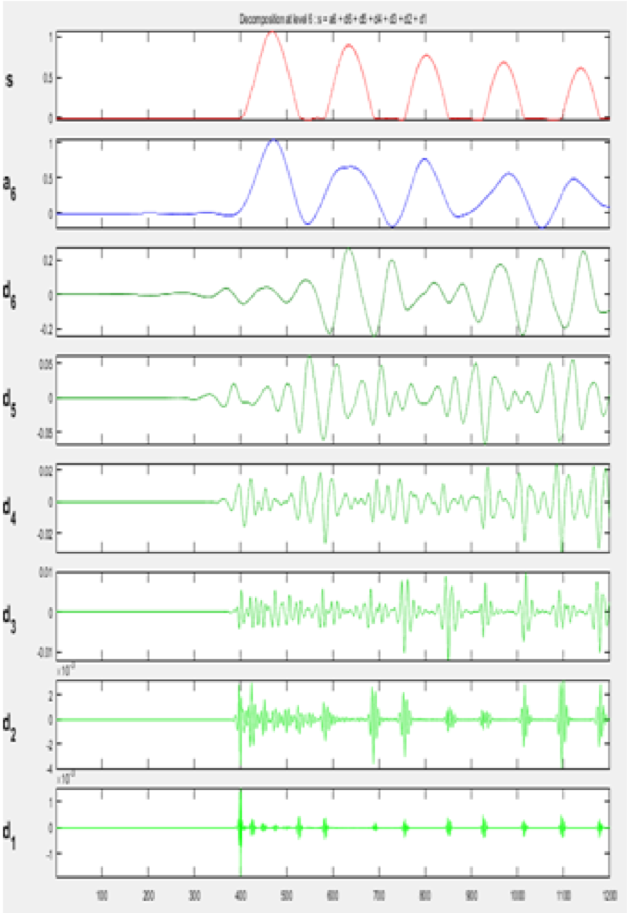

Figure 30: Different details and approximate signals of inrush current

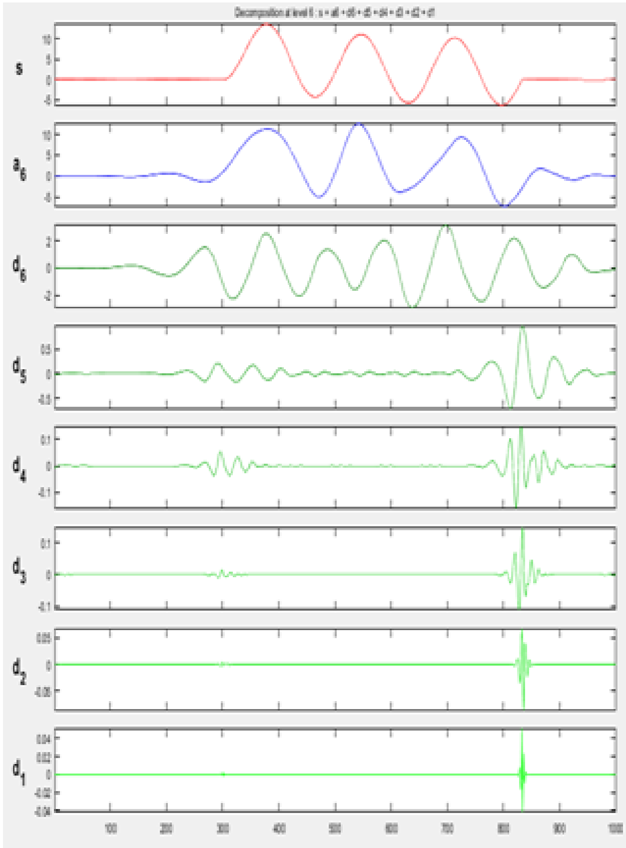

Figure 31: Different details and approximate signals of internal fault current

From those DWT frequency band only fourth level decomposed signal are passes through PCA for dimensions reduction these reduced dimensional signals are called features. This feature goes to the polynomial function based non-linear mapping SVM classifier for classification purposes. Figure explains how each phase of the differential currents samples passes through the protection algorithm. First 33 samples (1/5th cycle) from pre fault and 167 samples (1 cycle) from post fault of differential current for each phase is taken, then from these individual differential current, DWT (db8 mother wavelet) decomposed detail4(26 samples) computed. That means for each individual differential current total number of decomposed samples are 26 X 3 = 78 for all the three phases. These decomposed samples go to the three different PCA for three types of classifications using SVMs. The PCA1 reduces the dimensions from 78 to 9, the PCA2 reduces the dimension from 78 to 11 and PCA3 reduces the dimensions from 78 to 13. Using this algorithm, the final internal fault detection accuracy achieved is 98.15% on total number of different 2600 testing samples that s illustrated in the table.2. Apart from the internal fault detection there exist another two SVM. The second SVM identifies in which side of the transformer windings, fault has occurred and the third SVM discriminates between inrush and external fault. Table 3 and table 4 shows their classification accuracy.

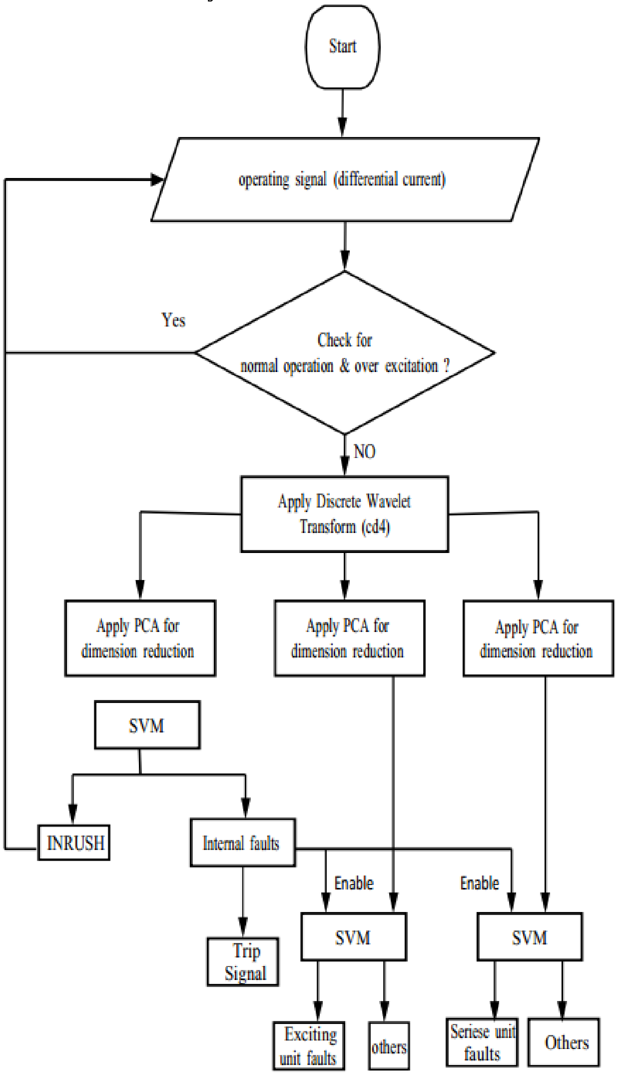

Figure 32: An Algorithm for phase shifting transformer in 9 bus system

In this proposed work 4096 training samples, 2600 testing samples, and 6696 total samples were generated. Training data is used to create a differential phase shifting transformer protection model and the testing samples are used to find the accuracy of that created differential protection model. To do that it took only one cycle data from occurrence time of inrush, exciting and primary unit faults fault. The above algorithm is performed in this thesis.

Table 2: Classification accuracy table for inrush and internal fault

Inrush and Internal Fault	Training Sample	Testing Sample	False Detection	Accuracy
Inrush	580	500	41	98.15
Internal fault	3516	2100	7	
Total Samples	4096	2600	48	

$$Classification\ accuracy\ table\ for\ inrush\ and\ internal\ fault =$$

$$\frac{total\ tested\ current\ signal - false\ identification}{total\ tested\ current\ signal} \text{ X } 100$$

$$Classification\ accuracy\ table\ for\ inrush\ and\ internal\ fault =$$

$$\frac{2600-48}{2600} \times 100 = 98.15\ \%$$

Table 3: Classification accuracy table for exciting unit faults and inrush / series unit

Exciting unit faults and Inrush / Series unit fault	Training Sample	Testing Sample	False Detection	Accuracy
Exciting unit faults	696	600	0	100%
Inrush / Series unit fault	3400	2000	0	
Total samples	4096	2600		

$$Classification\ accuracy\ table\ for\ primary\ exciting\ unit\ faults\ and\ inrush\ series\ unit =$$

$$\frac{total\ tested\ current\ signal - false\ identification}{total\ tested\ current\ signal} \text{ X } 100$$

$$Classification\ accuracy\ table\ for\ primary\ exciting\ unit\ faults\ and\ inrush\ series\ unit =$$

$$\frac{2600-0}{2600} \times 100 = 100\%$$

Table 4: Classification accuracy table for series unit and inrush / exciting unit faults

Series unit faults and Inrush / Exciting unit fault	Training Sample	Testing Sample	False Detection	Accuracy
Series unit faults	2820	1500	39	98.30%
Inrush / Exciting unit fault	1276	1100	5	
Total Samples	4096	2600	45	

$$Classification\ accuracy\ table\ for\ series\ unit\ faults\ and\ inrush\ /\ exciting\ unit\ fault =$$

$$\frac{total\ tested\ current\ signal - false\ identification}{total\ tested\ current\ signal} \text{ X } 100$$

Classification accuracy table for series unit faults and inrush / exciting unit fault =

$$\frac{2600-44}{2600} \times 100 = 98.30\%$$

6. Conclusion and Scope of Future Work

The proposed protection based on combined wavelet and SVM algorithm provides a differential protection for Phase shifting Transformer. Which provides much more security than the other existing SVM and conventional dual slope percentage differential-based protection. Here DWT extracted the very good features from differential current that further leads to the PCA for dimension reduction and then SVM based classifier. This algorithm achieved an accuracy of 98.15% to detect the internal faults from magnetizing inrush current. To achieve that much accuracy, it only took one cycle data from differential current for the processing which leads to the fast phase shifting transformer protection. And it also provides an additional information on which unit of the PST is damaged with an accuracy of 98.30 and 100% for exciting units and series unit faults.

In the future to enhance the speed of operation the data require for the processing would be reduce and search for the new features so that SVM classify most accurately. And this proposed algorithm can be implemented in real time.

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