Power Transformer Differential Protection using S-transform and Support Vector Machine

Ashesh M. Shah
Electrical Engineering Department,
Government Engineering College,
Bharuch, India

Dr. Bhavesh R. Bhalja
Electrical Engineering Department,
Indian Institute of Technology,
Roorkee, India

Dr. Rajesh M. Patel
Electrical Engineering Department,
HJD Institute of Technology,
Kera, India

***Abstract*—This paper proposes a power transformer differential protection scheme combined with S-transform and Support Vector Machine (SVM) that distinguishes internal faults and non-internal faults/disturbances such as different kinds of inrushes, over-excitation condition and external fault. In the proposed scheme, feature vectors, generated by performing S-transform of differential currents of a power transformer, are used as an input to SVM to classify internal faults with the non-internal faults. The proposed scheme is validated by generating more than 12000 simulation cases containing internal faults, external faults and other disturbances by modeling 3-phase power transformer of Gujarat Energy Transmission Corporation Limited (GETCO), Gujarat, India with the help of PSCAD/EMTDC software. The scheme is implemented using MATLAB and the simulation results indicate that the proposed scheme is capable to discriminate different internal faults with the other non-internal faults effectively with an accuracy of more than 97%. Further, a relative assessment of the current scheme is performed with an another digital scheme based on Probabilistic Neural Network (PNN) and the results are found to be superior to the existing scheme.**

Keywords— Support Vector Machine, Transformer protection, S-Transform

I. Introduction

Power transformers are significant apparatus in power system to transfer electrical energy. Instantaneous detachment of the faulty transformer is exceptionally necessary not only to keep away from widespread destruction but to conserve stability of power system too. The percentage differential protection scheme which is widely used for the protection of power transformer may maloperate due to magnetizing inrush currents in the transformer. This is due to a higher value of differential current flowing through the relay as the magnetizing current circulates only in the primary winding of the transformer. To stay away from unnecessary tripping facing magnetizing inrush situation, the usual transformer protection scheme restrains harmonic components or the second order and sometimes the fifth order harmonic also [1]. However, due to utilization of appropriate material in the power transformer core, the harmonic components can be considerably reduced [2].

Later on, techniques based on incremental flux linkages and power differential principles have been suggested by researchers [3]-[4]. However, the fundamental constrain of these methods is requirement of potential transformers in conjunction with current transformers resulting into increase in the total cost of protection system. Zaman *et. al* employed Artificial Neural Network (ANN) as a pattern classifier to distinct magnetising inrushes and internal faults in the power transformer [5]. However, the prime limitation of ANN based scheme is slow convergence in training, requirement of enormous training data samples, and trend to over fit the data. Furthermore, to bring out useful separation between magnetising inrush and internal fault current, researchers have used the concept of Wavelet transform [6]-[7]. However, requirement of larger size of the data window and complex algorithmic computations are the prime limitations of such schemes.

Afterwards, Samantaray and his colleagues [8] proposed power transformer protection method depend on pattern recognition and complex window approach of S-transform. However, this method is unable to distinguish internal faults with the other disturbances of the power transformer. Later on, Tripathy *et al.* [9] presented Probabilistic Neural Network (PNN) based scheme for power transformer protection which presents efficient discrimination between the internal fault and magnetizing inrush. However, the prime limitation of the said scheme is that the algorithm has been figured out on limited test cases of transformer. Moreover, this said scheme needs frequency and voltage data in supplementary with the differential current which may raise expenditure of the protection system. Later on, researchers have presented an algorithm based on model parameters estimation with the application of differential evolution, which classifies internal fault and magnetizing inrush [10]. However, the above method has not considered for the classification of over excitation condition and internal fault condition. Then, Hamid *et al.* [11] suggested an adaptive multiregion differential protection scheme to discriminate the different disturbances and internal faults based on adopted weighting factors in conjunction with differential current trajectory. However, the major constrain of the above method is adaption of weighting factor during two different zone (within zone and out of zone) fault situations. Other methods depends on magnetic pseudo characteristic and sine-wave least square curve fitting have been also reported to distinguish internal fault and magnetizing inrush [12]-[13]. Nevertheless, the said two schemes have not been carried out for the over excitation condition. Moreover, these schemes have not been tested for different ratings and different connections of power transformer.

Although, a large number of schemes for the transformer protection have been reported as yet, there presents a scope of enhancement, specifically for the effective segregate internal faults with non-internal faults/disturbances like different types of external faults, over-excitation of transformer and different types of inrushes such as residual inrush, recovery inrush and sympathetic inrush. In the current paper, the authors have proposed a new fault discrimination scheme based on features extraction of differential current signals using S-transform and discrimination of those features with SVM. The performance of the proposed scheme has been carried out by modelling three phase power transformer of GETCO, Gujarat, India. The three phase power transformer has been modelled with the help of PSCAD/EMTDC software [14]. The developed algorithm of the proposed scheme has been tested over a wide range of test dataset. The cases have considered with wide abnormality in fault and system conditions which have been achieved by an automatic data formation simulation models developed by authors.

II. Modeling And Simulation

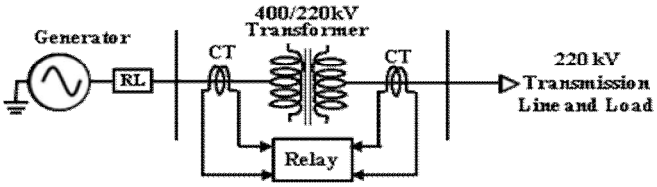


Fig. 1 Single line diagram of system modelled for simulation

Fig. 1 indicates the simulation model of a three phase, 400/220 kV, 315 MVA, 50 Hz, Y/Δ power transformer of GETCO produced to generate the different types of cases in PSCAD/EMTDC software package. The transformer and source parameters are given in Appendix. Generation of different types of simulation cases for various types of non-internal and internal faults are shown in the following sections.

A. Internal Faults

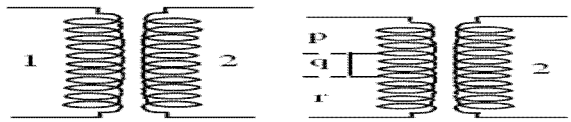
Different types of internal faults like Line-to-ground (LG), Line-to-line-to-ground (LLG), Line-to-line (LL), Primary-to-secondary and Turn-to-turn faults have been generated with the help of model developed in PSCAD.

Internal faults (Line-to-ground, Line-to-line and Line-to-line-to-ground) have been applied at different points of winding from the terminal of the transformer such as 5%, 10%, 25%, 50%, 75%, 90% as well as terminal faults with different fault inception angles (FIA) varying from 0° to 165° in 15° equal steps and having source impedance changing at ±20% with respect to source data provided in Appendix.

Two matrices for resistance (R) and inductance (L) are depicted based on short-circuit and excitation tests in case of two winding transformer. The order of these matrices are 2×2 for a one phase two winding transformer and given by equation (1). The same has also been indicated in Fig. 2(a).

$$R=\begin{bmatrix} R_1 & 0 \\ 0 & R_2 \end{bmatrix} \text{ and } L=\begin{bmatrix} L_1 & M_{12} \\ M_{21} & L_2 \end{bmatrix} \quad (1)$$

In order to develop customized model of turn-to-turn fault in PSCAD/EMTDC software package, authors have used various parameters like the total percentage of faulty turn and rule of proportionality [15]. During the turn-to-turn fault, faulted coil of winding is partitioned into three sub-coils of winding as shown in Fig. 2(b), which modifies matrices of the order of 4×4 and given by equation (2).



(a) (b)

Fig. 2(a) Two winding transformer model, (b) Simulation model developed for turn-to-turn fault

$$R=\begin{bmatrix} R_p & 0 & 0 & 0 \\ 0 & R_q & 0 & 0 \\ 0 & 0 & R_r & 0 \\ 0 & 0 & 0 & R_2 \end{bmatrix} \text{ and } L=\begin{bmatrix} L_p & M_{pq} & M_{pr} & M_{p2} \\ M_{qp} & L_q & M_{qr} & M_{q2} \\ M_{rp} & M_{rq} & L_r & M_{r2} \\ M_{2p} & M_{2q} & M_{2r} & L_2 \end{bmatrix} \quad (2)$$

The turn-to-turn fault simulations have been brought out for different percentage of shorted turns such as 0.1%, 0.2%, 0.5%, 1%, 2% and 5%. These simulations have been carried out at FIAs changing from 0° to 165° in sixteen equal steps of 15° and at different source impedance with 100% ± 20% variation which is given in Appendix.

As shown in Fig. 3, the customized model of primary-to-secondary winding fault has been developed by the authors in PSCAD/EMTDC software package. The winding is divided into four sub-coils with each winding consists of two coils in order to simulate this type of fault. The matrices of equation (1) have been modified and given by equation (3). Transformer data and percentage fault location are the input.

$$R=\begin{bmatrix} R_p & 0 & 0 & 0 \\ 0 & R_q & 0 & 0 \\ 0 & 0 & R_r & 0 \\ 0 & 0 & 0 & R_s \end{bmatrix} \text{ and } L=\begin{bmatrix} L_p & M_{pq} & M_{pr} & M_{ps} \\ M_{qp} & L_q & M_{qr} & M_{qs} \\ M_{rp} & M_{rq} & L_r & M_{rs} \\ M_{sp} & M_{sq} & M_{sr} & L_s \end{bmatrix} \quad (3)$$

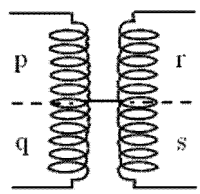


Fig. 3 Simulation model for primary-to-secondary winding fault

The primary-to-secondary winding (or inter-winding) faults simulation have been brought out at different fault locations of transformer windings. The locations have been chosen at different location from the terminal of transformer such as 5%, 10%, 25%, 50%, 75% and 90%. These types of faults have

been carried out at different FIAs from 0° to 165° in equal steps of 15° and at different source impedance of 100% ± 20% variation with respect to source data provided in Appendix.

B. Non - Internal Faults

With the help of model developed in PSCAD/EMTDC software, different types of non-internal faults/disturbances such as external faults, over excitation situation, various types of inrush conditions (e.g. residual inrush, recovery inrush and sympathetic inrush) and normal condition have been simulated and explain in following sub-section.

1) Magnetizing inrush:

Magnetizing inrush current flows in the transformer at the instant switching on a transformer at the moment when steady state flux and the instantaneous flux are different. If transformer disconnected from the supply after energization, it may possible that the amount of flux does not become completely zero. This type of remaining flux is recognized as residual flux and flowing inrush at that switching moment is known as Initial Inrush including Residual Magnetism. In the present paper, authors have simulated this condition with different source impedance of 100% ±20% variation with respect to source data provided in Appendix. The loading conditions have been also varied from no load to full load in 5 equal steps of 25% of the rated load on the transformer. Switching angles (SA) have been varied from 0° to 165° in 16 equal steps of 15° with both the positive and negative polarity of residual flux.

Upon energizing parallel connected transformer, sympathetic magnetizing inrush current flows for an in-service transformer. Saturation of the energized transformer can be resulted due to dc component of the inrush current and can produce the flow of sympathetic inrush current through the in-service transformer [16]. The sympathetic inrush current simulation has been carried out at various loading conditions of five equal steps from no load to full load. The simulation have been carried out for different source impedance phase angles and different switching angles in sixteen equal steps from 0° to 165° on the transmission line.

Recovery magnetizing inrush may take place when voltage restores to regular value after a temporary dip in voltage or external fault. The severe recovery inrush produces when the three phase external short circuit fault nearby has been taken place, cleared and the voltage returns to the normal value [16]. However, the severity of initial inrush is higher than recovery inrush. In simulating the recovery inrush, the severity of this type of inrush current has been found when LL, LLG, LLL and LLLG types external faults on transmission line taken place and cleared. The simulation for the recovery inrush has been carried out at different FIA from 0° to 165° in sixteen steps.

2) Over-excitation and other conditions

The over-excitation condition is simulated with various overvoltage varying in steps of 10% from 110% to 150% of rated voltage of power transformer. Frequency has been also varied for simulation at ±5% from fundamental frequency (50 Hz). Simulations have been also carried out for normal/healthy operating state. It is brought out at various loading conditions in five equal steps from no load to full load, along source impedance variation in ±20% in source impedance and 0° to 165° in sixteen equal steps in SAs with respect to source data provided in Appendix. Various external faults such as LG, LL, LLG and LLLG have been simulated at various values of FIAs, source impedance and fault locations on transmission line.

Thus, the total 6480 cases have been developed for internal fault whereas a total 6384 cases for non-internal faults have been generated, considering system parameter variations. Hence, overall 12864 (6480+6384) cases have been generated and investigated in this paper.

III. THE S-TRANSFORM

The S-transform is a time-frequency analysis technique which incorporates two types of properties of wavelet transform and short time fourier transform. S-transform is combining a frequency dependent resolution of the time-frequency space with absolutely referenced local phase information. This permits to describe the meaning of phase in a local spectrum. It also exhibits a frequency invariant amplitude response, while maintaining a direct relationship, frequency dependent resolution is provided by S-transform with the Fourier spectrum [17].

The relation between the S-transform and Fourier transform of a time series h(t) can be written as,

$$s(\tau, f) = \int_{-\infty}^{\infty} H(\alpha + f)\; G(f, \alpha) e^{j2\pi\alpha\tau}\, d\alpha \tag{4}$$

Where, Gaussian window function $G(f,\alpha) = e^{-\frac{j2\pi^2\alpha^2}{f^2}}$, $f \neq 0$.

The discrete analog of equation (4) is being applied to calculate the discrete S-transform. During the computation, it takes the advantage of the effectiveness of the convolution theorem and fourier transform.

If h[kT], k varying from 0 to N – 1, denotes a discrete time series analogous to h(t) with a time interval of T for sampling, equation (5) shows the discrete fourier transform.

$$H\left[\frac{n}{NT}\right] = \frac{1}{N}\sum_{k=0}^{N-1} h[kT]\, e^{-\frac{j2\pi nk}{N}} \tag{5}$$

Where, N is the number of samples/cycle.

Using equations (4) and (5) and making $f \to n/NT$ and $\tau \to jT$, the discrete time series h[kT]'s S-transform is given by equation (6).

$$S\left[jT, \frac{n}{NT}\right] = \sum_{m=0}^{N-1} H\left[\frac{m+n}{NT}\right] e^{-\frac{j2\pi m^2}{n^2}} e^{\frac{j2\pi mj}{N}} \quad n \neq 0 \quad (6)$$

Where j, m, and n are samples vary from 0 to N-1.

The output of the S-transform from equation (6) is a complex matrix of size (N/2+1) × N. It is known as S-matrix in which rows are related to frequency and columns to time complex values. Each complex value of S-transform localizes the real and imaginary components of the spectrum independently and can be converted to amplitude spectrum and phase angle values corresponding to S-transform. Moreover, features such as frequency, mean, standard deviation and energy of the transformed signal can be extracted in terms of information of the original signal. The two features consist of standard deviation of phase contour and maximum magnitude of frequency component of S-transform provides highest internal fault and inrush condition discrimination and hence, these features are used for the process.

In this paper, two features are extracted using S-transform for the process of classification. *Feature* 1 consists of the maximum magnitude of each frequency components present in the transformed signal and given by,

$$feature\ 1 = maximum\left(\begin{vmatrix} frequency\ from \\ s-matrix\ of\ each\ signal \end{vmatrix}\right) \quad (7)$$

Feature 2 is selected as standard deviation (SD) of the S-transform phase contour of the transformed signal and presented by,

$$feature\ 2 = SD\{angle(s-matrix\ of\ each\ signal)\} \quad (8)$$

The extracted *feature* 1 gives a vector of the size of (N/2+1) and that of *feature* 2 gives size of N for the total number of samples from the original time series signal. These two features are combined together to make a final *feature vector* for advance process and given by equation (9).

$$feature\ vector(\phi) = [feature1, feature2] \quad (9)$$

Afterwards, these features are sent to a nonlinear classifier SVM to train and classify the original signal.

IV. THE PROPOSED SCHEME

The schematic block diagram of the proposed scheme is shown in fig. 4. A non-linear version of Support Vector Machine (SVM) has been applied to cater practical classification problem. It shifts the training data from lower dimension space into a higher dimension with the help of the non-linear transformation using different kinds of kernel functions. Now, the original non-separable data may turn into separable data in the extended space. The different types of kernel functions are Radial basis function, Polynomial and Sigmoid function. After going through the many literatures, it has been found that training of data should be done using Radial Basis Function (RBF) kernel as RBF maps data samples of nonlinearly into higher dimensional space most productively than the other kinds of kernel function [18]-[20].

Initially, training data set must be prepared to configure SVM. To obtain the data samples, one cycle post fault data of differential currents (I_{dR}, I_{dY} and I_{dB}) of each of the three phases of power transformer are acquired. In this paper, sampling frequency of 2 kHz (i.e. 40 samples per cycle) for fundamental frequency of 50 Hz is used. Two features namely maximum magnitude of frequency components (*feature* 1) and standard deviation of the phase contour (*feature* 2) have been extracted using S-transform. Former feature (*feature* 1) has the size of 21 samples per cycle per phase whereas the size of *feature* 2 is 40 samples per cycle per phase. Thus, the *feature vector* of each phase of differential signal is of the order of 61 samples per cycle. Hence, a *feature vector* of 1 x 183 has been obtained from all the three phases of differential currents. Finally, the *feature vector* of 12864 x 183 dimensions is obtained in which each column represents feature and each row represents operating condition. This *feature vector* is divided into training and testing dataset with reference to FIA/SA to distinguish the internal fault conditions and non-internal faults/disturbances as shown in Table I.

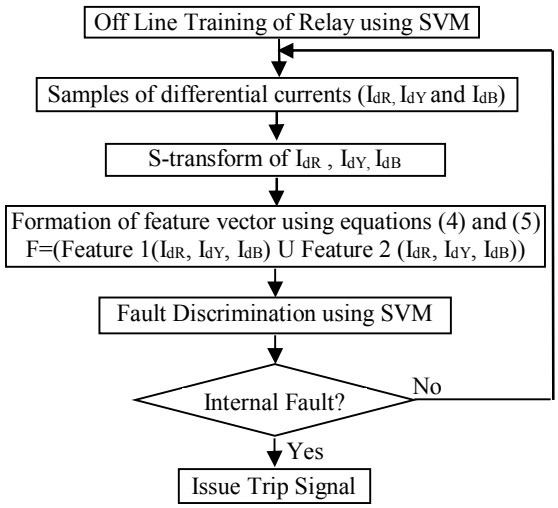


Fig. 4 Block diagram of the proposed scheme

TABLE I: Train and Test cases for different operating condition

Different conditions	*FIA/SA*	Operating Condition		
		Internal Faults	Non-Internal Faults	Number of Data
Training Data	0°, 30°,60°, 90°, 120°, 150°	3240	3192	**6432**
Testing Data	15°, 45°, 75°, 105°, 135°, 165°	3240	3192	**6432**
Total		6480	6384	**12864**

V. RESULTS OF PROPOSED SCHEME AND DISCUSSION

A. SVM Parameter Selection and Training

Lib-SVM toolbox has been used to implement SVM in MATLAB environment in the proposed scheme [21]. To obtain accurate discrimination of internal fault condition and non-internal fault condition/disturbances, it is very much

important that SVM should be trained properly. So, for proper training, the data with FIA/SA with 0˚, 30˚, 60˚, 90˚, 120˚ and 150˚ and other conditions as shown in Table I have been selected for the training. Thus, out of the total 12864 cases, the authors have chosen 6432 cases (50% of total) for training the data which compromises of different system and fault parameters. In the proposed scheme, remaining cases (6432) have been adopted as test data to achieve discrimination accuracy (η) which is given by,

$$\eta = \frac{Correct\ discrimi\ nation\ of\ test\ cases}{Total\ test\ cases\ (6432)} \times 100\% \quad (7)$$

In case of RBF kernel function of SVM, optimum values of the associated parameters C and γ have been carried out by fivefold cross validation technique. This can be achieved by changing the values of these two parameters which avoids over-fitting of training data model. Table II shows the cross-validation accuracies for different values of γ and C. It has been observed from Table II that the maximum cross validation discrimination accuracy of 99.7823% has been obtained for C = 10^3 and γ = 10^{-3}. Hence, the authors have selected these values for training the SVM.

TABLE II Accuracy of cross validation for training dataset

Fivefold cross validation accuracy in (%) for varying values of regularization parameter (C) and gamma (γ)						
C→ γ↓	10^0	10^1	10^2	**10^3**	10^4	10^5
10^{-5}	77.3787	82.9913	87.8887	93.579	96.553	97.8078
10^{-4}	86.3184	92.7861	96.4552	98.0721	98.6629	98.9117
10^{-3}	94.6673	98.4608	99.5647	**99.7823**	99.7668	99.7668
10^{-2}	98.9894	99.3004	99.3004	99.3004	99.3004	99.3004
10^{-1}	93.7034	94.3252	94.3252	94.3252	94.3252	94.3252

B. *Performance Evaluation*

The performance evaluation of the proposed scheme has been brought out for various kinds of internal and non-internal faults/disturbances by varying system parameters as shown in Table I for a total 6432 test cases. In the proposed scheme, correctly detected and incorrectly detected test cases are denoted as True Positive (TP) and True Negative (TN), respectively. The overall performance of the proposed scheme is shown in Table III. It achieves overall accuracy of 97.9478%. To compare the proposed combined scheme of S-transform and SVM, a comparison is also shown with reference to PNN based scheme [9] for a total 6432 test cases in Table III. It has been observed from Table III that the proposed scheme is more efficient to distinguish the internal faults with the non-internal faults/disturbances. The current proposed scheme is able to provide 97.9478% overall accuracy compared to only 91.7133% in case of PNN based scheme even at the most suitable smoothing factor. Hence, the proposed scheme is capable to provide higher efficiency in case of internal faults and better stability during non-internal faults.

TABLE III Accuracy of the proposed scheme and the existing scheme

Different conditions	Number of test cases	Proposed scheme			Existing scheme based on PNN		
		TP	TN	η (%)	TP	TN	η (%)
Internal faults	3240	3201	39	98.7963	3076	164	94.9383
Non-internal faults	3192	3099	93	97.0865	2823	369	88.4398
Total data (Overall accuracy)	6432	6300	132	97.9478	5899	533	91.7133

Limited fault records are available for training of SVM in an actual field and it is not feasible to generate such fault cases in real practical power system. However, the tools like PSCAD is universally accepted to replicate such practical scenarios if modeled efficiently. It has been observed from Table III that though the data samples are very less, the proposed scheme gives equally promising accuracy (97%).

C. *Effect of change in SA/FIA on % accuracy*

Table IV shows the comparison of the proposed scheme with the existing scheme based on PNN in terms of percentage fault discrimination accuracy at different SA/FIA. From Table IV, it has been observed that even using best smoothing factor (4.0), the overall percentage accuracy obtained by PNN based scheme is 94.93% for internal faults and 88.61% for non-internal faults, respectively. Conversely, proposed scheme provides 98.79% total accuracy for internal faults and 97.13% for non-internal faults. Moreover, Table IV shows that the PNN based scheme provides lowest accuracy (85.92%) during 45˚ SA/FIA compared to the proposed scheme which provides an accuracy of 98.89%. Hence, the proposed scheme is preferable over the PNN based scheme.

TABLE IV Comparison of proposed and existing scheme at different SA/FIA

SA/FIA (deg)	Total test cases	Internal Faults						Non-Internal Faults					
		Proposed scheme			Existing scheme based on PNN			Proposed scheme			Existing scheme based on PNN		
		TP	TN	η (%)	TP	TN	η (%)	TP	TN	η (%)	TP	TN	η (%)
15	540	532	8	98.52	490	50	90.74	508	32	94.07	486	54	90
45	540	535	5	99.07	519	21	96.11	534	6	98.89	464	76	85.92
75	540	538	2	99.63	508	32	94.07	532	8	98.52	472	68	87.41
105	540	539	1	99.81	519	21	96.11	531	9	98.33	482	58	89.26
135	540	532	8	98.52	520	20	96.30	522	18	96.67	488	52	90.37
165	540	525	15	97.22	520	20	96.30	520	20	96.30	479	61	88.70
Overall % accuracy				98.79	-	-	94.94	-	-	97.13	-	-	88.61
TP= True Positive, TN= True Negative													

D. *Advantages of the proposed scheme*

The primary advantages of the S-transform and SVM based proposed scheme have been pointed out below based on results discussed in previous sub-sections:

(i) A very high accuracy have been achieved with the proposed scheme even with 50% training data set (6432 out of 12864 total cases) compare to test data set. Conversely, the existing scheme requires large training data set compare to testing data set. Hence, the proposed

scheme is superior to the existing scheme as it requires much reduced training data set.

(ii) From Table III, it is observed that the proposed scheme is highly reliable against internal faults as it gives very high accuracy (more than 98%) as compared to existing scheme (94.8343%), which must be correctly identified and cleared as fast as possible in order to minimize the damage to the power transformer as well as to the power system network.

(iii) The proposed algorithm gives the same amount of accuracy against various inrush, over-excitation and external fault conditions, in which the relay must not operate as this will cause unwanted isolation of a power transformer.

(iv) A Statistical Learning Method (SLM) based SVM, with correct features extracted from S-transform, provides non-linear classification which can be more powerful compared to other methods. The same has been observed as an outcome of result analysis in Table IV.

VI. CONCLUSION

A distinct fault discrimination scheme for protection of power transformers combined with S-transform and SVM is presented in this paper. The proposed S-transform and SVM based scheme utilizes one cycle post disturbance CT secondary three phase differential current to distinguish internal faults with non-internal faults/disturbances. Features extraction is carried out using S-transform and two features namely standard deviation of phase contour and the maximum magnitude of each frequency components are given as information to SVM. Feasibility of the proposed scheme has been achieved by modeling the power transformer in PSCAD/EMTDC software package. A large number of test cases have been examined to validate the proposed scheme and provides fault discrimination accuracy of more than 97.9%. The simulation dataset has been prepared for 12864 cases with various system and fault conditions. At the end, a comparative evaluation with the existing scheme shows that the proposed scheme is superior to the existing scheme.

APPENDIX

Data for Source:

Z_1=0.8715+j9.9615Ω, Z_0=1.743+ j19.923Ω, f = 50 Hz

Data for Transformer:

Power rating = 315MVA, voltage rating = 400/220 kV, frequency = 50Hz, total phase = 3, connection of phase = Star/Delta, Reactance per phase = 12.5%, Magnetizing current = 0.1 %

REFERENCES

[1] M.A. Rahman and P.K. Dash, "Fast algorithm for digital protection of power transformers," *IEE Proc.,* vol. 129, no. 2, pp. 79-85, Mar. 1982.

[2] Myong-Chul Shin, Chul-Won Park, Jong-Hyung Kim, "Fuzzy Logic-Based Relaying for Large Power Transformer Protection," *IEEE Transactions on Power Delivery*, vol. 18, no.3, pp.718-724, July 2003.

[3] Y.C. Kang, B.E. Lee, S.H. Kang., P.A. Crossley, "Transformer protection based on the increment of flux linkages," *IEE Proc.- Gener. Transm. Distrib.,* vol. 151, no.4,pp.548-554, July 2004.

[4] Kuniaki Yabe, "Power Differential Method for Discrimination between Fault and Magnetizing Inrush Current in Transformers," *IEEE Transactions on Power Delivery,* vol. 12, no.3, pp.1109-1118, July 1997.

[5] M.R. Zaman, M.A Rahman, "Experimental Testing of the Artificial Neural Network Based Protection of Power Transformers," *IEEE Transactions on Power Delivery,* vol.13, no.2, pp.510-517, April 1998.

[6] Jawad Faiz, S. Lotfi-Fard, "A Novel Wavelet-Based Algorithm for Discrimination of Internal Faults From Magnetizing Inrush Currents in Power Transformers," *IEEE Transactions on Power Delivery,* vol.21, no.4, pp.1989-1996, October 2006.

[7] Omar A., S. Youssef, "A Wavelet-Based Technique for Discrimination between Faults and Magnetizing Inrush Currents in Transformers," *IEEE Transactions on Power Delivery,* vol.18, no.1, pp.170-176, January 2003.

[8] S.R. Samantaray, B.K. Panigrahi, P.K. Dash, G. Panda, "Power transformer protection using S-transform with complex window and pattern recognition approach," *IET Generation Transmission Distribution,* vol.1, no.2, pp.278–286, 2007.

[9] Manoj Tripathy, Rudra Prakash Maheshwari, H. K. Verma, "Power Transformer Differential Protection Based On Optimal Probabilistic Neural Network," *IEEE Transactions on Power Delivery,* vol. 25, no.1, pp. 102-112, January 2010.

[10] Haung, S. R., Chen Hong-Tai, Chueh-Cheng Wu, Chau-Yu Guan, Chiang Cheng, "Distinguishing Internal Winding Faults From Inrush Currents in Power Transformers Using Jiles-Atherton Model Parameters Based on Correlation Coefficient", *IEEE Transactions on Power Delivery*, vol. 27, no. 2, pp. 548-553., April 2012

[11] Hamed Dashti and Majid Sanaye-Pasand, "Power Transformer Protection Using a Multiregion Adaptive Differential Relay," *IEEE Transactions on Power Delivery*, vol. 29, no. 2, pp. 777-785, April 2014.

[12] Babak Khalkhali and Javad Sadeh, "Transformer Differential Protection by Online Core Modeling and Orthogonal Polynomials," *IEEE Transactions on Power Delivery*, vol 30, no. 5, pp. 2146-2153, Oct. 2015.

[13] Mohammad Ahmadi, Haidar Samet and Teymoor Ghanbari, "Discrimination of internal fault from magnetising inruch current in power transformers based on sine-wave least squares curve fitting method," *IET Science, Measurement & Technology*, vol. 9, no. 1, pp. 73-84, Feb. 2015

[14] PSCAD/EMTDC Power Systems Simulation Manual, Winnipeg, MB, Canada, 1997.

[15] Bastard P. , Bertrand P. and Meunier M., "A Transformer Model For Winding Fault Studies", *IEEE Transactions on Power Delivery,* vol. 9, no. 2, April 1994, pp. 690-699.

[16] S. H. Horowitz and A. G. Phadke, *Power System Relaying*, John Wilsey & Sons, 3rd Ed., pp. 201 – 205.

[17] R. G. Stockwell, L. Mansinha, and R. P. Lowe, "Localization of the Complex Spectrum: The S Transform," *IEEE Transactions on signal processing,* vol. 44, no. 4, pp. 998-1001, April 1996.

[18] Vladimir N. Vapnik, "An Overview of Statistical Learning Theory", *IEEE Transactions on Neural Networks,* vol. 10, no. 5, pp. 988-999, Sep. 1999.

[19] B. Ravikumar, D. Thukaram and H.P. Khincha, "Application of support vector machines for fault diagnosis in power transmission system", *IET Generation, Transmission & Distribution*, vol. 2, no. 1, Jan. 2008, pp. 119–130.

[20] Chothani N.G., Bhalja B.R., Parikh, U.B., "New fault zone identification scheme for busbar using support vector machine", *IET Generation, Transmission & Distribution,* vol. 5, Oct. 2011, pp. 1073-1079.

[21] C.C.Chang, LIBSVM-A Library for Support Vector Machines [Online]. Available: http://www.csie.ntu.edu.tw/~cjlin/libsvm/