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A classification approach using SVM to detect magnetic inrush in power transformers

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ABSTRACT: In Order to avoid mal operation of differential relay in transformer it is essential to distinguish between inrush and fault conditions. For accurate discrimination between inrush and fault current SVM technique is proposed. The merit of this method is demonstrated by simulation of different faults and switching conditions using MATLAB/SIMULINK. The inrush current values are obtained by varying the switching angle and the fault currents are obtained by varying the fault resistance. The Proposed method is tested on a 3000MVA, 230 kV Y-Y connected transformer by varying fault resistance, and switching angle. The performance of SVM is compared in terms of classification accuracy. The accuracy obtained using SVM is found to be more than other methods such as neural networks, ANFIS, etc. The results obtained with SVM are far better than other methods earlier used. SVM is preferred here over other methods because it is based on structural risk minimization whereas neural networks and ANFIS are empirical based. Moreover this method seems to be very effective for modern transformers with high harmonic contents and it requires less training. A SVM based protective field programmable gate array relay logic can be implemented further in future which will be verified against the simulation results.

KEYWORDS: Inrush Current, Support Vector Machine, Fault current, Sequential minimization method, Radial basis function.

1 INTRODUCTION

Power transformer is one of the indispensable elements in power systems and thus protection of transformer play an imperative role. When the energization of transformer occurs with no load, inrush current flowing into the transformer will become excessive such that it will be eight to thirty times of full load current. This high current forces the relay to operate falsely. The relay provided has to work only for internal fault and inrush current and not for external fault and normal conditions.

In former protective schemes of transformer, it is confined based on transformer inductance during saturation of current transformer [1] and then algorithms have been developed based on second order percentage differential harmonic restraint concept [2]. Since inrush current usually contains a large second order harmonic component than internal fault, earlier transformer protection systems are planned to restrain during magnetic inrush phenomena by filtering this large second order harmonic component owing to saturation of current transformer or the presence of a dispersed shunt capacitance in a lengthy EHV transmission line to which the transformer may be connected [3]. In undeniable cases, the level of the second order harmonic in an internal fault current can be nearer to or bigger than that of inrush current. In addition, the second order harmonic components in inrush currents likely to be reasonably small in modern large power transformer because of enhancement in the power transformer core substance. In view of the above factors, many researchers accomplish their work to develop new algorithm for transformer protection [4]-[6]. However all these algorithms developed so far are either based on the transformer equivalent circuit model and/ or require some transformer data and thus may vulnerable to parameter variations. In [6], transformer is protected based on the active power flowing in to transformer, which is almost zero in case of energization. New methods have been employed using fuzzy logic and neural network for protection of power transformer [7]-[10]. In [8], neural network based schemes for protection of a single phase transformer has been carried out while applications of the neural network for protection of a three phase power transformer have been shown in [9] and [10].

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However the Artificial Neural Networks used in existing systems are confined to particular power transformers, and would have to be trained again and again for other system which seems to take more time. Several protective schemes of power transformer with wavelet transform are also developed in [11]- [14]. In [15] SVM technique is applied to classify between inrush and fault of a 3 phase 35 MVA, 50 HZ, 132/11 KV Y/Y transformer and 132 KV transmission line. The combined discrete wavelet and SVM technique is applied in detecting and classifying the fault in transmission line [16]. Bus bars are also protected with the help of support vector machines [17].

In this paper, a modern approach is put forward for discrimination of L-G fault and inrush current in power transformer using Support Vector Machine (SVM). The system is tested on a 3000 MVA, 500/230 kV Y-Y connected transformer under variety of fault and inrush conditions. The SVM based approach discriminate between magnetic inrush and L-G fault in power transformer more accurately.

2 SUPPORT VECTOR MACHINES

As with any supervised learning methods training the network is very important. The SVM is therefore first trained and the trained network is used to classify or predict new data. In addition to obtain more accurate results various SVM kernel functions are used and the parameters of kernel functions must be tuned .

The main features of SVM are:

- The upper bound on the generalization error does not depend on the dimension of the space
- The error bound is minimized by maximizing the margin g.

Considering the binary classification task with data point xi(i = 1,2,…,m) having labels yi = ±1 and the decision function be

$$f(x) = sign(w.x + b) \qquad (2.1)$$

Where w is the n dimensional vector and b is the scalar. The vector w and scalar b determines the position of the separating hyper plane. If the dataset is separable then the data will be correctly classified where yi (w.x+b)>0"i. Thus canonical hyper plane is such that w.x+b = 1 for closest points on one side and w.x+b = -1 for closest points on other side as in Fig. 2..For separating w.x+b = 0 the normal vector is w and hence, the margin is given by the projection of x1-x2 on to this vector. Since, w.x1+b = 1 and w.x2+b = -1, the margin is g = 1/||w||. To maximize the margin the task is, therefore, subject to the constraints $y_i(w.x_i+b) = 0$;and the learning task can be reduced to minimization of the primal Lagrangian

$$\min g(w) = \frac{1}{2(||w||)2} \qquad (2.2)$$

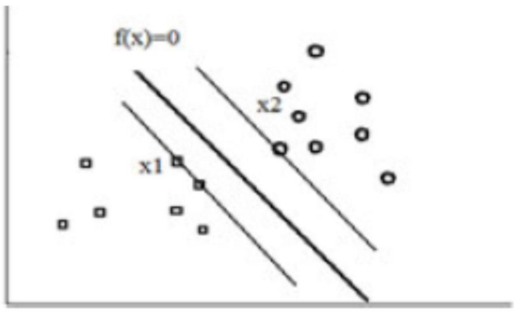

Fig. 1. ***Sample SVM classifier***

A) Separable Data

An SVM classifies data by finding the best hyper plane that separates points of one class from those of the other class. The best hyper plane for an SVM means the one with the largest margin between the two classes. Margin means the maximal width of the slab parallel to the hyper plane that has no interior data points. The support vectors are the data points that are closest to the separating hyper plane; these points are on the boundary of the slab. The following figure illustrates these definitions, with + indicating data points of type 1, and – indicating data points of type –1.

Mathematical Formulation: The data for training is a set of points (vectors) xi along with their categories yi. For some dimension d, the xi ∊ Rd, and the yi = ±1. The equation of a hyper plane is

$$< w, x > + b = 0 \qquad (2.3)$$

where w ∊ Rd, <w,x> is the inner (dot) product of w and x, and b is real.

$$yi(< w, xi > + b) \geq 1 \qquad (2.4)$$

The following problem defines the best separating hyper plane. Find w and b that minimize ||w|| such that for all data points (xi,yi),

For mathematical convenience, the problem is usually given as the equivalent problem of minimizing <w,w>/2. This is a quadratic programming problem. The optimal solution w, b enables classification of a vector z as follows:

$$class(z) = sign(< w, z > + b) \qquad (2.5)$$

B) Non separable Data

There are two standard formulations of soft margins. Both involve adding slack variables si and a penalty parameter C.

The L1-norm problem is:

$$\min_{w,b,s}(\frac{1}{2}(w, w) + C \sum_i s_i \qquad (2.6)$$

$$y_i\big((w, x_i) + b\big) \geq 1 - s_i \qquad (2.7)$$

$$s_i \geq 0 \qquad (2.8)$$

The L^1–norm refers to using s_i as slack variables instead of their squares.

The L^2 -norm problem is

$$\min_{w,b,s}(\frac{1}{2}(w, w) + C \sum_i s_i^2 \qquad (2.9)$$

C) Sequential Minimal Optimization

Platt (1999) proposes to always use the smallest possible working set size, that is, two elements. This choice dramatically simplifies the decomposition method. Each successive quadratic programming sub problem has two variables. The equality constraint makes this a one dimensional optimization problem. A single direction search is sufficient to compute the solution.

3 SYSTEM STUDIED

The single line diagram of the system studied is shown in Fig.2.. Transformer and line configuration details are given in Appendix A. The test system is modeled and simulated using MATLAB/simulink.

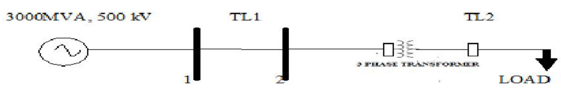

Fig. 2. Test system

3.1 PROPOSED ALGORITHM USING SVM

The schematic order of the fault classification scheme using SVM for power transformer is shown in Fig.2. MATLAB/ Simulink are used to simulate magnetizing inrush conditions due to change in switching angle and L-G fault conditions by varying fault resistance.

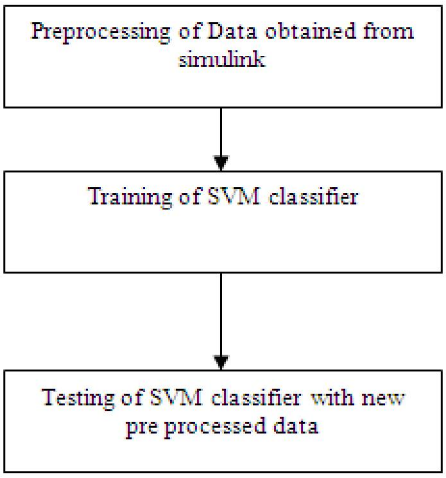

Fig. 3. Block diagram of the proposed method for discrimination between magnetic inrush and L-G fault in power transformer

The output of the SVM is such that the value “1” denotes L-G fault; the value “-1” denotes a magnetizing inrush current.

3.2 Feature Extraction

The inrush current signals are obtained by varying the energization angle from 0 to 360^{0}and the L-G fault current samples are generated by varying the fault resistance. Matlab/simulink is used to generate the signals.Fig.3-4 shows the magnetizing inrush current and L-G fault current samples.

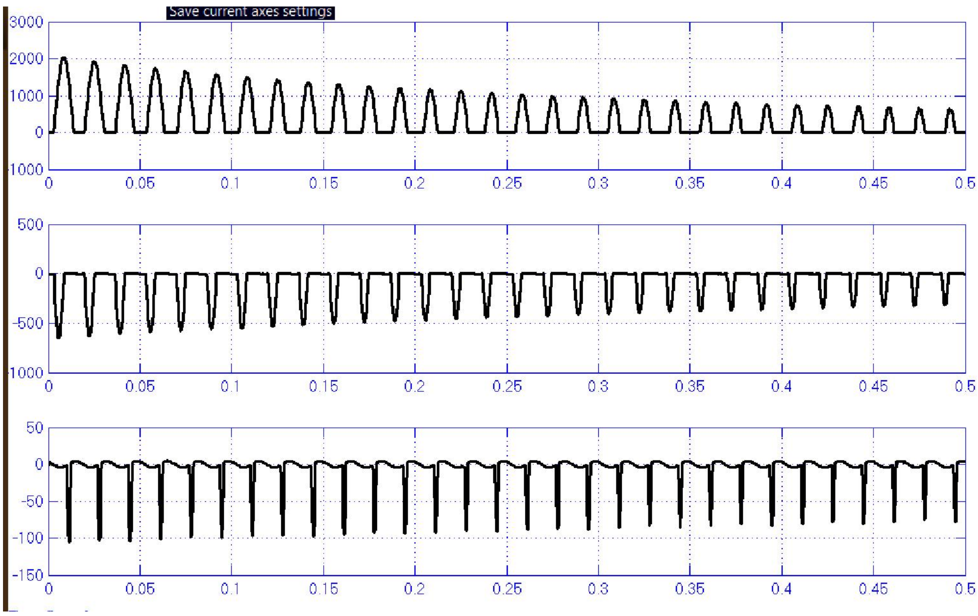

Fig. 4. Simulated three phase current waveforms for inrush current

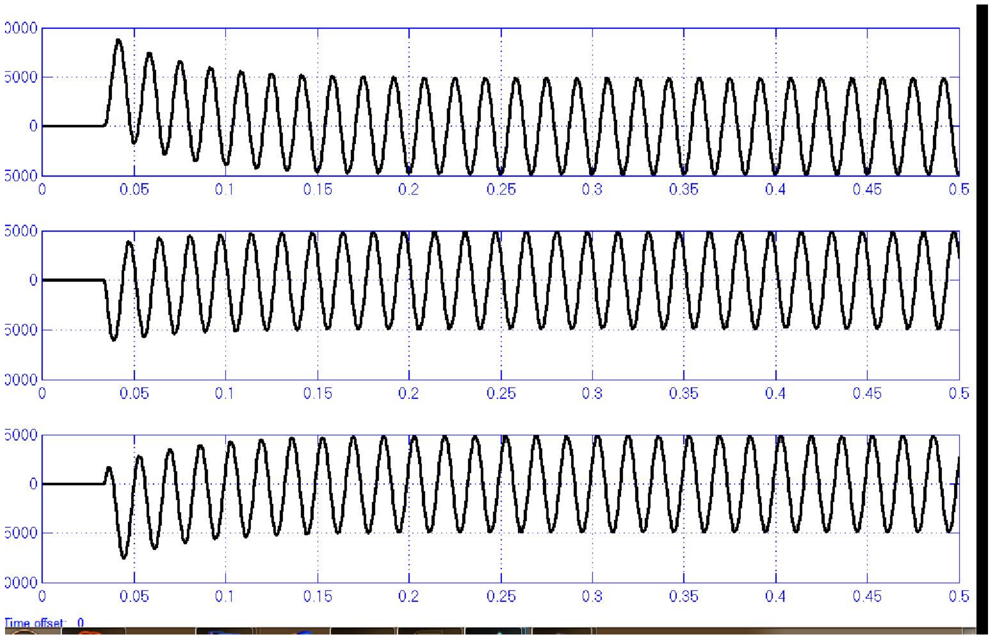

Fig. 5. Simulated three phase current waveforms for L-G fault current

3.3 SVM Training and Testing

The SVM is trained for various training patterns of fault and inrush current. 2000 datasets are simulated for different fault and inrush conditions. The fault is simulated by varying fault resistance. The inrush current changes correspond to energization angles of 0^0 and 360^0 from phase-a voltage zero crossing. The 2000 datasets are used for testing the classifier with the SVM structure obtained in training. The same system is trained and tested with LMBPNN to compare the overall performance of SVM.

All the simulations for the SVM and LMBPNN algorithms are carried out in MATLAB 7 platform. In SVM, RBF kernel is used for fault classification of transient events. The simulations for SVM are carried out using SVM toolbox in MATLAB/simulink platform.

4 Simulation results and discussions

An extensive series of studies are carried out in order to ascertain the overall performance of the two networks. The test sets (which not included as part of the training sets) are composed of over 2000 cases including different fault resistance and magnetizing inrush current. The SVM structure is created by training the SVM classifier with the data obtained from simulation.

Fig.6. shows that the points indicated with red colour denotes the inrush current and with green colour denotes the fault current used for training .The black line is the optimum hyper plane that separates the two data. SMO method is used to optimize the parameters of SVM kernel functions. After training with the simulation data of inrush and fault currents, SVM structure is created The SVM structure includes support vectors, alpha ,bias, kernel functions, support vector indices . The number of support vectors determines the overall performance of SVM classifier. Here the number of support vectors obtained is 15The alpha is the vector weights to support vectors. The sign of weights is positive for the inrush current and negative for fault current. Kernel function used here is radial basis function which maps training data into kernel space. Support Vector indices are the vectors of indices that specify the rows in training, the training data that were selected as support vectors after the data was normalized according to the auto scale argument. Then the SVM structure is used to classify the new sets of fault current and inrush current data. Fig.6. shows both training and testing details of SVM.As already mentioned the new sets of data were discriminated with the help of SVM structure created using the training data.Here the blue colour indicates the no of new set of correctly classified fault data and pink colour indicates the correctlclassified inrush current data. The accuracy is calculated using the formula A= (1-MCR)*100%.

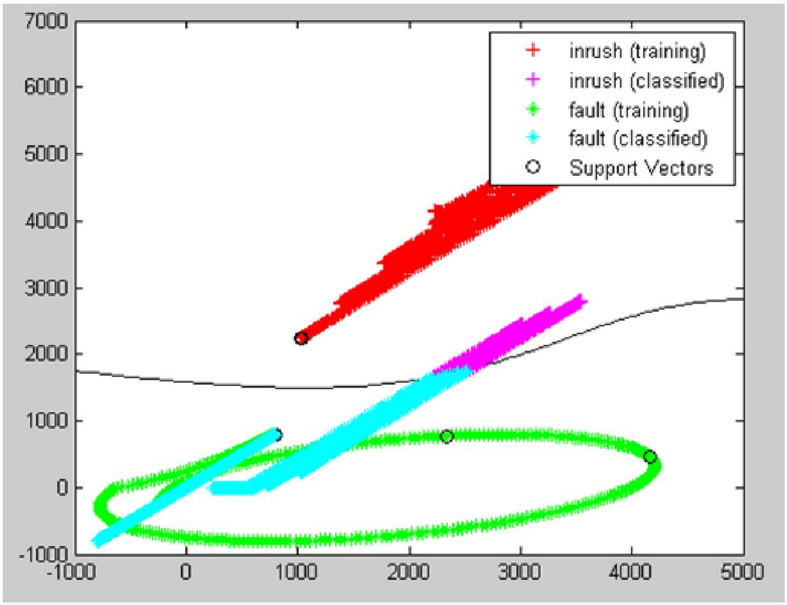

Fig. 6. SVM Classifier result with data

5 CONCLUSION

This study proposes a modern method for discrimination between magnetic inrush and L-G fault in power transformer using SVM. The method is done based on current signature verification. Therefore, for modern transformers with high harmonic components in internal fault current, this method seems to be more effective. The results obtained on simulated data of a three phase two winding Y-Y connected transformer showed that SVM classifier outperforms greatly in discrimination between magnetic inrush and L-G fault currents. In the future the discrimination of magnetic inrush and other types of internal faults using SVM can be done and to be implemented in hardware.

REFERENCES

[1] K. Ingaki, Higaki, M., Matsui, Y., et al., “Digital protection method for power transformer based on an equivalent circuit composed of inverse inductance”, *IEEE Trans., on Power Delivery,* vol. 3(4), 1988, 1501-1510.

[2] M.A. Rahman, B. Jeyasurya, “A state-of-the-art review of transformer protection algorithms”, *IEEE Trans., on Power Delivery,* vol. 3(2), 1988, 534-544.

[3] Pei Liu, O.P. Malik, Deshu Chen et al., “Improved operation of differential protection of power transformers for internal faults,” *IEEE Trans., on Power Delivery,* vol. 7(1*),* 1992,1912-1919.

[4] T.S. Sidhu, M.S. Sachdev, H.C. Wood et all, “Design, Implementation and testing of a microprocessor-based high-speed relay for detecting transformer winding faults,” *IEEE Trans., on Power Delivery*, 7(1), 1992, 108-117.

[5] T.S. Sidhu, M.S. Sachdev, “Online Identification of magnetizing inrush and internal faults in three-phase transformers,” *IEEE Trans., on Power Delivery,* 7(4), 1992, 1885-1891.

[6] Yabe, K., “ Power differential method for discrimination between fault and magnetizing inrush current”, *IEEE Trans., on Power Delivery, vol. 12(3), 1997,*1109-1118.

[7] Wiszniewski, A., kasztenny, B., “A Multi-criteria differential transformer relay based on fuzzy logic”, *IEEE Trans., on Power Delivery,* 10(4), *1995,* 1786-1792.

[8] Perez, L.G, Floechsig, A.J., Meador, J.L., and Obradovic, Z., “Training an artificial neural network to discriminate between magnetizing inrush and internal faults”, *IEEE Trans., on Power Delivery*, 9(1), *1994,* 434-441.

[9] Pihler, J., Grcar, B., and Dolinar, D., “Improved operation of power transformer protection using artificial neural network”, *IEEE Trans., on Power Delivery*, 12(3), 1997, 1128-1136.

[10] M.R. Zaman and M.A. Rahman, “Experimental testing of the artificaial neural network based protection of power transformers,” *IEEE Trans.on Power Delivery,* 13(2), 1998, 510-517.

[11] Moises Gomez-Morante, Danies, W.Nicoletti, “A wavelet based Differential Transformer protection,” *IEEE Trans.on Power Delivery,* 14(4), *1999,* 1351-1358.

[12] P.L. Mao and R.L. Aggarval, “A Novel approach to the classification of the transient phenomena in Power Transformer using combined wavelet transform and Neural Network”, *IEEE Trans. on Power Delivery,* 16, 2001,654-660.

[13] Omar A.S. Youssef, “A wavelet based technique for discrimination between faults and magnetizing inrush currents in Transformers”, *IEEE Trans. on Power Delivery,* 18*,* 2003, 170-175.

[14] Javad Faiz and S. Lotfi-Fard, “A Novel Wavelet based algorithm for discrimination of internal faults from magnetizing inrush currents in Power Transformer”, *IEEE Trans. on Power Delivery*, 21, 2006, 1989-1996.

APPENDIX A

1) Transformer parameters:

Three phase 450 MVA 50 Hz 500/230 kV Y-Y connected windings with earth neutrals.

2) Transmission line parameters:

500 kV 100 km transmission lines.

BIBLIOGRAPHY

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