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Support Vector Machine for Discrimination Between Fault and Magnetizing Inrush Current in Power Transformer

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Abstract: This study presents a novel technique based on Support Vector Machine (SVM) for the classification of transient phenomena in power transformer. The SVM is a powerful method for statistical classification of data. The input data to this SVM for training comprises fault current and magnetizing inrush current. SVM classifier produces significant accuracy for classification of transient phenomena in power transformer.

Key words: Power transformer, magnetizing inrush current, fault current, support vector machine

INTRODUCTION

In power systems, the power transformer is one of the expensive and essential elements and, thus, protection of transformer is of critical importance. To improve the reliability, it is essential to minimize the frequency and unwanted outage of power transformer. When the transformer is energized, magnetizing inrush current flowing into the transformer may be as great as ten times the full load current. So during energization there is a possibility of false tripping caused by the magnetising inrush current. The relay provided has to operate only for fault condition and not for inrush condition. In order to have reliable protection it is essential to classify the transient phenomena in power transformer.

Discrimination between fault and a magnetizing inrush current has long been recognized as a challenging power transformer protection problem. Since, a magnetizing current generally contains a large second harmonic component in comparison to an internal fault, conventional transformer protection systems are designed to restrain during inrush transient phenomena by sensing this large second harmonic[1]. However the second harmonic component may also be generated during faults in the power transformer. This may be due to CT saturation or the presence of shunt capacitor or the distributive capacitance in a long EHV transmission line to which he transformer may be connected[2]. In certain cases, the magnitude of the second harmonic in fault current can be close to or greater than that present in the magnetising inrush current. Moreover, the second harmonic components in the magnetizing inrush currents tend to be relatively small in modern large power transformers, because of improvements in the power transformer core material. Consequently, the commonly employed conventional differential protection technique based on the second harmonic restraint, will thus have difficulty in distinguishing between fault and inrush current thereby affecting transformer stability. Alternatively, improved protection techniques for accurately and efficiently discriminating between fault and magnetizing inrush current have thus to be found.

Several researchers in recent years have presented results aimed at distinguishing magnetising inrush current from fault current. Digital protective relaying has greatly beneficial from the development of artificial neural network[3] and more recently , from new signal processing techniques such as the wavelet transform[4,5,6]. A combination of these approach for transformer protection has also been proposed in[7]. In this study, SVM is used for classification of transient phenomena in three phase power transformer. The SVM which is based on statistical learning theory is a general classification method and its theoretical foundation is described in[8,9]. The SVM algorithm has been successfully implemented in pattern recognition problem[10]. Since the particular problem can also be considered as a current recognition problem, the use of SVM seems to be good choice. Application of SVM to power system is reported in[11,12]. The aim of the work is to investigate the performance of SVM classifier for classification of transient phenomena in power transformer.

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SUPPORT VECTOR MACHINE

SVM have the potential to handle very large feature spaces, because the training of SVM is carried out so that the dimension of classified vectors does not have as a distinct influence on the performance of SVM as it has in the conventional classifier. This will also benefit in classification of transient phenomena in power transformer, because the number of features to be the basis for classification of transient events may not have to be limited. Also SVM based classifiers are claimed to have good generalization properties compared to conventional classifiers, because in training the SVM classifier, the structural miscellaneous risk is to be minimized, whereas traditional classifiers are usually trained so that the empirical risk is minimized.

SVM is a computational learning method based on the statistical learning theory. In SVM, the input vectors are non-linearly mapped into a high dimensional feature space. In this feature space the optimal hyper-plane is determined to maximize the generalization ability of the classifier.

The motivation for considering binary classifier SVM comes from the theoretical bounds on the generalization error[13]. 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 γ

Considering the binary classification task with data point x_i($i = 1,2,\ldots,m$) having labels $y_i = \pm 1$ and the decision function be

$$f(x) = \text{sign}\ (w.x+b) \quad (1)$$

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$\forall$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. 1. For separating w.x+b = 0 the normal vector is $\frac{w}{\|w\|}$ and hence, the margin is given by the projection of x_1-x_2 onto this vector. Since, $w.x_1+b = 1$ and $w.x_2+b = -1$, the margin is $\gamma = 1/\|w\|$. To maximize the margin the task is, therefore,

$$\min g(w) = \frac{1}{2}\left(\|w\|\right)^2 \quad (2)$$

subject to the constraints $y_i(w.x_i+b) = 0\forall i$ and the learning task can be reduced to minimization of the primal Lagrangian

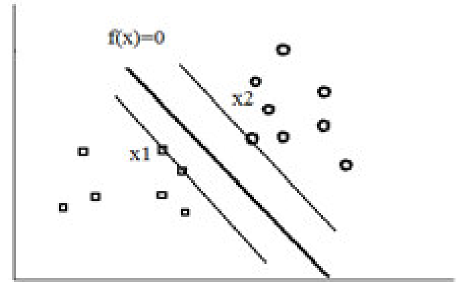

Fig. 1: Sample SVM classifier

$$L = \frac{1}{2}(w.w)-\sum_i^m \alpha_i(y_i((w.x+b)-1)) \quad (3)$$

where α_i is Largrangian multipliers, hence $\alpha_i = 0$.
The Wolfe dual Lagrangian for the equation (3) is given by

$$W(\alpha) = \sum_i^m \alpha_i - \frac{1}{2}\sum_{i,j}^m \alpha_i\,, \alpha_j y_i y_j (x_i.x_j) \quad (4)$$

which must be maximized with respect to α_i subject to the constraint $\sum_i^n \alpha_i y_i = 0$ and $\alpha_i>0$.

In Eq. 4 the data points x_i only appears inside an inner product. To get the potentially better representation of the data, we can map the data points into an alternate space generally called feature space through the replacement

$$x_i.x_j \rightarrow \varphi(x_i).\varphi(x_j) \quad (5)$$

The functional form of mapping $\varphi(x_i)$ not need to be known, since, it is implicitly defined by the choice of kernel k (xi.xj) = φ (x_i).φ (x_j) or inner product in Hilbert space. With a suitable choice of kernel the data can become separable in feature space despite being non separable in original space.

For binary classification with given choice of kernel, the learning task, therefore, involves maximization of the Lagrangian

$$W(\alpha) = \sum_i^m \alpha_i - \frac{1}{2}\sum_{i,j}^m \alpha_i\,, \alpha_j y_i y_j k(x_i,x_j) \quad (6)$$

subject to the constraint $\sum_i^n \alpha_i y_i = 0$ and $\alpha_i>0$.

The decision function, after finding the optimal value of α_i is

$$f(x) = \text{sign}\left(\sum_i^m \alpha_i y_i k(x_i,x_j)\right) \quad (7)$$

where the bias term is given by

$$b = -\frac{1}{2}\left(\left\{min_{[y_i|x_i]=-1} \Big| \sum_{[sv]} \alpha_i\, y_i\right\} + \left\{max_{[y_i|x_i]=-1} \Big| \sum_{[sv]} \alpha_i\, y_i\right\}\right) \quad (8)$$

where {SV} is a set of points for which $\alpha_i>0$ and called the support vectors.

PROPOSED ALGORITHM USING SVM

To obtain the required current signals for investigation of the proposed algorithm, a part of the power system is shown in Fig. 2. The proposed power system consists of a three phase 35 MVA, 50 HZ, 132/11 KV Y/Y transformer and 132 KV transmission line .The sample system is modelled and simulated using MATLAB 7. An extensive series of simulation studies have been carried out to obtain various power transformer transient signals for subsequent analysis. The simulations provide samples of currents in each phase when the transformer is energized or when a fault occurs on the system. Figure 3-4 show example test simulation results: the fault current and magnetizing inrush current. Data from the simulations are used as input to train SVM classifier.

Figure 5 shows the block diagram of training process. The training samples are the L-G fault and inrush currents respectively. The aim of the training process is to calculate the support vectors which are the parameters that define the optimal hyper plane. The SVM classifier distinguishes the fault current and magnetizing inrush current.

RESULTS AND DISCUSSION

The designed SVM is trained for various training patterns of fault and inrush current. The system is trained with 200 datasets and the optimum hyper plane is obtained. The optimum hyper plane for polynomial kernel function of order 2 is shown in Fig. 6. In this Fig., fault current and inrush current are denoted by two different colour circles with different colour surface. The 100 datasets are used for testing the classifier. Table 1 shows the number of support vectors and performance for each kernel. For classification of fault current and inrush current, the number of support vectors mainly depends on the choice of kernel. The system that gives fewer support vectors gives better performance.

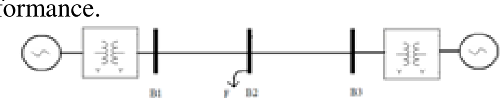

Fig. 2: Sample System

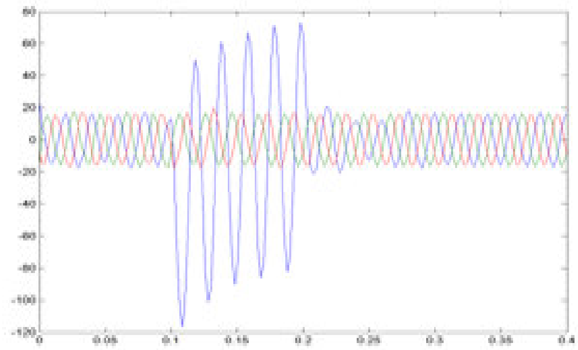

Fig. 3: L-G Fault current

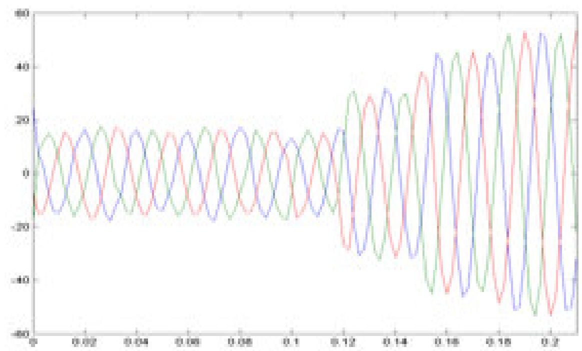

Fig. 4: Magnetising inrush current

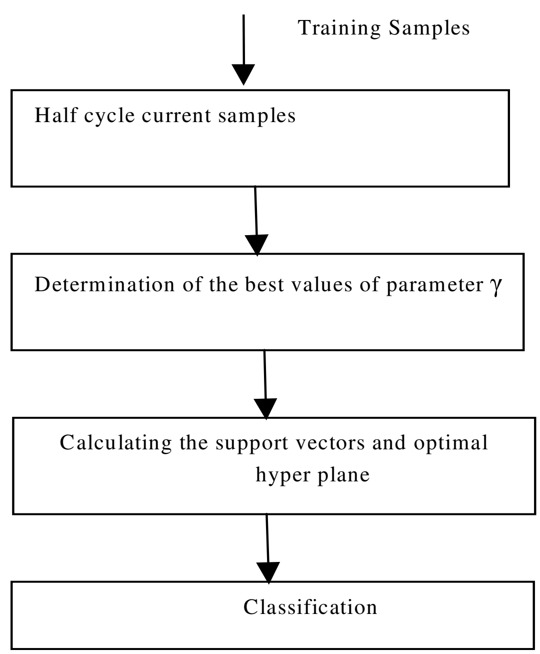

Fig. 5: Block diagram of the training process

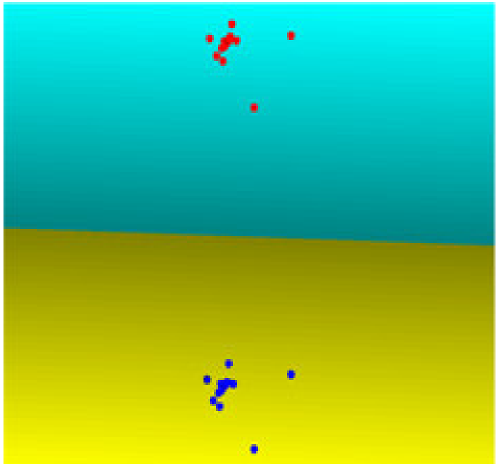

Fig. 6: Optimum hyper plane for polynomial kernel of order 2

Table 1: Performance for different kernel

Kernel	No. of support vectors	Performance %
Linear	20	95.1
Poly (n = 2)	16	98.2
Poly (n = 3)	17	98.4
RBF	15	99.55

SVM provide a new approach to the problem of distinguishing fault current from inrush current with a base of statistical learning theory. They differ from comparable approaches such as neural networks: SVM training always finds a global minimum. SVM is largely characterized by the choice of its kernel, for a particular application. For distinguishing fault current from magnetizing inrush current, Radial basis (RBF) kernel gives the better performance.

This study proposes a novel method for classification of transient events in power transformer using SVM. The method neither depends on the equivalent circuit model nor the harmonic contents of the differential currents, rather makes the decision based on current signature verification. Therefore, for modern transformers with unpredictable harmonic components, this method would be more effective. The results proved that the proposed technique is capable of classifying accurately with the RBF kernel rather than linear and polynomial kernel.

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