V.MALATHI
N.S.MARIMUTHU
S.BASKAR

J. Electrical Systems 3-5.6(2009): 64-81

Regular paper

MODERN APPROACHES FOR PROTECTION OF AUTO-RECLOSING EHV TRANSMISSION LINE

This paper proposes two approaches based on Support Vector Machine (SVM) and Extreme Learning Machine (ELM) for discrimination between line charging inrush current and the current resulting from auto- reclosing a faulted EHV transmission line. The wavelet transform is first applied to decompose the current samples into a series of wavelet coefficients. These wavelet coefficients are then employed to train SVM and ELM to classify transient events in auto-reclosing EHV transmission line. The merit of this method is demonstrated by simulation of different faults and switching conditions in a transmission line using MATLAB Simulink. The proposed methods using SVM and ELM are tested on a 230-kV, 144.4-km transmission line by varying fault resistance, fault distance, fault inception angle and switching angle. The performance of SVM and ELM is compared in terms of training time and classification accuracy with Probabilistic Neural Network (PNN) and Back propagation Neural Network (BPNN). The results proved that the classification accuracy of SVM is better than ELM, PNN and BPNN with less number of training samples. Also, SVM is robust to parameter variations such as fault resistance, fault inception angle and fault distance.

Keywords-: Extreme learning machine, inrush current, probabilistic neural network, support vector machine, Transmission line.

1. INTRODUCTION

Switching surges in transmission lines are caused by various factors. The most severe factors are the current generated due to, switching a faulted line or line charging. When breakers are closed, high line charging inrush current is generated. Also during closing or auto reclosing a faulted line, high fault current is observed. Unless, these two currents are distinguished properly, a false tripping can result. To discriminate line charging inrush current and the current resulting in closing or auto-reclosing of faulted transmission line a method is described in [1]. This technique is based on the current signal after switching and

Raja College of Engineering and TechnologyMadurai, Tamil Nadu-625 020,India1

E-mail: malathi_triven@yahoo.co.in

National EngineeringCollegeKovilpattii,Tamil Nadu,India

Thiagarjar College of EngineeringMadurai, Tamil Nadu-625 015,India

voltage signal as a reference before switching. Two cases should be recognized; closing of a breaker on a faulted line or line charging. If the case is recognized as closing a faulted line or unsuccessful auto-reclosing, the breaker should be tripped again. But, if the case is recognized as closing on line charging, the technique does not trip the breaker and the main protection takes over its normal function. The drawback of this method is that it requires the measurement of voltage in addition to current that increases the cost of hardware implementations.

Since the majority of power system protection techniques are involved in defining the system state through identifying the patterns of the associated voltages and currents the development of a normal classification techniques can be essentially treated as a problem of pattern recognition. The current resulting on closing of a breaker on a faulted line or line charging is totally different. Application of pattern recognition techniques could be employed to discriminate between current results from closing of a breaker on a faulted line or line charging. In this respect, Neural Networks (NNs) are ideally suited to deal with the complex non-linear classification problem [2-4]. Support Vector Machine (SVM) and Probabilistic Neural network (PNN) are recently used popular method for classification [5-6]. Application of SVM and PNN to power system classification problems is reported in [7-9]. Extreme Learning Machine (ELM) is another recently proposed popular method for classification problems [10-11].

In this paper, a pre-processing module based on Discrete wavelet transform (DWT) in combination with classifiers such as SVM, ELM, PNN and BPNN is used for classification of current resulting on closing of a breaker on a faulted line or line charging. This approach is applied by considering different behaviours of the current resulting on switching a faulted line and inrush conditions. The wavelet transform is firstly applied to decompose the current samples into a series of wavelet components, each of which is a time domain signal that covers a specific frequency band. Thus more distinctive features of transient signals are extracted. These wavelet components are then employed to train classifiers to classify switching events. The proposed system is tested on a 230-kV, 144.4-km transmission line under variety of fault and switching conditions. The SVM based approach is compared with ELM, PNN and BPNN for similar case studies. The SVM based approach classifies current due to, switching a faulted line or line charging inrush current accurately with fewer number of training samples whereas ELM classifies the switching events with less training time.

2. SUPPORT VECTOR MACHINE AND EXTREME LEARNING MACHINE

2.1 Support vector machine

SVM is a computational learning method based on the statistical learning theory and its theoretical foundation is described in [5]. In SVM, the input vectors are nonlinearly mapped into a high dimensional feature space. In this feature space 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. The main features of the SVM are:

The upper bound on the generalization error does not depend on the dimension of the space.

2) The error bound is minimized by maximizing the margin.

2.1.1 Support vector classification

The set of training samples

$$X = \{x_1, x_2, x_3, ..., x_n\}, x_i \in R^M \tag{1}$$

where R is radius of hyper sphere enclosing all the data points and in equ(1) each training samples xi has M features describing a particular signature and belongs to one of two classes

$$Y=\{y1, y2,\ldots,yn\}, \; y_i \in \{+1,-1\} \tag{2}$$

When data is linearly separable there exists a vector $w \in R^N$ and a scalar $b \in R$ such that $y_i(w \cdot x_i + b) \geq 1$ for all patterns in the training set (i = 1, 2,..., l). Thus, canonical hyper plane is such that $w \cdot x + b = 1$ for closest points on one side and $w \cdot x + b = -1$ for closest points, on other side. The optimal hyper-plane separates points lying on opposite classes yielding the maximum margin of separation. A separating hyper-plane which generalizes well can be found by solving the following quadratic programming problem.

$$\text{Minimize } \frac{1}{2}\left\| w2 \right\| + \text{C}\left(\sum_{i=1}^{l} \varepsilon i \right) \tag{3}$$

subject to $yi(w \cdot xi + b) \geq 1 - \varepsilon i, \varepsilon i \geq 0 \; \forall i$

The constrained optimization problem is solved by constructing a Lagrangian

$$\lambda(w,b,\alpha) = \frac{1}{2}\left\| w^2 \right\| - \sum_{i=1}^{l} \alpha_i (y_i(w \cdot x_i + b) - 1) \tag{4}$$

The Lagrangian has to be minimized with respect to the primal variables w and b and maximized with respect to the dual variable α_i.The Karush-Kuhn-Tucker conditions lead to find the solution vector in terms of the training pattern,

$$w = \sum_{i=1}^{l} \alpha i \, yi \, xi \qquad \text{for some } \alpha_i \geq 0.$$

Notice that $\alpha_i \neq 0$ only for a subset of the training patterns, precisely those few vectors that lie on the margin, called the support vectors (SVs). In the case where a linear decision boundary is inappropriate the SVM can map the input vector, x_i, to higher dimensional feature space. Under this conditions, a kernel function K(.,.) can be introduced such that

$k(x_i, x_j) = x_i \cdot x_j$. An SVM uses then the convolution of the scalar product to build, in input space, the nonlinear decision function

$$f(x) = \mathrm{sgn}\left(\sum_{i=1}^{l} \alpha_i y_i k(x, x_i) + b\right) \quad (5)$$

where x is test vector, b is found from the primal constraints and is computed by $\alpha(y_i(w \cdot x_i + b) - 1) = 0,$ i = 1,....l, such that α_i is not zero and sgn is the signal function.

2.2 Extreme learning machine

Extreme learning machine is a new learning algorithm for Single Layer Feed forward Neural network (SLFN) whose learning speed is faster than traditional feed-forward network learning algorithm like back propagation algorithm while obtaining better generalization performance [10].

The architecture of ELM is given in Fig.1 and it has several significant features [10] different from traditional popular gradient based learning algorithms for feed forward neural networks:

The learning speed of ELM is extremely fast.

The ELM has better generalization performance than the gradient based learning such as back propagation in most cases.

The traditional classic gradient based learning algorithm has several issues like local minima, improper learning rate and overfitting. The ELM tends to reach the solutions straight forward without such trivial issues.

Unlike the traditional classic gradient based learning algorithms which only work for differentiable activation functions, ELM algorithm can be used to train SLFNs with many non differentiable activation functions.

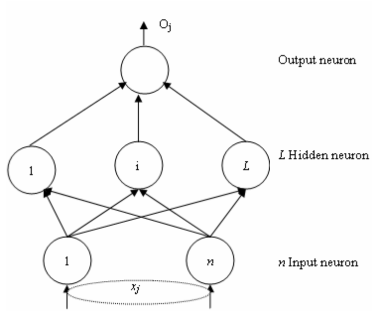

Figure.1 : Feed forward network architecture

ELM randomly assigns and fixes the input weights wi and biases bi based on some continuous probability distribution function in the case of learning a structured function only leaving output weights β to be adjusted according to

$$\min_{\beta}\left\|H\beta - T\right\|_2 \tag{6}$$

The above problem is well established and known as a linear system optimization problem. Its unique least-squares solution with minimum norm is given by:

β= H†T (7)

where H is hidden layer output matrix and H† is the Moore-Penrose generalized inverse of the matrix H. Given a training set $\mathrm{N}=\{(x_i, t_i) | x_i \in R^n, t_i \in R^m, i=1,\ldots,N\}$,

activation function g(x), and number of hidden node L, the algorithm is given by,

Step 1: Randomly assign input weight wi and bias bi, i = 1,.., $\tilde{N}$.

Step 2: Calculate the hidden layer output matrix H.

Step 3: Calculate the output weight β

β= H†T,

where T = [t1,…,tN]T.

3. SYSTEM STUDIED

The single line diagram of a Chekkanoorani- Tuticorin 230 KV line of Tamil Nadu Electricity Board, India is shown in Fig.2. System parameters and line configuration are given in Appendix A. The sample system is modelled and simulated using MATLAB Simulink.

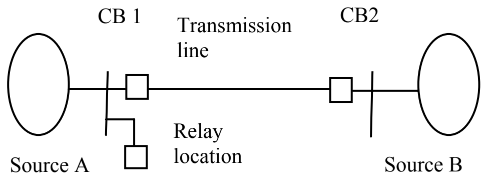

Figure.2. Sample system

4. PROPOSED ALGORITHM

The framework of proposed protection scheme is shown in Fig.3. MATLAB Simulink is used to simulate switching conditions and fault data for different power system conditions. The wavelet multi-resolution analysis is used for decomposing each signal into high frequency details. The information is used for extracting the features and forming the patterns for ELM, SVM, PNN and BPNN. The training and testing patterns are normalized to [+1 -1]. The target output of the SVM and ELM is built in such a way that the value “1” represents switching a faulted line; the value “-1” represents line charging inrush current.

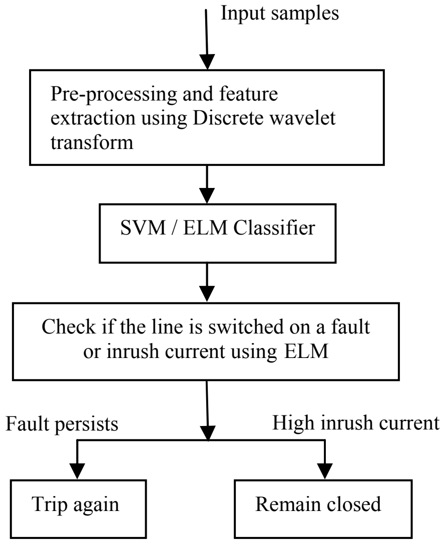

Figure.3 Flow diagram of proposed protection scheme using classifiers

4.1. Feature extraction using DWT

The signals are sampled at a sampling frequency of 20 kHz. The wavelet transform technique is first applied, in order to, decompose the different current signals into a series of wavelet components, each of which is a time domain signal, that covers a specific frequency band. The ability of the wavelet transform to focus on short time intervals for high frequency components and long time intervals for low frequency components improves the analysis of transient signals. For this reason, wavelet decomposition is ideal for studying transient signals and obtaining better current characterization and a more reliable discrimination [12]. In this paper, Daubechies wavelet (db4) is used as mother wavelet for feature extraction after several simulation studies. Based on 20 kHz sampling rate, the frequency components are confined to wavelet analysis according to the scheme listed in Table.1. Line charging inrush current and current resulting in auto-reclosing of faulted line for L-G fault is shown in Figs.4-5.

Table.1 Frequency allocation in wavelet analysis

Wavelet Analysis	Frequency components, kHz
D1	10-20
D2	5-10
D3	2.5-5
D4	1.25-2.5

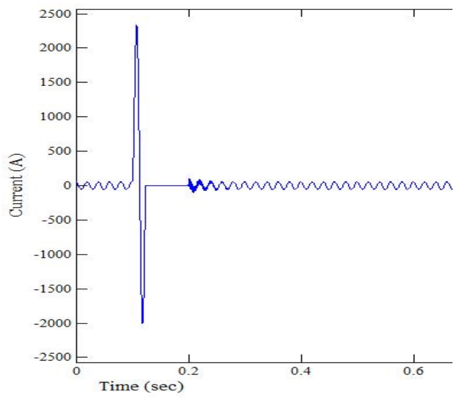

Figure.4: Current resulting in a closing of breaker after fault clearance

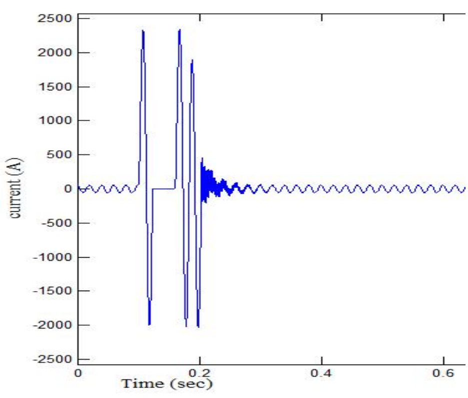

Figure.5 : Current resulting in a closing of faulted transmission line

4.2. Parameter Selection

In SVM, the generalized accuracy is estimated using different combinations of cost parameters C and kernel parameter σ. The value of the parameter range C is trailed between 1 and 1000 and σ is chosen between 0.05 and 1.5. The best performance is obtained for C as 100 and σ as 1.0 for classification problem. Although there are many variants of BP algorithm, a faster BP algorithm called Lavenberg-Marquardt is used in this paper. For Lavenberg-Marquardt BPNN and ELM, the parameter to be selected is only hidden neurons. For BPNN and ELM, the numbers of hidden neurons are gradually increased by 1 and the nearly optimal number of hidden neurons for BPNN and ELM are then selected based on cross validation method. The number of hidden neurons selected for classification problem with ELM and BPNN are 11 and 6 respectively. After several simulations the spread selected for PNN is 0.1.

4.3. Training and Testing

Training is carried out in two categories; one is training the classifiers with less number of training samples and another is with large number of training samples. The designed SVM and ELM classifiers are trained for various training patterns of fault and inrush current. In the first case, 160 dataset (120 dataset for fault condition and 40 dataset for inrush condition) is simulated for different fault and inrush conditions. The fault is simulated with a fault resistance of 1Ω and fault inception angle of 00 at 50% of transmission line length. In the second case the classifiers are trained with 560 dataset (480 dataset for fault condition and 80 dataset for inrush condition). The fault simulation studies have been carried out under variation of fault inception angle (0º, 45º), fault resistance (1Ω, 20Ω), and fault locations (30%, 50%, 80%). To prove the generalization ability of classifiers, the system is tested by varying the fault resistance (Rf=10Ω-50Ω), fault distance (20%-90%) and fault inception angle (FIA= 00- 900). The 100 datasets are used for testing the classifier. The same system is trained and tested with PNN and BPNN with same samples to compare the performance of the classifiers with SVM and ELM.

All the simulations for the ELM, SVM, PNN and BPNN algorithms are carried out in MATLAB 7 environment running in a Pentium IV, 1.75 GHz CPU. In SVM, RBF kernel is used for fault classification of transient events. For ELM and BPNN sigmoidal function is used as activation function. The simulations for SVM are carried out using SVM toolbox [13] in MATLAB environment. ELM is implemented in MATLAB version [14]. Probabilistic neural network and Lavenberg-Marquardt backpropagation algorithm available in MATLAB Neural Network Toolbox is employed.

5. SIMULATIONS RESULTS AND DISCUSSIONS

An extensive series of studies are carried out in order to ascertain the overall performance of the four networks. The test sets (which not included as part of the training sets) are composed of over 100 cases including different fault resistance, fault inception angle, fault distance and inrush current. The training accuracy and time for classifiers with 160 training set are given in Table.2. The classification accuracy of classifiers for 160 dataset is listed in Table.3. The classification accuracy of classifiers with 560 dataset is given in Table.4. As observed from Table.2, the training time of ELM is less than SVM, PNN and BPNN. From Table.3, the classification accuracy of SVM is better than ELM, PNN and BPNN with less number of training samples. Table.4 proved that classification accuracy of ELM is more or less similar to SVM with large number of training samples.

Table.2. Comparison of training accuracy, training time of ELM, SVM, PNN and BPNN for classification of switching events

Classifier	Training accuracy (%)	Training time(s)
ELM	99.5	0.0124
SVM	100	0.5304
PNN	100	0.4212
BPNN	100	1.5912

Table.3 Comparison of classification accuracy of ELM, SVM, PNN and BPNN with 160 dataset

Classifier	Number of samples tested	Classification rate (%)
ELM	100	84
SVM	100	98
PNN	100	78
BPNN	100	83

Table.4 Comparison of classification accuracy of ELM, SVM, PNN and BPNN with 560 dataset

Classifier	Number of samples tested	Classification rate (%)
ELM	100	96
SVM	100	99
PNN	100	89
BPNN	100	94

6. CONCLUSION

A technique for discrimination between the line charging inrush current and the current resulting on closing or auto reclosing a faulted transmission line using SVM and ELM is presented in this paper. Extensive studies indicate that the proposed approach using SVM is able to classify line charging inrush current and the current resulting on auto reclosing a faulted EHV transmission correctly with less number of training samples and its performance is not affected by the changing network conditions. The training time of ELM is less than SVM, PNN and BPNN and the classification accuracy of ELM is close to SVM and better than BPNN and PNN with large number of training samples. Though ELM has fast learning speed, SVM possesses better generalization performance than ELM, PNN and BPNN. Hence SVM can be used to discriminate between line charging inrush current and the current resulting on closing or auto reclosing a faulted transmission line accurately with less number of training samples.

References

[1] M.M.Eissa and O.P.Malik, A Novel Approach for Auto-Reclosing of EHV/UHV Transmission Lines, IEEE Trans.On Power Delivery, Vol.15,pp. 908-911, 2000.

[2] M.Sanaye-Pasans, H.Khorashadi-Zadeh, An extended ANN-based highspeed accurate distance protection algorithm, International Journal of Electrical Power and Energy Systems, Vol.28, pp. 387-39, 2006.

[3] P.K.Dash, A.K.Pradhan and G.Panda, Application of minimal radial basis function neural network to Distance protection, IEEE Trans. Power Delivery, Vol.16, pp. 68-74, 2001.

[4] P.K.Dash, S.R.Samantray , An accurate fault classification algorithm using a minimal radial basis function neural network, Engineering intelligent systems, Vol.4, pp. 205 – 210, 2004.

[5] V.N Vapnik, The nature of statistical learning theory, (Springer Verlag 1995).

[6] D.F. Specht, Probabilistic neural networks, Neural Networks, Vol.3, 109-118, 1990.

[7] P.K.Dash, S.R.Samantaray, Ganapathy Panda, Fault classification and section identification of an advanced series compensated transmission line using support vector machine, IEEE Trans. Power Delivery, Vol.22, pp. 67-73, 2007.

[8] Peter G.V Axelberg, Irene Yu-Hau Gu, Math H.J Bollen, Support vector machine for classification voltage disturbances, IEEE Trans. Power Delivery, Vol. 22, pp. 1297-1303, 2007.

[9] Mishra.S, Bhende.C.N, Panigrahi, B.K , Detection and classification of power quality disturbances using S-transform and Probabilistic Neural Network, IEEE Trans. on Power Delivery, Vol.23, pp. 280-287, 2008.

[10] Guang- Bin Huang, Qin-Yu Zhu, Chee-Kheong Siew, Extreme learning Machine:Theory and applications, Neurocomputing, Vol.70, pp. 489-501, 2006.

[11] Nan-Ying Liang, Paramasivam Saratchandran, Guang-Bin Huang , Classification of mental tasks from EEG signals using Extreme Learning Machine, International Journal of Neural Systems, Vol.16, pp. 29-38, 2006.

[12] Nan Zhang, Mladen Kezunovic, Transmission line boundary protection using wavelet transform and neural network, IEEE Trans. on Power Delivery, Vol.22, pp. 859- 869,2007.

[13] Steve R.Gunn, SVM Toolbox, Available

http://www.isis.ecs.soton.ac.uk/resources/syminfo
http://www.ntu.edu.sg/home/egbhuang/

Appendix A. Appendices

1) Source parameters

Fault level in Chekkanoorani 9439 MVA and fault level in Tuticorin 8448 MVA.

2) Transmission line parameters

230 kV 144.4 km transmission line.

Z_0= 0.2636+j 1.5077 Ω,

Z_1= 0.07913+j0.4028 Ω