Knowledge-Based Approach Using Support Vector Machine for Transmission Line Distance Relay Co-ordination

Ravikumar B. *, D. Thukaram† and H. P. Khincha*

Abstract – In this paper, knowledge-based approach using Support Vector Machines (SVMs) are used for estimating the coordinated zonal settings of a distance relay. The approach depends on the detailed simulation studies of apparent impedance loci as seen by distance relay during disturbance, considering various operating conditions including fault resistance. In a distance relay, the impedance loci given at the relay location is obtained from extensive transient stability studies. SVMs are used as a pattern classifier for obtaining distance relay co-ordination. The scheme utilizes the apparent impedance values observed during a fault as inputs. An improved performance with the use of SVMs, keeping the reach when faced with different fault conditions as well as system power flow changes, are illustrated with an equivalent 265 bus system of a practical Indian Western Grid.

Keywords: Apparent impedance loci, Distance relay, Fault resistance and knowledge-base, Support vector machines, Zonal co-ordination

1. Introduction

Transmission line protection using distance relays is widely used as it provides both primary and backup protection by its zonal settings correctly coordinated between distance relays. It is desired that a distance relay covers most of the line in its first zone of protection. Also, it must not operate for faults beyond the remote bus even for the most unfavorable of system conditions The usual practice is to set the relay to cover 80% - 90% of the line length. Since system uncertainties such as variations in system parameters, load current, charging current, metering errors, etc. are not usually considered in distance relay setting, the relay may unexpectedly fail to operate for an internal fault or mal-operate for an external fault under certain system conditions.

System-wide disturbances have once again become a major concern in the power industry as a result of the Northeast blackout on Aug. 14, 2003. The blackout affected an estimated 50 million people, and more than 61,800 MW of load was lost in parts of Ohio, Michigan, New York, Pennsylvania, New Jersey, Connecticut, Massachusetts, Vermont, and the province of Ontario. The blackout had several causes or contributory factors in common with the earlier outages, including inadequate coordination of relays and other protective devices or systems [1].

Many papers have been published in the literature on the computer aided protection of distance relays [2-4], investigating the problems related [5-7], and the application of new techniques to improve the protection philosophy [8-11].

Sidhu *et al.* [2] have presented a method for calculating zone-2 settings of distance relays. The method is based on conducting fault studies by taking into account single-level contingencies and the infeeds from all sources including those connected to the re-mote bus. In [3], Kim *et al.* have presented a scheme for transmission line fault detection using zone 3 and the transient components that are combined by using the state diagram. An automated methodology for distance protection settings of transmission-line protection based on the concept of events and consequences has been presented by El-Arroudi *et al.* [4].

The purpose of [5] by Horowitz and Phadke is to reexamine the application of zone 3, to describe situations where it can be properly utilized, where it can be removed without reducing the reliability of the system protection and, if used, how it can be modified or set. A table is presented for a variety of station designs and protection schemes including two common local backup relay systems and the associated application of a remote third zone. Tseng *et al.* [6] have proposed the use of load models to explore their effects on distance protective relay settings in Taiwan Power's extra-high voltage transmission lines system and has drawn significant conclusions. Reference [7] investigates the issues of the Detection of Electrical Center, Relay Ranking Problem, Fault or Contingency Ranking Problem, and Out-of-Step Detection Problems related to the performance of distance relaying under power swings.

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Received 29 February, 2008; Accepted 28 May, 2008

The adaptation of the relay operating region to system changing condition has been addressed by Li *et al.* in [8]. And the concept of using neural networks as a digital distance relay has been presented. Bhalja and Maheshwari have presented an adaptive distance relaying scheme for various power system effects using RBFNN to avoid the problems encountered by pilot independent relay in [9]. Orduña *et al.* [10] have suggested a system for online adaptive setting and coordination of protection relays in meshed networks. Brahma [11] has presented wavelet transform to detect power swings as well as any fault during a power swing. The out-of-step blocking function in distance relays is required to distinguish between a power swing and a fault.

However, as the power systems undergo fundamental changes, such as those brought on by open access and deregulation, one must reexamine this traditional protection philosophy, especially when the power system is stressed. Due to operational demands imposed on the transmission network, it has become clear that the need for adapting intelligent-based schemes in protection philosophy is increasing. This paper presents a transmission line distance relaying co-ordination approach along with the detailed analyses of the apparent impedance as seen from the relaying location taking into account the flow of line and fault resistance. Support Vector Machines as a pattern classifier are used for obtaining distance relay co-ordination. The scheme utilizes the apparent impedance values observed during a fault as inputs. SVMs are used to build the underlying concept between reach of different zones and the impedance trajectory during fault. An improved performance with the use of SVMs, maintaining the reach when faced with different fault conditions as well as line flow changes, are illustrated with an equivalent 265-bus system of a practical Indian Western grid.

2. Transmission Line Distance Relay Co-ordination

2.1 Conventional

Power system protection at the transmission level is based on distance relaying. Conventional distance relaying algorithms are setup for the particular condition of a system. Generally, the protection system using distance relays involves three zones [12-15]. The first zone (Z_1) of the relay is set to detect faults on 80%-90% of the protected line without any intentional time delay. The second zone (Z_2) is set to protect the remainder of the line plus an adequate margin. Second zone relays are time delayed for 15-30 cycles to coordinate with relays at the remote bus. The settings of the third zone (Z_3) ideally will cover the protected line, plus all of the longest line leaving the remote station. Z_3 of a distance relay is used to provide the remote backup protection in case of the failure of the primary protection. Since Z_3 covers an adjacent line, a large infeed (outfeed) from the remote terminal causes the relay to underreach (overreach). Thus, a very large load at the remote terminal may cause distance relays to mal-operate. Settings for conventional distance relays must be selected to avoid overreach/underreach operation under the worst case scenarios.

2.2 Proposed Co-ordination using SVMs:

Following a disturbance, the distance relays at different locations will observe different swing characteristics in the R-X plane, and if a swing trajectory enters zone-1, then it is considered as severe enough to cause system instability, and the relay will trip depending on the Time Dial Setting (TDS). The characteristics trajectory will also be different for different points on a line.

Suppose a stable system at time t_0 is subjected to a fault on a transmission line at time t_1. The conventional relay algorithm will detect the fault, fault type, discriminate the zone settings based on preset reach values and TDSs, and clear the fault at time t_2. During this period, possible events are opening of the faulted line, some generators falling out-of synchronism, and some load rejection. The transient stability program [16] is used to obtain the apparent impedance trajectory seen by different relays of the system. This program is extensively used for stability studies of several of India's Power Networks. The program simulates the impedances seen during three time laps. The first time lap T_1 consists of impedances seen before the occurrence of a fault ($T_1 = t_1 - t_0$ Sec.). The second time lap T_2 consists of impedances seen during a fault ($T_2 = t_2 - t_1$ Sec). After the fault has been cleared and we have observed the system till time t_3, then the third time lap T_3 consists of impedances seen during post-fault time ($T_3 = t_3 - t_2$). The feature vector consists of the apparent impedances seen by the relay located on a line during fault time T_2.

Let a conventional fault detection algorithm detect the fault at time t_d ($t_1 < t_d < t_2$). From t_d to the next one or two cycles (t_e) fault data information will be captured to form a feature vector. The size of the feature vector now will depend on the simulations time step during the gap $t_e - t_d$. In this paper, we are mainly concentrating on discriminating the zones based on the available knowledge obtained from the simulations, which is an important aspect of protecting a transmission line. Fig. 1(a) shows the collection of apparent impedance values observed by the relay and Fig. 1(b) shows the training/testing of the SVM. Fig. 1(a) and Fig. 1(b) collectively display the implementation of the proposed method at a relay location. Support Vector Machines are used to capture the underlying concept/model between reach of different zones and the impedance swing trajectory characteristics. In this paper, this information is intelligently utilized for identifying the different zonal settings of a relay.

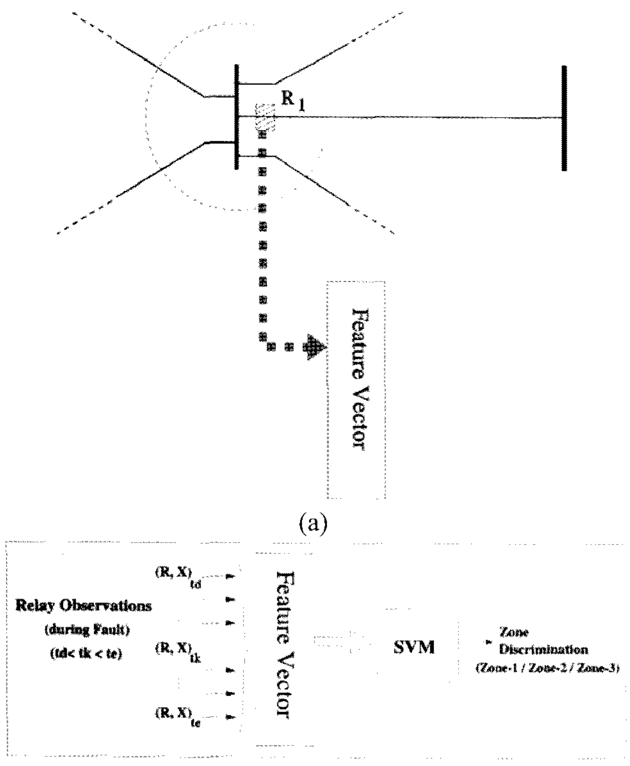

Fig. 1. Substation Implementation of the Proposed Method; (a) Collection of features from relay input to generate input data for SVM; (b) Discrimination of feature data using SVM for identifying the zones

3. Brief Review on Support Vector Machines:

Support Vector Machines are a new learning-by-example paradigm spanning a broad range of classification, regression, and density estimation problems. They were first introduced by Vapnik *et al.* [17, 18] and are described in more detail by B. Schölkopf *et al.* [19, 20]. The roots of this approach are the so-called support vector (SV) methods of constructing the optimal separating hyperplane for pattern recognition. The SV technique was generalized for nonlinear separating surfaces in [20], and it was further extended for constructing decision rules in the non separable case. The training task involves optimization of a convex cost function conveying to a technique without local minima.

3.1 Support Vector Classification

The problem of classification consists of estimating a function $f: R^N \rightarrow \{\pm 1\}$ using 1 i.i.d. input–output training data $(X_1, y_1), \ldots, (X_l, y_l) \in R^N \times \{\pm 1\}$ from a dataset D such that f classifies correctly unobserved data (x, y) (i.e., $f(x) = y$ for examples (x, y) generated from some underlying probability distribution $P(x, y)$). In other words, the loss function L can be defined by (1)

$$L(y_i, f(x_i)) = |1 - y_i f(x_i)|_+ \tag{1}$$

Where $|val|_+ = \max\{0, val\} \quad val \in R.$

A brief review of support vector classification (SVC) [21-24] is presented in this section; 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 $(i = 1, \ldots l)$. The optimal hyper plane separates points lying on opposite classes yielding to the maximum margin separation. A separating hyper plane which generalizes well can be found by solving the following quadratic programming (QP) problem (for $i = 1, \ldots l$):

$$\begin{aligned} &\underset{w}{\text{Minimize}} \quad \frac{1}{2}\|w\|^2 \\ &\text{subject to} \quad y_i(w \cdot x_i + b) \geq 1, \quad \forall i. \end{aligned} \tag{2}$$

This constrained optimization problem is solved by constructing a Lagrangian

$$\lambda_P(w, b, \alpha) = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{l} \alpha_i \left(y_i (w \cdot x_i + b) - 1\right) \tag{3}$$

The Lagrangian has to be minimized with respect to the primal variables w and b and maximized with respect to the dual variables α_i. The Karush–Kuhn–Tucker (KKT) conditions lead to find the solution vector in terms of the training patterns, $w = \sum_{i=1}^{l} \alpha_i y_i x_i$ 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). Under certain conditions, a kernel function $K(.,.)$ can be found such that $K(x_i, x_j) = x_i \cdot x_j$. An SVM then uses the convolution of the scalar product to build, in input space, the nonlinear decision function

$$f(x) = \operatorname{sgn}\left(\sum_{i=1}^{l} \alpha_i y_i K(x, x_i) + b\right) \tag{4}$$

Where b is found from the primal constraints and is computed by $\alpha_i\left(y_i\left(w\cdot x_i+b\right)-1\right)=0, i=1,\ldots l,$ such that α_i is not zero and sgn is the signal function.

When the training data is not linearly separable, a separating hyper plane does not exist. Besides, when real data sets are used, SVMs can fit noise and outliers leading to poor generalization. Thus, a hard margin classifier is no longer adequate. Introducing a soft margin, the learning task is essentially the same as indicated in (2) except for the introduction of the penalty term C and the slack variable ξ. The classifier then tries to separate the data by minimizing the objective function

$$\begin{aligned} &\underset{w}{\text{Minimize}}\ \frac{1}{2}\|w\|^2+\frac{C}{l}\sum_{i=1}^{l}\xi_i \\ &\text{subject to}\ y_i\left(w\cdot x_i+b\right)\geq 1-\xi_i, \\ &\qquad 0\leq\alpha_i\leq C/l,\quad \xi_i\geq 0 \end{aligned} \tag{5}$$

for $i=1,\ldots,l$. In this sense, it acts by controlling the classifier capacity and the number of training errors. In other words, the task is now to minimize the sum of errors $\sum_{i=1}^{l}\xi_i$ in addition to $\|w\|^2$. Again this optimization problem can be transformed into a QP problem. The value of C can be found by experimentation in a validation set and cannot be determined from either the model or the data set.

3.2 Multi Class Classification

Basically, the two types of approaches usually followed for the extension from the binary two-class problem to n classes are: 1) to modify the design of the SVMs in order to incorporate multi-class learning in the quadratic solving algorithm [25] and 2) to combine several binary classifiers [26]. In the second case, methods like "one-against-all" and "one-against-one" have been proposed where typically a multi-class classifier is constructed by combining binary classifiers. In this paper "one-against-one" method is used for multi-class classification, because of its less training time over "one-against-all".

3.3 Kernel Choice

The use of kernel methods [27] provides a powerful way of obtaining nonlinear algorithms capable of handling non-separable data sets in the original input space. The basic idea is to construct a mapping into a higher dimensional feature space by the use of reproducing kernels. The kernel function is a positive definite function $R^n\times R^n$ to R^n that defines an embedding of input patterns into feature vectors.

Training is carried out with different types of kernel function like Linear Kernel $K(x,y)=x^1\cdot y$, Polynomial Kernel $K(x,y)=\left(\gamma(x\cdot y)+r\right)^{Degree}$ with $\gamma>0$, Radial Basis Kernel $K(x,y)=\exp\left(-\gamma\|x-y\|^2\right)$ where $\gamma>0$ related with the kernel width, Sigmoid Kernel $K(x,y)=\tanh\left(\gamma(x\cdot y)+r\right)$ where γ and r are kernel parameters.

3.4 SVM Model Selection:

In any predictive learning task, such as classification, an appropriate representation of examples as well as the model and parameter estimation method should be selected to obtain a high level of performance of the learning machine. Under the SVM's approach, the usual parameters to be chosen are the following:

1. the penalty term C which determines the trade-off between the complexity of the decision function and the number of training examples misclassified; and
2. kernel function parameters.

4. System Studies and Results:

The proposed distance relay co-ordination approach using SVMs has been tested on the Western regional grid of India. The geographical network of the system is shown in Fig. 2. The equivalent system consists of 265 busses, 105 transformers, 389 transmission lines (includes 400 kV and 220 kV lines), 54 generators (hydro and thermal units), 155 loads, and 16 shunt compensators. The system has about 14337.0 MW real and 6461.0 MVAR reactive loads. The generators are represented by IEEE Standard models.

Fig. 2. Geographical Diagram of Indian Western Regional Grid

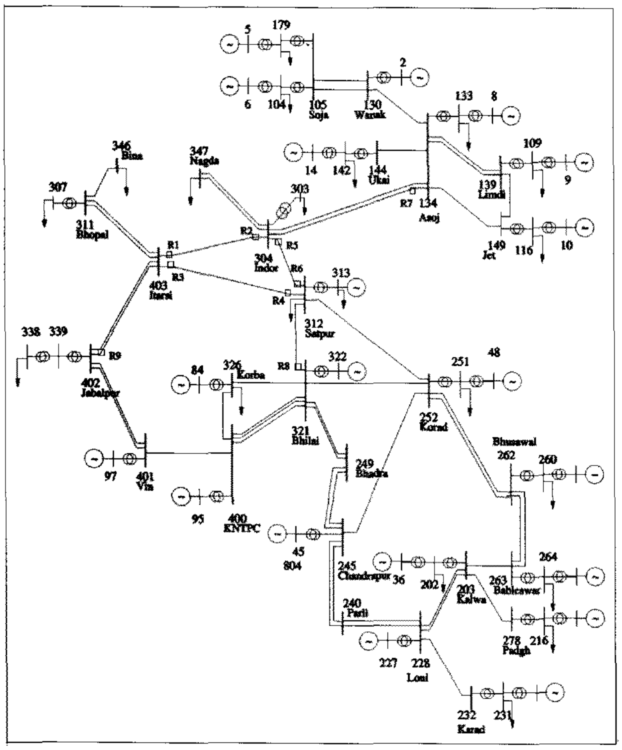

Fig. 3. Single Line Diagram of a Portion of the Indian Western Grid

The single line diagram of a part of the system under consideration for relay co-ordination is shown in Fig. 3. The buses are numbered to facilitate the identification of the regional area of different parts of the western region grid. In this paper, the relay R_1 at substation 403 of the line connected between busses 403 and 304 is considered for applying the proposed approach. Line 403-304 has adjacent transmission lines 304-312, 304-134 (parallel double circuit lines), and 304-347 (parallel double circuit lines). The lines 134-149, 134-144, 134-139 (double circuit), 134-130, 312-403, 312-321, and 312-252 are next adjacent to 403-304 as given in Fig. 3.

4.1 Conventional Method

The mho characteristics of relay R_1 at substation 403 (on the line 403-304) are worked out using the rules developed in [13-15]. These mho characteristics are also indicated in Figures 4 to 9 for comparison purpose.

4.2 Illustration of Proposed Approach

The substation at bus 403 and the relay R_1 at substation 403 on the line connecting busses 403 and 304 (line 403-304) is considered for applying the proposed approach of distance relaying. The transient stability program is used to obtain the apparent impedance trajectory seen by different relays of the system during the time laps T_1, T_2, and T_3. Fig. 4 shows the observations made by some relays during the times T_1, T_2, and T_3 for a three-phase fault with fault resistance (R_f) value of 0Ω on line 403-304 at 55% distance away from bus 403. This indicates that the relays at different locations will see different apparent impudent loci following a fault on a line. Fig. 5(a) to Fig. 5(f) shows the R_1 relay's observations for a 3-phase fault (R_f=0Ω) on the lines 403-304 (on its own line), 304-347, 304-134, 304-312, 402-403, and 312-403 at 55% distance from the buses respectively. As such, relay observations for different fault conditions are different. Fig. 4 and Fig. 5 give the impedance loci for times T_1, T_2, and T_3.

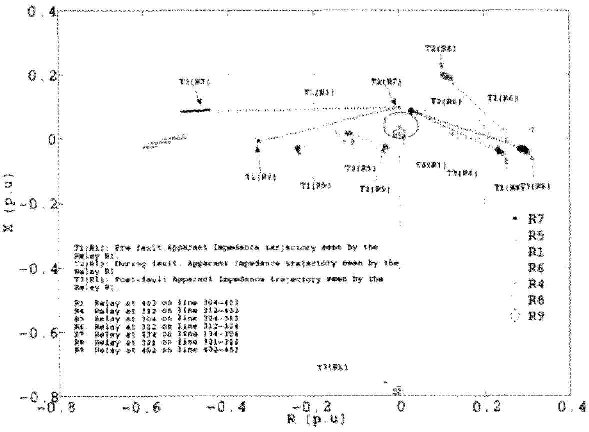

Fig. 4. Observations made by Relays (R_1, R_4, R_5, R_6, R_7, R_8, and R_9) at different locations when fault occurs on line 403-304 at 55% distance away from 403 (R_f is 0 ohms)

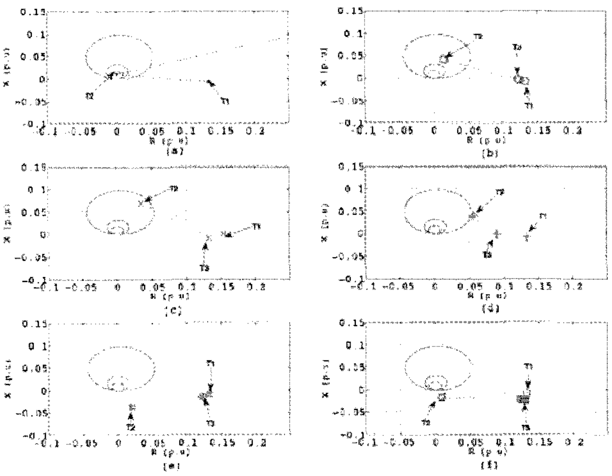

Fig. 5. Observations of Relay R_1 (located at 403, on line 403-304) for faults on the lines (a) 403-304 (b) 304-347 (c) 304-134 (d) 304-312 (e) 402-403 and (f) 312-403 with 0 Ω fault resistance at 55% distance from the substation, respectively.

a) Effect of fault location and fault resistance (R_f):

Fig. 6 provides the relay observations of R_1 during time

T_2 for 3-phase faults (R_f =0Ω) on lines 304-403, 304-312, 312-403, 402-403, 312-321, 312-252, 304-347, 134-304, 321-326, 134-149, 130-134, and 134-139 at 10% distance increments beginning from 5% from their from bus substations. Fig. 7 shows the observations made by relay R_1 for variation in fault resistance value over 0Ω, 10Ω, 20, 30, 40, and 50Ω and fault location varied over 5% to 95% in 10% distance increments. From the above observations it is clear that a trained and frozen classifier with different fault conditions is well suited in the distance relaying algorithm. Support vector machines are adopted as classifiers. To illustrate the algorithm, only 3-phase faults are considered in this paper. A normal operating system at time 0 seconds is subjected to 3-Ph fault on a line time of 0.1Sec and cleared the fault by isolating the line from operation at time 0.2 seconds. The time of simulation is taken up to 1.0 Sec after the fault is cleared. In this case, the time laps T_1 is 0.1Sec, T_2= (0.2-0.1) =0.1Sec and T_3= (1.0-0.2) =0.8Sec.

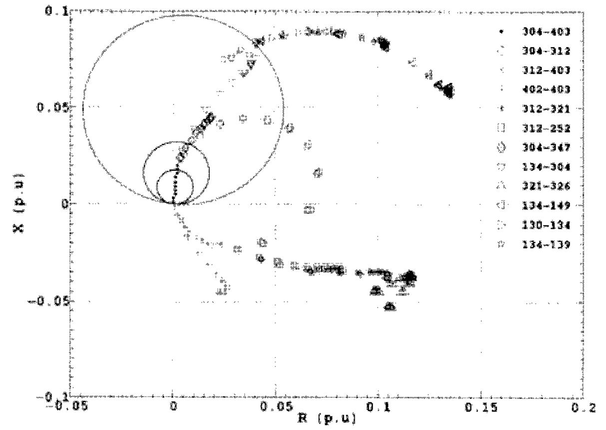

Fig. 6. During fault time T_2, Relay R_1 observations for faults on various lines, with varying distances (5% to 95% in increments of 10%) from the substations (with R_f= 0Ω)

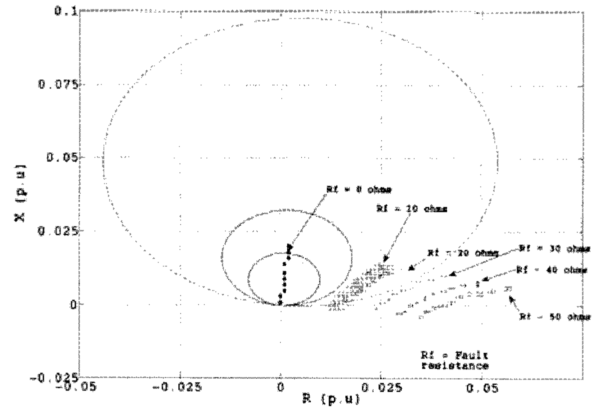

Fig. 7. During fault time T_2, Relay R_1 observations for faults on the line 403-304 with varying fault locations and fault resistance values that are used for training in Table 1.

Unlike the rules developed for identifying zone-1, zone-2, and zone-3 settings of the conventional algorithm, the proposed approach classifies the zones based on the connectivity of the lines. Zone-1/ Class-1 represents the primary protection of its own line on which the relay of interest is located (in this case, the line for R_1 is 403-304). Zone-2/Class-2 represents the lines that are connected to the receiving end of the primary line. In this case, the lines 304-347 ($\|^{el}$), 304-134 ($\|^{el}$), 304-312, and a transformer 304-303 supplying load are connected to the primary line 403-304. So Zone-2 elements are 304-347 ($\|^{el}$), 304-134 ($\|^{el}$), and 304-312. Zone-3/Class-3 represents the lines that are adjacent to the primary line. The lines 134-149, 134-139 ($\|^{el}$), 134-144, 134-130, 312-321, 312-252, and 312-403 are under the Zone-3 backup of relay R_1. The details of generating the training patterns and testing patterns for evaluating the classifier performance are listed in Table 1. Once the SVM is trained using the training data with optimal model parameters, the zone settings in terms of decision boundaries described by (4) are frozen by SVM and are ready to be tested on unseen testing data.

Table 1. Details of training and test pattern generation

<table>
<tr><th rowspan="2">Line (From-to buses)</th><th rowspan="2">Class/ Zone Label</th><th colspan="2">Fault distance from relay location and fault resistance values</th></tr>
<tr><th>Training</th><th>Testing</th></tr>
<tr><td>403-304</td><td>1</td><td rowspan="2">At 5%, 15% … 95% distances of their total line length (total 10)</td><td rowspan="2">At 20%, 40%, 60%, and 80% distances of their total line length (total 4)</td></tr>
<tr><td>304-347($\|^{el}$), 304-134($\|^{el}$), 304-312</td><td>2</td></tr>
<tr><td>134-149, 134-139($\|^{el}$) 134-144, 134-130, 312-321, 312-252, 312-403</td><td>3</td><td>R_f is varied over the values of 0Ω, 10, 20, 30, 40, and 50Ω</td><td>R_f is varied over the values of 3Ω, 15, 25, 45, and 60Ω</td></tr>
</table>

Table 2. 403-304 line flow details for different generator schedule cases

	Case No.	Flow in the line 403-304 (MVA)
Training	1	571.6 - j 60.5
	2 (Base case)	718.4 - j 44.9
	3	487.9 - j 33.0
Testing	4	555.6 - j 32.0

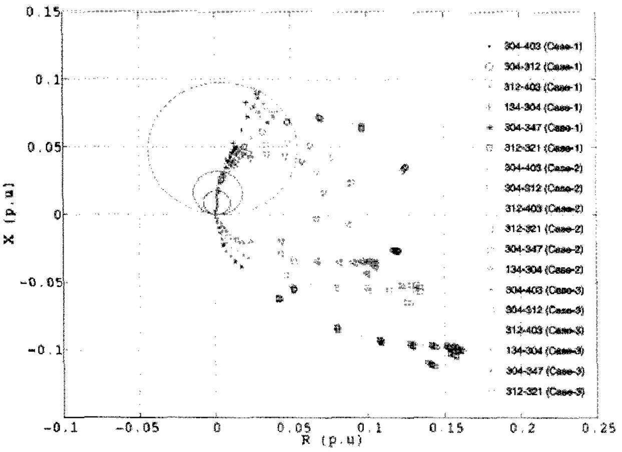

Fig. 8. Apparent impedance loci observed by relay R_1 during fault time T_2, when flow through the line 403-304 is varied over the operating range (case-1 to case-3) while faults are created at various locations on its own line, adjacent lines, and on next adjacent lines (with $R_f = 0\ \Omega$).

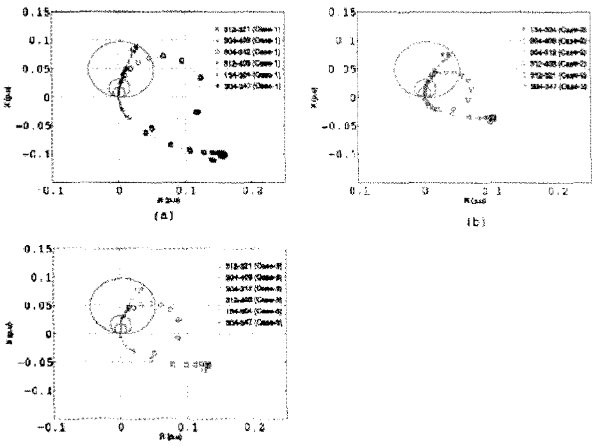

Fig. 9. (a)-(c): Apparent impedance loci observed by relay R_1 during fault time T_2 for case-1 to case-3 respectively, while faults are created at various locations on its own line, adjacent lines, and on next adjacent lines ($R_f = 0\ \Omega$).

b) Effect of Transmission Line Flow Variations:

As the power systems undergo fundamental changes, because of the load variations in day-to-day operation, we are observing unusual generation and power flow patterns with its associated uncertainties regarding protection and control. To incorporate the operational demands imposed on the transmission network, the variations in the transmission line flows are considered in the proposed SVM distance relaying approach. This is achieved by simulating the training patterns corresponding to the possible changes in the line flows to meet the load variation. The load variations are set to have a wide range of variations in the flow of the line 403-304. Among these combinations, 3 different line flow variations are identified for simulating training patterns and another value of line flow variation is recognized for simulating testing patterns as shown in Table 2.

c) Generation of Training and Testing Patterns:

To train the SVMs, the training patterns are generated for the 3 cases, case-1 to case-3, by simulating the 3-Ph faults at different locations with different fault resistance values as given in Table 1. Fig. 8 shows the apparent impedance loci observed by the relay R_1 for different operating conditions of the system and varying fault locations on the Zone/Class-l, Zone-2/Class-2, and Zone/Class-3 lines. Fig. 9(a)-(c) gives the detailed relay R_1 observations for case-1 to case-3 respectively for fault simulations as given in Table 1 and Table 2. The total number of training patterns generated are 3 (cases) X 11 (lines of 3 zones) X 6 (fault resistances) X 10 (distances), which = 1980 in number.

The test data for validation is generated completely on the unseen data during training. The testing patterns are generated for Case 4 by simulating the 3-Ph faults at different locations with different fault resistance values as given in Table 1. The total number of test patterns generated are 1 (case) X 11 (lines of 3 zones) X 5 (fault resistances) X 4 (distances), which = 220 in number.

The input patterns (training and test patterns) are normalized to [-1, +1] before inputting to the SVM module. For the normal scaling method, if the maximum and minimum values of the i^{th} attributes are M_i and m_i respectively, then, scaling to [-1, +1] means $x^1=2(x-m_i)/(M_i-m_i)-1$.

Training of SVM requires selecting the cost function (C) and kernel function parameters, which influence the ensuring model performance. In our simulations, we have considered radial basis function (RBF) as kernel function. RBF kernel is advantageous in complex non-separable classification problems due to its ability of nonlinear input mapping. So proper selection of the parameter γ $\{\gamma=1/(2\sigma^2)$, where σ: kernel width$\}$ is important in selecting a good RBF kernel. In this paper, LIBSVM [28, 29] is used for training and testing the support vector machines.

4.3 Model Parameter Selection:

a) Trial & Error Method

In the first series of experiments we run the classifier with several values of C and γ somehow trying to guess which combination of parameters might be the best for a "good" model. For each combination of C and γ, the SVM undergoes learning and retrieval modes. During learning mode, the network is trained with training data and is tested on the test data during retrieval mode. During these series of experiments, we found that Larger C corresponds to less number of SVs as well as higher testing accuracy although over-fitting cannot thus be avoided. Further explanation is required for these results taking into account both C and γ parameters. In fact, minimizing (½) $||w||^2$ in Equation (2) corresponds to maximize the margin $2/||w||^2$ between two classes of data. For non-separable data, the penalty term is able to reduce the training errors in the working data set. Therefore, the margin is an indicator of the generalization accuracy. In the absence of a method to compute the best trade-off between the regularization term and the training errors, the balance sought by the SVM's technique is hard to find. Thus, a larger C corresponds to assign a higher penalty of training errors and clearly over-fitting occurs. On the other hand, when the kernel parameter γ becomes higher, a greater variety of decision boundaries can be formed, originating in a more complex model. The added flexibility initially decreases the generalization error as the model can better fit the data.

b) Interactive Grid Search Selection for SVMs:

Choosing the best parameters can be timing consuming if a systematic approach is not used and/or the problem knowledge does not aid for proper selection. Therefore, an interactive grid search model selection has been accomplished for SVM and the generalized accuracy evaluated on the train data. Fig. 10 portrays the generalization graphic contours for the SVM after a five-cross validation, thus, reducing the search space. The efficient heuristic way of searching points in that space with small generalization errors will lead to a good understanding of the hyper-parameter space [30]. We can then do a refined search of the (C, γ) pairs for proper model selection.

Fig. 10 shows the parameter selection using interactive grid search for classifier SVM. The grid search is on for C= 2^0, 2^1 … 2^{20} and for γ= 2^{-7}, 2^{-6}, 2^{-5}…$2^{6.0}$, $2^{7.0}$. The highest cross validation accuracy resulted for SVM is 98.3% on the training data with extracted model parameters of C=1024.0 and γ=0.0625. Once the SVM is learned with these parameters, all parameters of the trained SVM are frozen and then used in retrieval mode for testing the capabilities of the system on the data not used in learning. The test data samples have been extracted using the transient stability program as explained earlier for Case 4. The % testing accuracy is defined by {No. of samples correctly classified*100/total number of samples presented}. The obtained model parameters during grid search are merit listed for selecting the best parameters with highest testing accuracy. Table 3 gives the list of model parameters obtained from grid analysis sorted for descending test accuracies.

The parameters C= 4096 and γ= 0.0312 have resulted in the highest test accuracy of 98.2% (216 patterns are correctly classified out of the total 220 test patterns). The extracted model parameters with their training and testing accuracies, number of iterations for completion of the optimization process, and number of support vectors resulted is given in Table 3. Fig. 11 shows the plot of target values and the output classification results from SVM for the pair of model parameters of highest testing accuracy from Table 3. Table 3 illustrates the results obtained choosing the pair of parameters conveyed to the learning model with the smallest capacity and, thus, the highest generalization.

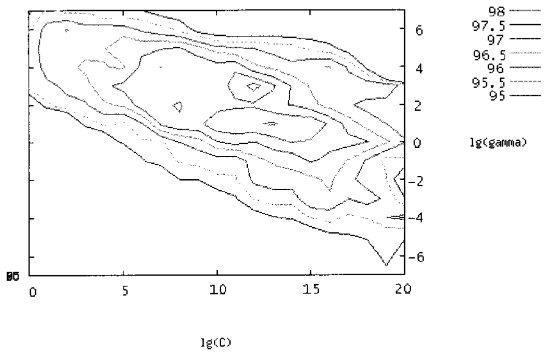

Fig. 10. SVM Parameter selection using interactive Grid Search

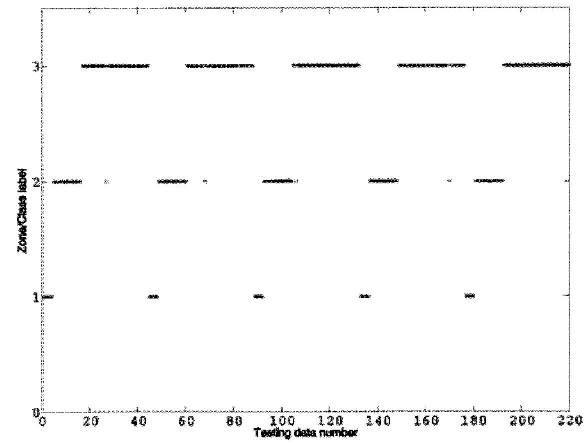

Fig. 11. Graph showing the plot of target values and the output results from SVM for different zone/class classifications

Table 3. Results from interactive Grid search selection for choosing SVM parameters

C	γ	# of Iters.	# of SVs	% Training Accuracy	% Testing Accuracy
4096	0.0312	1928723	364	96.2	98.2
8192	0.1250	1972758	358	95.7	98.1
1024	0.0625	272430	267	98.3	97.7
2048	0.1767	175748	227	97.2	97.2
2048	0.0883	128679	263	97.7	96.8

c) Observations:

Based on the large number of transient stability simulations and training of the SVM, the following observations are made:

- In Fig. 8 the line flow variations affect the Zone 3 settings of the relay rather than Zone-1 and Zone-2.
- When the relay is close to the fault location point, the relay will trip regardless of the flow of the line.
- Fig. 6 and Fig. 8 reveal that presence of short line in the Zone-2/Class-2 elements pull the relay observations for faults on the Zone-3/Class-3 elements during fault towards the Zone-2 observation area.
- Fig. 7 indicates that the fault resistances pull the loci away from the origin, which affect the Zone-1 settings of a conventional relay.

5. Conclusions

The application of the SVMs for distance relay co-ordination in transmission system protection is presented. From the large number of transient stability simulations on the practical 265 bus Indian western region system, it is clear that the relay settings for zone-3 backup protection are sensitive to line flow variations and the fault resistance will have affect on the Zone-1 settings of a conventional relay. This has indicated the need for applying intelligent tools at the relay location of distance protection. In this paper, SVMs are used as an intelligent tool to discriminate between different zonal element faults for varying operating conditions and fault resistance values. The basic idea of the SVMs is to determine the structure of the classifier by minimizing the bounds of the training error and generalization error. Regarding the implementation issues, training of SVMs are considerably faster, even for large-size problems, requiring less heuristics and, thus, are more preferable. Our results demonstrate that the SVMs have the potential to obtain reliable transmission line distance relay coordination.

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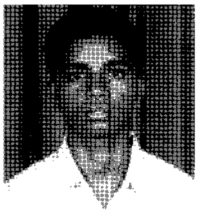

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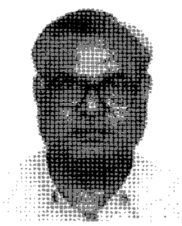

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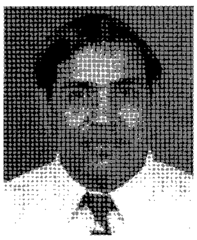

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