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Support Vector Machine Approach for the Switching Transient Peak Overvoltages During Line Energization

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Abstract- ***At the time of restoration transmission line switching is one of the major causes, which creates transient overvoltages. Though detailed Electro Magnetic Transient studies are carried out extensively for the planning and design of transmission systems, such studies are not common in a day-today operation of power systems. However it is important for the operator to ensure during restoration of supply that peak overvoltages resulting from the switching operations are well within safe limits. This paper presents a support vector machine approach to classify the various cases of line energization in the category of safe or unsafe based upon the peak value of overvoltage at the receiving end of line. Operator can define the threshold value of voltage to assign the data pattern in either of the class. For illustration of proposed approach the power system used for switching transient peak overvoltages tests is a 400 kV equivalent system of an Indian southern grid***

I. INTRODUCTION

The power system must be prepared for the rare occasion when all or partial portion of the system is forced out of service. If this occurs, the system must be able to be restored to normal operations as quickly as possible. The three phases of power system restoration are [1]:

- Planning of restart and reintegration of the power supply
- Action during system degradation for saving and retaining critical sources of power
- Restoration when the power system has stabilized at some degraded level

In the planning phase, problems can be addressed primarily by offline analysis and simulation. During the degradation phase, control problems need solutions in real-time and within the short time ratings of lines and equipment. In restoration Phase, problem can be addressed by online simulation, presenting results to the operator for implementation.

During the early stages of restoring EHV overhead transmission lines, transient voltages or switching surges are caused by energizing large segments of a transmission system or by switching capacitive elements [2]. The magnitude and shape of the switching overvoltages vary with the system parameters and network configuration. Even with the same system parameters and network configuration, the switching overvoltages are highly dependent on the characteristics of the circuit breaker operation and the point-on-wave where the switching operation takes place.

Extensive EMTP simulation studies are carried out during planning stage of transmission system. A line energization is an intended operation, certain initial condition are required in the studies and the main purpose of studies is to provide proper protection system, such as lightning arrester, shunt reactor etc. to limit the overvoltages to specified design limits as per the utility limit. However during system operation a large disturbances or a partial blackout, the system condition can be very abnormal. Thus during such situation many transmission lines indented to be energized. It is important obtain the safe order of the transmission lines for restoration in sequence.

The knowledge of switching overvoltages severity during the intended operations of transmission lines are important from the operator point of view to take safe decisions about the operations. Digital computer tool such as Electro Magnetic Transients Program (EMTP) is universally accepted as industry standard for computation of both switching and temporary over voltages at the planning stage but in a day-to-day operation of power systems [3][4], EMTP simulations are not common due to enormous cases require to be carried out to estimate the worse switching overvoltages. However during day-to-day operation such studies, by the operators are prohibitive due to actual detail data required and also large computational time involved. During power system restoration there is a need for real time tool, which can provide crucial knowledge about peak overvoltages, generated during energization of transmission line.

This paper applies a learning-based nonlinear classifier, the support vector machine (SVM) for peak over voltages under switching transients during line charging. The proposed methodology adopts the pattern recognition approach to classify the switching overvoltages generated during line energization in two classes safe and unsafe. A tool such as proposed in this paper that can give the idea about switching overvoltage severity would be helpful for the operator. Data pattern assign to either of the class on the basis of peak overvoltage appears at receiving end bus. The proposed SVM is expected to learn many scenarios of operation to give the maximum peak overvoltage in a shortest computational time, which is the requirement during online operation of power systems. In the proposed approach we have considered the most important aspects, which influence the transient

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overvoltages such as line length, switching angle, source strength and receiving end reactor. This information will help the operator to select the proper sequence of transmission line to be energized safely with transients appearing safe within the limits. Results of the studies are presented for a sample system and also for an equivalent EHV system of Indian southern grid to illustrate the proposed approach. Operator can define the threshold value of voltage to assign the data pattern in either of the class.

II. SWITCHING TRANSIENTS

An electrical transient is the outward manifestation of the sudden change in circuit conditions, as when a switch opens or close or a fault occurs on a system. Generally a switching operation in a power system changes the state of the system from those conditions existing prior to switching to those existing after the operation, this generates transient phenomena. The power frequency voltage before and after the switching operation may be of a different value due to the change in the state of the system. This means that the total amplitude of the overvoltage due to switching may be considered in two parts; namely a transient component which is superimposed on a power frequency component [5]. In EHV and UHV systems there are a number of switching operations, which require special consideration as they may lead to magnitudes of the switching transient, which influence the choice of the system insulation level. However the overvoltages produced during the switching of reactors and transformers may readily be limited by surge diverters [5] and are therefore not considered here. Of the other switching operations, line closing and reclosing generally produce the larger overvoltages and consequently we concentrate on line energization in this paper. In general, the highest switching overvoltage in a high voltage network is caused by energizing and re-energizing of unloaded line. When the line is connected to the source, traveling wave will start to travel along the line towards the receiving end and double there at the open end with an overvoltage near to 2 p.u.

A 400kV 3-bus system with a transmission line of 200kms is shown in Fig.1. For the system considered normal peak voltage in a phase is ($400\sqrt{2}/\sqrt{3}$)kv and this value is taken as base for voltage pu and in the system studies 400kv is base voltage and 100 MVA is base power. Line is switched from bus 2 and the switching transients observe at bus 3 when line is energized. In practical system a number of factors affect the overvoltages factors due to energization or re-closing.

In energizing transmission lines during power system restoration, operators are often concerned with the length of line to be energized, the adequacy of on-line generation, and the presence of reactor. In general, it is desirable to energize as large sections of lines as the sustained and transient over-voltages will allow [2]. Energizing small sections tends to prolong the restoration process. In energizing a large section however, there is the risk of damaging the equipment insulations because as line length increases charging current also increases which creates higher overvoltage at receiving end bus [6]. The effect of transmission line length on switching overvoltage at bus 3 is shown in Fig 2.

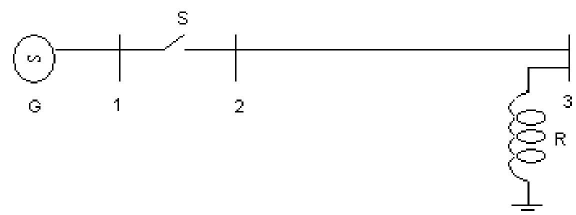

Fig. 1. Sample system G: Generator S: Switch R: Reactor

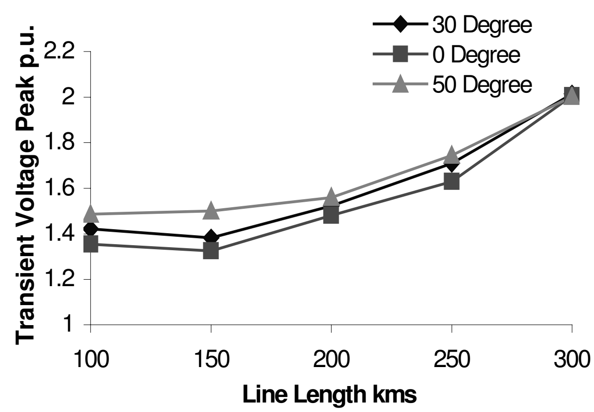

Fig. 2. Transient Voltage peak at bus 3 as line length increases, while the source strength is 1000 MVA with PIR

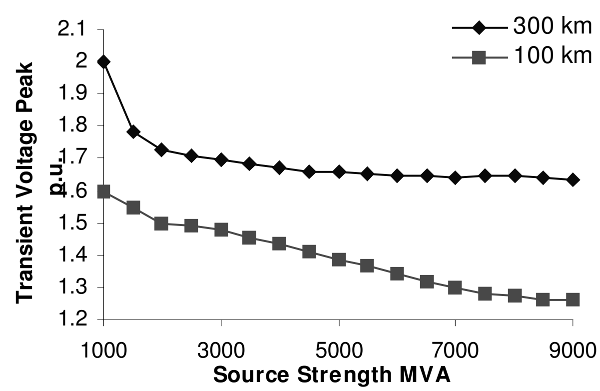

Fig. 3. Transient Voltage peak at bus 3 as source strength increases, while the switching angle is kept fixed at 50^{o} with PIR

Energizing lines with inadequate sources could result in higher sustained and transient voltages than equipment can withstand. The start-up of more out.of-sequence generators however, would use critical time, and delay the overall restoration process [2] [6]. Overvoltage reduces as the size of system increases; this reduction is due to the superposition of a number of different frequencies not due to the damping of switching overvoltage. Fig.3 and 4 shows the effect of source strength on overvoltage at different line length and switching angle respectively.

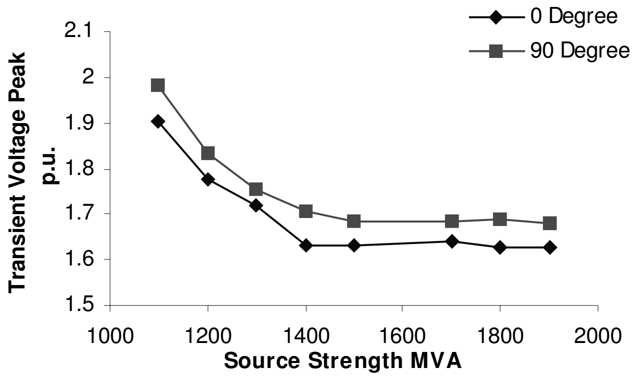

Fig. 4. Transient Voltage peak at bus 3 as source strength increases, while line length is 300km with PIR

Shunt reactors either permanently connected or switchable are used on the EHV transmission systems for limiting the steady-state overvoltages during light load condition and also to avoid leading power factor operation of generators, which may cause stability problem. Fortunately, they are also effective in reducing switching surges to a considerable degree. The reason for this reduction is primarily the lower steady-state voltage at receiving end of the line resulting from the shunt reactor supplying the line's capacitive var requirement. The reactor at receiving end of the offers a finite impedance, which tends to reduce the coefficient of reflection, thus also contributing surge reduction [5]. The shunt compensation effect is shown in the Fig. 5.

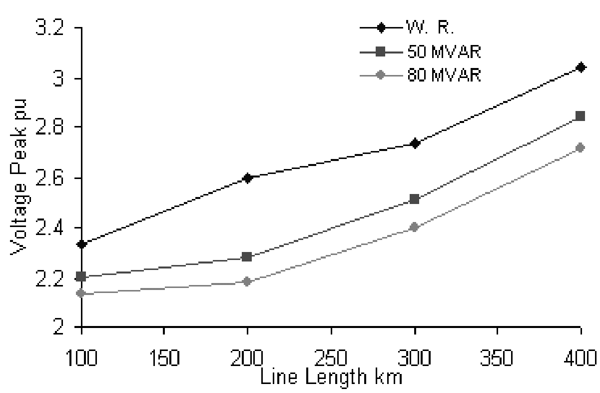

Fig. 5. Transient Voltage peak at bus 3 at various values of receiving end reactor and without PIR, source strength is 1000 MVA and switching angle 90°. W.R. = Without Reactor

Controlled Switching of high-voltage circuit breakers has become a commonly accepted means of reducing switching transients in power systems. The primary motivation for using controlled switching of transmission lines is to minimize the switching overvoltages during energization. If switching takes place at the voltage maximum i.e. at 90° the voltage at first oscillate along the whole the line length to almost twice the value of the system voltage [7]. Fig.2 and Fig. 4 shows that for a particular line length and source strength transient voltage will be more at 90° than 0°.

As discussed above for an existing system the main factors, which affect the peak value of switching overvoltage, are switching angle, line length, source strength and shunt reactor. Here it should be mentioned that a single parameter often can not be regarded independently from the other important influencing factors. The magnitude of the overvoltages normally does not depend directly on any single isolated parameter and a variation of one parameter can often alter the influence of another parameter, in other words there exists an interaction between the various system and breaker parameters. This forbids the derivation of precise generalized rule of simple formulae applicable to all cases. So a support vector approach can help to classify the peak value of switching overvoltages generated during line energization.

This paper applies a recently introduced learning based nonlinear classifier, the support vector machine (SVM). In next section brief description of the proposed methodology, some theoretical background relevant to the SVM approach used for the present problem is given.

III. SUPPORT VECTOR MACHINE

In recent years, Support Vector Machines (SVMs) have risen as powerful tools for solving classification and, regression problems. Support vector machines (SVMs), a recently introduced learning paradigm, have very interesting theoretical and practical characteristics. They rely on so called support vectors (SVs) to identify the decision boundaries between different classes. The SVs are located near the separation surfaces, which are critical to achieve correct classifications. The SVs define the largest possible margin of separation. SVMs can map complex nonlinear input/output relationships [8]. SVMs are based on a linear machine in a high dimensional feature space, nonlinearly related to the input space, which has allowed the development of somewhat fast training techniques, even with a large number of input variables and big training sets. Traditional quadratic programming algorithms have been proposed, but these algorithms require enormous matrix storage and do expensive matrix operations. To avoid these problems, fast iterative algorithm like the Sequential Minimal Optimization (SMO), which is easy to implement is chosen for training the SVMs. In proposed approach two different kernel functions have been used, the RBF kernel and the Polynomial kernel. The parameters C, ρ and σ have been chosen by validation method.

The SVMs employed for two-class problems are based on hyperplanes to separate the data, as shown in Fig. 6. An orthogonal W vector and a bias b, which identifies the points that satisfy, determine the hyperplane $\mathbf{w}^t.\mathbf{x}+b=0$. By finding a hyperplane that maximizes the margin of separation, where **x** is a real valued n-dimensional input vector. The hyperplane with the largest margin on the training set can be completely determined by the nearest points to the hyperplane known as support vectors (SVs) [9] [10] [11]. Therefore, SVMs learn linear decision rules as

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

Cost function to minimize is

$$V(\mathbf{w}) = \frac{1}{2}\mathbf{w}^t.\mathbf{w} \quad (2)$$

Subject to the constraint that all training patterns are correctly classified, that is

$$y_i.[\mathbf{w}_t.\Phi(\mathbf{x}_i) + b] \geq 1, \quad (3)$$
$$i = 1, \dots, N.$$

Constraints can be modified to allow for training errors to make margin soft as shown in Fig.6.

$$y_i.[\mathbf{w}_t.\Phi(\mathbf{x}_i) + b] \geq 1 - \varepsilon_i, \quad (4)$$

The new cost function to minimize is become now

$$V(\mathbf{w}, \varepsilon) = \frac{1}{2}\mathbf{w}^t.\mathbf{w} + C\sum_{i=1}^{N}\varepsilon_i \quad (5)$$

ε_i is the slack variable and $\varepsilon_i > 1$. Error control parameter, C used to penalize training errors. By minimizing the first summand of, the complexity of the SVM is reduced, and by minimizing the second summand of, the number of training errors is decreased. C is a preselected positive penalty factor that acts as a tradeoff between the two terms. The dual of the optimization problem can be written as

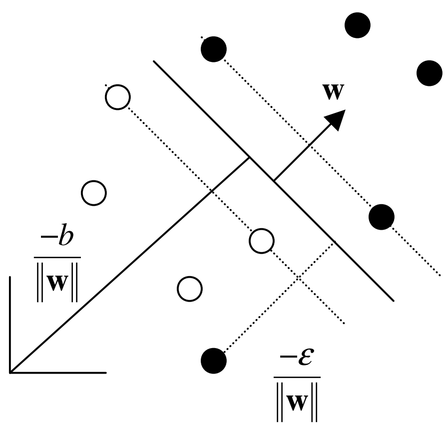

Fig. 6 Linear separating Hyperplane for the non separable case

$$\min W(\alpha) = -\sum_{i=1}^{N}\alpha_i + \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} y_i y_j \alpha_i \alpha_j K(\mathbf{x}_i, \mathbf{x}_j) \quad (6)$$

Subject to $\sum_{i=1}^{N} y_i\alpha_i = 0$ and

$$0 \leq \alpha_i \leq C$$
$$i = 1, \dots, N.$$

Which is a quadratic optimization problem. The nonlinear mapping is indirectly obtained by the so-called Mercer Kernel functions, which correspond to inner products of data vectors in the expanded feature space. However, by substituting the nonlinear mapping by the Kernel function, all calculations are performed in the original input space dimension

$$K(\mathbf{a}, \mathbf{b}) = \Phi(\mathbf{a})^t.\Phi(\mathbf{b})$$
$$\mathbf{a}, \mathbf{b} \in R^n \quad (7)$$

The most commonly used functions are the RBF kernel

$$K(\mathbf{a}, \mathbf{b}) = e^{\frac{-\|\mathbf{a}-\mathbf{b}\|^2}{\sigma^2}} \quad (8)$$

and the polynomial kernel

$$K(\mathbf{a}, \mathbf{b}) = (\mathbf{a}^t.\mathbf{b} + 1)^p \quad (9)$$

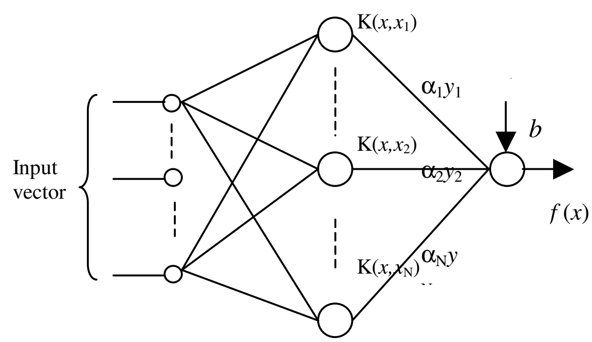

Fig. 7. SVM architecture.

SVM architecture is shown in Fig.7. The parameters ρ and σ affect how sparse and easily separable the data are in the expanded feature space, and consequently, they affect the complexity of the resulting SVM classifier and the training error rate. The parameter C also affects the model complexity. In practice, a range of values has to be tried for C and for the Kernel parameters, and then the performance of the SVM classifier is estimated for each of these values

Proposed scheme

As discussed in section II for an existing system the main factors, which affect the peak value of switching overvoltage, are switching angle, line length, source strength and shunt reactor. So in proposed scheme input vector consist four variables

- Switching angle.
- Source strength.
- Transmission line length.
- Receiving end reactor value.

For training data are classified in safe (class 1) and unsafe class (class 2), according to the peak absolute value of overvoltage occurred at bus 3 shown in Fig 1. The threshold value of overvoltage is kept at 2.2 and 2.4 p.u for two different case analyses. It is assumed that operator has choice about the receiving end reactor of various values. The block diagram of proposed scheme is shown in Fig.8.

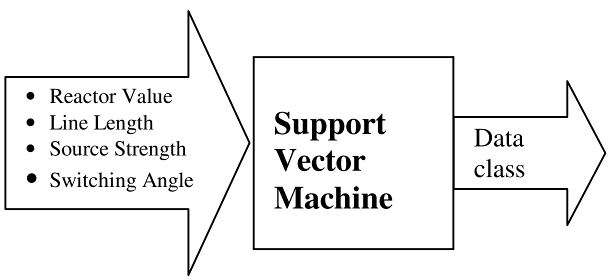

Fig 8. Block diagram of Proposed scheme

IV. SIMULATED STUDIES AND RESULTS

A. *System Study*

The power system used for switching overvoltage classification tests is a subsystem of the Indian southern grid. The proposed scheme is trained with a sample three-bus 400kV system. Single line diagram is shown in Fig. 1. The case of power system restoration stage is taken as an example for the proposed methodology. Studies are carried out with and without the receiving end reactor at bus3. Switching transients are simulated for various combinations of system parameters as follows:

- Source strength: 1000-10000 MVA in step of 1000 MVA
- Line length : 100kms - 400 kms in step of 50 kms
- Switching angle: 0° - 90° in step of 30°

In the case of reactor presence at bus 3, the standard reactor values 50, 63 and 80 MVAR are considered. Testing of model is done by an 11-bus system shown in Fig.9.

B. *Data preprocessing*

Learning will be more quickly and give better performance if the input variables are pre-processed before being used to train the network. Using zero mean inputs can minimize the learning time. Input variables have different range like line length is in the order of 100kms, switching angle is in the order of 10° and source strength is in the order of 1000MVA. Normalization of data is done to preprocessed inputs and single output, which is peak voltage in the range of 1-3 p.u. and which scaled into the range of (-1, 1). The data and targets are normalized can be done as follows:

$$x = y - y_{\min}\left[\frac{x_{\max} - x_{\min}}{y_{\max} - y_{\min}}\right] + x_{\min} \qquad (10)$$

x = normalized input; y = raw input
$x_{max} = +1$; $x_{min} = -1$
y_{min} = minimum value of raw input
y_{max} = maximum value of raw input

Here, y represents each element of the input vector and also that of target vector. The targets in this case are scalar. As the dimension of input vector is four in proposed scheme, curse of dimensionality do not affect the convergence of learning.

C. *SVM Training*

The SVM classifier is based on a subset of the training patterns, the support vectors, located at the separation region between the two classes. The SVs define the largest possible margin of separation. SVMs are nonlinear models based on theoretical results from the statistical learning theory. This theoretical framework formally generalizes the empirical risk minimization principle that is usually applied for NN training (i.e., the minimization of the number of training errors). In traditional NN training, several heuristics are applied in order to estimate a classifier with adequate complexity for the problem at hand. An SVM classifier minimizes the generalization error by optimizing the tradeoff between the number of training errors and the so-called Vapnik-Chervonenkis (VC) dimension, which is a new concept of complexity measure.

The SVM training process consists of a quadratic optimization problem in which the support vectors represent the minimum solution. The use of an augmented training set as in the MLP training is not appropriate because of linear dependencies in the constraints. Instead, to account for the training set unbalance, different values for C can be used. A large value of C for the unstable patterns and a small value for the stable ones have been adopted during the training process. In this way, the optimization process emphasizes the minimization of the unstable patterns training errors.

Upon the data sets we prepare, SVM model is built to classify the switching transient overvoltage in safe or unsafe class denoting as class 1 and class 2 respectively on the basis of peak transient voltage occurring at the receiving end bus. The threshold value for the peak overvoltage to assign data either of the class is chosen 2.2 p.u. and 2.4 p.u. When training an SVM model, there are some parameters to choose. They would influence the performance of an SVM model. Therefore, in order to get a "good" model, these parameters need to be selected properly. Some important ones are:

I. The mapping function;
II. Cost of error;
III. Constant ρ and σ

As searching for the proper parameters, we need to access the performance of models. To do this, usually we divide the training data into two sets. One of them is used to train a model while the other, called the validation set, is used for evaluating the model. According to their performance on the validation set, we try to infer the proper values of constants and mapping function. Total 1120 pattern is generated to train the SVM. Two different kernel functions have been used, the RBF kernel and the Polynomial kernel. The software SVM^{light} has been used for training and testing the SVM models. The RBF kernel SVMs have shown satisfactory results, because in the test set they have minimum misclassified data no matter the values of the parameters. On the other hand, polynomial kernel SVMs also have been trained successfully, and the results of their performance on the test set will be presented in next sub section but it has less accuracy for test data.

D. SVM Testing and results

All experiments have been repeated for different system parameters. After learning, all parameters of the trained networks have been frozen and then used in the retrieval mode for testing the capabilities of the system on the data not used in learning. The testing data samples have been generated through the EMTP program by placing the parameter values not used in learning, by applying different source strength values, and different switching angle and line length. A large number of testing data have been used to check the proposed solution in the most objective way at practically all possible parameters variation.

i.) *Results for 3 bus model.*Test data obtained by EMTP program, where line length varied in steps of 25kms, switching angle in steps of 10^o and source strength in steps of 500MVA. Varying the parameter in the steps mention above 250 patterns are generated. Table 1 shows the results for 3-bus system shown in Fig 1.

Table 1: Results for proposed 3 bus model

Type of kernel Function RBF	Threshold Voltage p.u.	No of SVs	Class1 sample (Safe)	Class 2 sample (Unsafe)	SVM's Accuracy %
RBF	2.2	243	43	207	98.0
	2.4	455	104	146	98.4
Polynomial	2.2	252	43	207	97.6
	2.4	476	104	146	96.4

ii.) *Results for 11 bus system*. The proposed SVM approach is also tested with an 11-bus system (Fig. 9), which is an equivalent EHV system of Indian southern grid shown in Fig.10. The various cases of line energization are taken into account and corresponding peak overvoltages are computed from EMTP program. Equivalent source strengths were obtained at all buses for various conditions. Energization of lines from either end of a transmission line is considered. Typical system scenarios are considered for exhaustive training patterns for proposed ANN. Summary of few results are presented in the table 2. It can be seen from the results that the SVM is able to learn the patterns and give results to acceptable accuracy.The threshold value of overvoltage is kept at 2.4 pu. Both RBF and polynomial kernel function model is used to classify data in safe and unsafe class. RBF SVM has accurately classified all cases but the polynomial kernel SVM has misclassified one case.

Table 2. Results for 11 bus system

Line	Switching End Bus No.	R MVAR	LL km	SS MVA	SA Deg.	EMTP voltage Peak pu	SVM output	
							RBF	Polynomial
11-5	11	0	295	4756	0	2.38	1	1
		0	295	4756	60	2.56	2	2
		63	295	4756	60	2.37	1	1
		63	295	4756	90	2.27	1	1
	5	0	295	1006	60	2.64	2	2
		0	295	1006	90	2.64	2	2
11-4	11	0	257	4188	0	2.14	1	1
		0	257	4188	90	2.51	2	2
		50	257	4188	60	2.30	1	1
		50	257	4188	90	2.40	1	2
	4	0	257	3000	0	2.20	1	1
		0	257	3000	60	2.57	2	2
11-10	11	0	282	4555	0	2.27	1	1
		0	282	4555	90	2.37	1	1
		50	282	4555	0	2.25	1	1
		50	282	4555	90	2.35	1	1
	10	0	282	1289	0	2.52	2	2
		0	282	1289	90	2.59	2	2

R : Receiving end Reactor; LL : Line Length; SS : Source Strength; SA : Switching Angle ; 1 = Safe (Class 1); 2 = Unsafe (Class 2)

V. CONCLUSION

A support vector machine approach to distinguish safe or unsafe the peak over voltages under switching transient was proposed and implemented. Both RBF and polynomial kernel function is used to map input vector into higher dimension feature space. The performance of RBF SVM is better than polynomial SVM. The proposed methodology is tested with a three bus and an 11-bus system. The simulated results clearly show that the proposed technique can classify the peak values of switching overvoltages with good accuracy into the safe and unsafe class. Further work can be carry out by taking the various optimal values of PIR and PIR duration time.

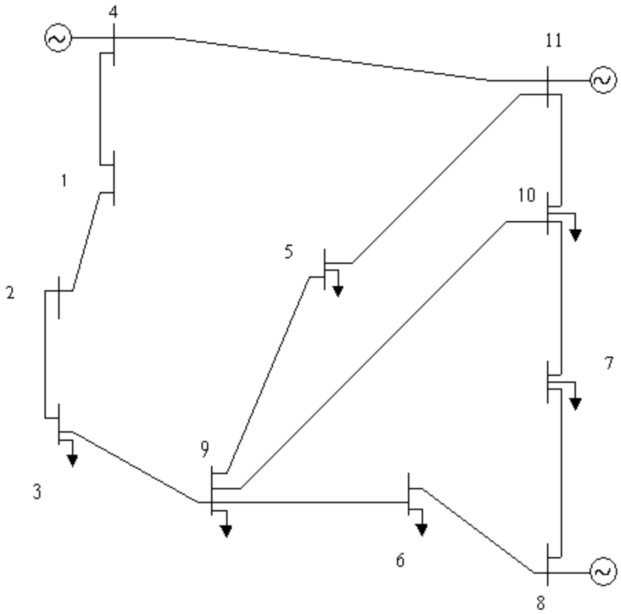

Fig. 9. 11 Bus transmission system

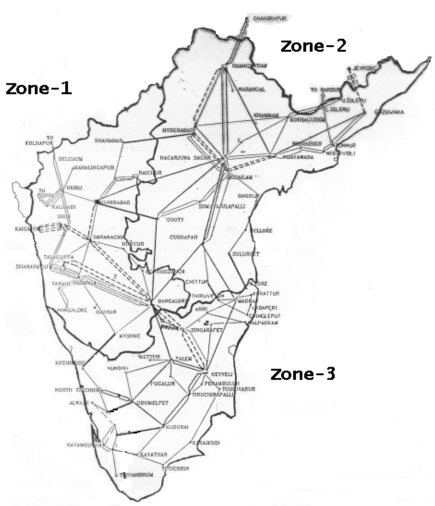

Fig. 10 Indian southern grid

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