SERBIAN JOURNAL OF ELECTRICAL ENGINEERING
Vol. 6, No. 1, May 2009, 135-148
UDK: 514.742.2:621.31

Support Vector Classifier with Enhanced Feature Selection for Transient Stability Evaluation

Dora Arul Selvi Balasingh[1], Kamaraj Nagappan[2]

Abstract: Today's power transmission systems have a tendency to operate closer and closer to their stability limits. In this scenario, there have been continuous efforts to develop new techniques and tools for assessing the stability status of power systems. This paper presents a Support Vector Classifier (SVC) to identify the transient stability of power systems subjected to severe disturbances. The nonlinear relationship between the pre-fault, during-fault and post-fault power system parameters and the stability status of the system under post-fault state is captured by the SVC trained offline. Significant generators are selected by feature selection based on the sensitivity of stability margin and the features other than generators are selected based on a step wise feature selection by three fold cross validation. The performance of the proposed SVC is demonstrated through the simulations carried out on the IEEE 17 generator reduced Iowa system.

Keywords: Transient stability, Support Vector Classifier (SVC), Dimensionality reduction, Feature selection, Energy margin.

1 Introduction

Stability problems in power systems are being highly emphasized during recent years, due to the limited investments in new facilities and the current deregulation trends of electric power industries. Even though power system stability may be broadly defined according to different operating conditions, an important problem that occurs frequently is that of transient stability. It concerns the maintenance of synchronism between generators after being subjected to severe disturbances. There are two main classes of transient stability analysis methods available, namely, the Time Domain Simulation Method [1] and the Direct Methods, which are based on Energy Function [2] and Extended Equal Area Criterion [3]. Computational Intelligence (CI) techniques are a new class of stability analysis method, which has been receiving great deal of attention for the past few years. In the earlier works, the

[1]Electrical and Electronics Engineering Dept., Dr. Sivanthi Aditanar College of Engineering, Tiruchendur-628 215 Tamilnadu, India; E-mail: doragopal@yahoo.co.in
[2]Department of Electrical and Electronics Engineering, Thiagarajar College of Engineering, Madurai-15, Tamilnadu, India; E-mail: nkeee@tce.edu

CI techniques like, Decision Trees [4], Pattern Recognition [5] and Artificial Neural Networks [6] are applied to solve transient stability assessment.

Support Vector Machine (SVM) is currently a hot topic in the machine learning community, creating a similar impact now as ANN did previously. SVMs are very well suited for TSA, since the learning focus is on the security border. Followed by the introduction of Support Vector Machines by Vapnick and his co-workers, many transient stability assessment applications based on SVM have been presented. The authors of [7] presented a SVC with polynomial kernel. In [8] a *v*-SVM with thirteen features is used. In [9] and [10], linear SVM is applied to classify the stability of power systems using scaled variables. A combined Support Vector Classifier based on Fuzzy -C- Means clustering is presented in [11]. The stability classification performance of SVM is compared with MLPNN by the authors of [12].

Input feature selection/extraction plays an important role in neural network based approaches. For this purpose several statistical methods have been presented in the transient stability assessment problem. The measure of class separability of the variables has been used as the criterion to select the input features by Suresh *et al*. [13]. The inter-class distance measure of *i*-th variable is defined as follows:

$$F_i = \left| \frac{m_i^S - m_i^U}{\sigma_i^{S2} + \sigma_i^{U2}} \right|, \tag{1}$$

where, m_i^S and m_i^U are the mean of the variable i for the stable and unstable classes and σ_i^S and σ_i^U are their variances. They have also used the linear correlation between the input variables as an index for feature selection for their RBF network model.

To perform dimensionality reduction of input vectors, three feature extraction techniques namely, sequential search, genetic algorithm and principal component analysis have been employed in [7]. The authors of [14] have also applied Principal Component Analysis (PCA) for reducing the dimensionality of the training data to their SVC.

The interclass-distance measure assumes gaussinity in the input domain. If they fail, serious errors may occur in feature selection. In the correlation coefficient method the criteria is to discard a variable if the correlation between two variables is high. It fails to indicate which out of the two variables should be discarded. PCA is an orthogonal transformation that seeks the directions of maximum variance in the data and is commonly used to reduce the dimensionality of the data. In situations, where the principal components are not orthogonal and the data sets do not follow the Gaussian distribution, the PCA fails as presented by Scholkopf in [15]. In this paper, a two stage feature selection method has been proposed. Since the dimension of input data to the learning machine mainly depends on the generators present in the power systems, the generators having major effect on the fault are selected in the first stage by filtering. The subset of features other than generators is selected by a backward stepwise selection based on cross validation.

The paper is organized as follows. In section 2, the methodology of transient stability assessment is furnished. Key features of SVC are discussed in section 3. Section 4 discusses the feature selection methods. Simulated results are analyzed in Section 5 and finally a conclusion is drawn in Section 6.

2 Methodology for Transient Energy Margin Estimation

The proposed method for transient stability evaluation is based on SVC machines. The objective is, to identify the transient stability status of power systems after severe disturbances. The study presented in this paper focuses on three phase short circuit faults at three buses of the power system one at a time.

The derivation of transient energy function and its application to transient stability assessment has been presented in [2]. The stability assessment is done by comparing the system energy (V_{SCl}), computed at the end of the disturbance with the critical transient energy (V_{cr}). Critical transient energy is the transient energy at the point where the fault-on trajectory crosses the Potential Energy Boundary Surface. The difference between the critical transient energy and the energy at the end of the disturbance is the energy margin (ΔV). It is the parameter of interest in transient stability assessment and is used as an indication of stability. A positive energy margin indicates the system's ability to absorb the transient energy at the instant of fault clearing before the post disturbance stable operating point. So the system retains its stable operation. A negative energy margin means the system moves to an unstable state.

$$\text{Energy Margin} = V_{cr} - V_{SCl}\,. \tag{2}$$

For model development, a large number of training data is generated through off line power system simulation. Pre-fault real (*P*)and reactive power (*Q*)outputs of all generators, real power flow over all the lines (PF), total system real (P_L)and reactive load(Q_L), voltage behind transient reactance of generators (E), internal voltage angle of generators (δ), machines inertia constants (*H*), kinetic energy of all generators at the instant of faults (KE_F), kinetic energy of all generators at the instant of fault removal (KE_R), a three bit binary code indicating the location of fault (BC) and fault clearing time (T_C) are the inputs to the models and Stability Status (-1 for Unstable and $+1$ for Stable) is the output of the network. A two stage feature selection procedure has been used to acquire the attributes properly describing the status of power systems. Higher performance of the network is expected by including only the relevant variable obtained using feature selection methods in the input feature set.

3 An Overview of Support Vector Classifier

Given a binary classification task with *k* samples: $(x_1, y_1),....,(x_k, y_k)$, where $x_i \in R^N$ belongs to one of the classes $y_i \in \{-1,+1\}$ for $i = 1,\ldots,k$. To classify these samples, a SVM will search for a separating hyperplane with largest margin. If a linear separable classification problem is encountered, a linear SVM could be used and the hyperplane could be represented as $xw + b = 0$. (Where *w* is weight vector and *b* is bias) This hyperplane can classify a sample point x_i according to the following function:

$$f(x_i) = \text{sign}(x_i w + b) \tag{3}$$

If $f(x_i) \geq 0$ then x_i belongs to positive class otherwise negative class. To construct an optimal separating maximum margin classifier, a SVM attempts to classify the data in the training set using the smallest norm of weights. This can be solved as an optimization problem as follows:

$$\textit{Minimise} \quad \frac{1}{2}\|w\|^2, \tag{4}$$

where

$$y_i((x_i \cdot w) + b) \geq 1, \quad i = 1,\ldots,k. \tag{5}$$

Classical Lagrangian duality enables the primal problem represented by equations (4 and 5), to be transformed to its dual, which can be solved in an easier way. The dual problem is given by equations (6-8):

$$\text{MaxJ}(w,b,\alpha) = \sum_{i=1}^{k}\alpha_i - \frac{1}{2}\sum_{i=1}^{k}\sum_{j=1}^{k}\alpha_i\alpha_j y_i y_j x_i x_j, \tag{6}$$

where

$$\alpha_i > 0, \quad i = 1,\ldots,k, \tag{7}$$

and

$$\sum_{i=1}^{k}\alpha_i y_i = 0. \tag{8}$$

The non-linear SVM is built by computing the inner products in the feature space directly as a function of original input data points. This is possible through the kernel function. The optimal hyperplane for this kind of problem could be found by solving the dual Quadratic Programming (QP) problem as given by equations (9-11):

$$\mathrm{MaxJ}(w,b,\alpha,\zeta)=\sum_{i=1}^{k}\alpha_i-\frac{1}{2}\sum_{i=1}^{k}\sum_{j=1}^{k}\alpha_i\alpha_j y_i y_j k(x_i x_j)\,, \tag{9}$$

where

$$0\le\alpha_i\le C,\quad i=1,\ldots,k\,, \tag{10}$$

and

$$\sum_{i=1}^{k}\alpha_i y_i=0\,. \tag{11}$$

The above QP problem computes a vector α, each element of which specifies the weight of each training datum, and the support vectors (SV) are the data whose corresponding α is greater than zero. The support vectors capture all the relevant data in the training set and the solution of optimal hyperplane can be written as a combination of the support vectors only. Thus fast training results will be acquired even with the large number of input features. $k(x_i,x_j)$ is a symmetric positive definite kernel function satisfying Mercer's conditions. In this work radial basis kernel function represented by equation (12) has been used.

Radial basis function kernel

$$k(x_i,x_j)=\exp\left(-\frac{1}{2\sigma^2}\left\|x-x_i\right\|^2\right),\ \text{where}\ \sigma>0\,. \tag{12}$$

4 Feature Selection Methods

An operating state of power system can be represented by a very large number of power system variables. From the immense number of variables the set chosen should adequately characterize a system state and they should be independent. The practical and well known method for measuring the performance of a classifier is the method of cross validation. Since each feature present in each subset is treated separately it needs heavier computation. To reduce the computational burden of feature selection by cross validation the input features related to generators are selected in the first stage by an easier sensitivity index method.

4.1 Sensitivity Index

In this section the sensitivity of the Energy Margin with respect to the input variables (real power generation) is computed to find the generators having significant effect on the contingency. The feature set will consist of only the parameters of those generators. This can be achieved by computing the Energy Margin sensitivity numerically [2]. For a particular fault, the active power output of *i*-th generator is increased by some fixed amount (ΔP_{Gi}) keeping the others intact. The energy margins for original active power and increased values are found. The difference between the two gives the change in energy margin (ΔV_i) value. Then the numerical energy margin sensitivity of *i*-th generator can be described as:

$$\frac{\mathrm{d}(V_i)}{\mathrm{d}P_{Gi}} = \frac{\Delta V_i}{\Delta P_{Gi}} \tag{13}$$

Based on this the sensitivity index of all generators are calculated. The generators having larger sensitivity index have a significant effect on the contingency. The features other than generators are selected by the following sensitivity analysis scheme.

4.2 Stepwise Cross Validation

Here, first the performance of SVC trained using all the input features after sensitivity index is evaluated by a three fold cross validation done by splitting the training set into three groups. Every time two groups are engaged for training and one group for cross validation. The performance of the classifier is measured by the Classification Accuracy given by equation (14):

$$\text{Classification Accuracy} = \frac{\text{No. of Correctly Classified States}}{\text{No. of Validation States}} \tag{14}$$

Afterwards one feature at a time is removed from one of the subset and the network is trained using the reduced set and the cross validation is carried out. The steps are repeated for all the features except the 3 bit binary code indicating the location of fault. By the three fold cross validation, the deterioration effect of each variable on the network performance if removed is found. Then the network is pruned of input variables having least deterioration effect on the network performance. That means higher classification accuracy is maintained even in the absence of those variables.

5 Simulation Results

All the simulations have been done in Matlab 7.0 environment. To illustrate the effectiveness of the proposed SVR model for TSI estimation for assessing power system stability, the IEEE 17 generator reduced Iowa system and IEEE 50 generator equivalent North American system [16] are considered as test systems.

5.1 Test System 1: IEEE 17 Generator Reduced Iowa System

This system consists of 17 generators, 162 buses and 284 transmission lines. The various steps involved in developing and evaluating the system for stability investigation are presented below.

A. *Generation of training and testing patterns*

Since the training data is the only information available to develop a learning machine the set of training patterns generated should represent all probable operating conditions of the power system. Various operating states of the power system have been created by adopting the following procedure:

- 3 major lines of system (15-58, 52-117, and 92-102) are opened for maintenance individually. Lines having maximum active and reactive power flows are declared as major lines.
- For each major line outage 3 bolted faults (95-97, 52-79 and 110-141) are created at the beginning end of transmission lines one at a time. Opening the circuit breakers on both ends of the transmission lines clears faults.
- 3 levels of load pattern are considered in each load bus (Totally 30 load buses) providing significant changes in operating conditions. The load levels are: Low (50 to 80%), Normal (81 to 105%) and Heavy (106 to 140%) of base load level.
- For each load level 3 fault clearing times (0.25s, 0.35s and 0.45s) are assumed.
- Each of the above operating conditions generated, Structure Preserving Energy Function is constructed and the critical transient energy is computed using Potential Energy Boundary surface method.

Based on the above simulation procedure, a data set of 2430 samples has been generated .Out of the 2430 total samples, for each fault location 810 samples are generated. The performance of the learning machine will be correctly valuated only when the training and testing samples are different. So, with in the 810 samples, 760 examples are allotted for training and the remaining 50 are used for testing in each case. The final training set consists of 2280 and testing set of 150 samples.

B. *Feature Selection*

The input to the network consists of several power system parameters under different operating states of the system as mentioned in section II. This constitutes a sum of 408 input features. This huge number of features necessitates the use of feature selection/extraction techniques. Only the generators nearer to the faults have major impact on the faults. Based on this idea, the sensitivity index of each generator is calculated using equation (13) and plotted in Fig. 1.

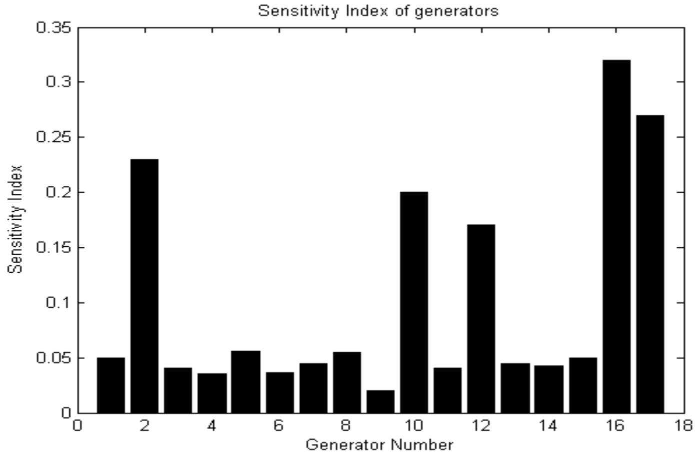

Fig. 1 – *Sensitivity Index of Generators.*

The results shows that the generators 130, 131, 6, 114 and 121 have highest sensitivity index when the fault occurs near bus 9 along the transmission line between buses 9 and 75. These are the first priority candidates and are included in the feature set. **Table 1** below lists the generators to be included in the feature set. The remaining features (326) are selected by the feature extraction based on stepwise cross validation. The first few variables, the removal of those result least classification accuracies obtained using equation (14) are selected as features to train the network and they are also reported in **Table 1**.

Table 1
Results of feature selection.

Sl. No.	Major line	Location of fault	Selected Generators after I stage	Final Features after II stage
1	15-58	9-75	130, 131,6, 114 ,121	P_{130}, $P_{121,}Q_{131}$,PF_{19}, PF_{46}, PF_{88}, PF_{115}, 1 0 0
		95-97	114,121,130,131,76	
		110-114	114,121,130,131,76	
2	52-117	9-75	130, 6, 114 ,121,73,	P_{118},P_{121},Q_6,PF_{28},PF_{204}, PF_{207}, PF_{235}, 0 1 0
		95-97	118,76,130,121,114	
		110-114	114,121,130,131,76	
3	92-102	9-75	130, 131,6, 114 ,121	P_{130},P_{76},Q_{114},PF_{15}, PF_{19}, PF_{224}, PF_{225}, 0 0 1
		95-97	118,76,130,121,114	
		110-114	114,121,130,131,76.	

C. *Training and Testing the Learning Machine*

Initially, a training data set of 2430 examples each with 408 attributes has been generated. After feature selection by sensitivity index, 325 features are selected. By applying sensitivity analysis, 10 features are chosen. Radial Basis Function kernel represented by equation (12) is used for training SVC. For a specified value of soft margin parameter C in equation (10), the kernel parameter σ in equation (12) is fixed at 10, 600, 1500, 2000 and 2500. Before training, the input patterns are normalized so that each dimension of input data has zero mean value and unit variance.

After training, the generalization performance of the SVC is evaluated with the 150 testing data. **Sensitivity**, **specificity** and **classification accuracy** are the statistical measures of performance of a binary classifier. The **sensitivity** measures the proportion of actual positives which are correctly identified as such (i.e. the percentage of stable states that are identified as operating stably); and the **specificity** measures the proportion of negatives which are correctly identified (i.e. the percentage of unstable states that are identified as not operating stably). **Classification accuracy** is the ratio of correctly identified operating states (both stable and unstable) to the total number of testing states. By denoting the following terms: TP - True Positive (Stable states correctly classified as stable), TN - True Negative (Unstable states correctly classified as unstable), FP - False Positive (Unstable states incorrectly classified as stable) and FN - False Negative (Stable states incorrectly classified as unstable), the Specificity, by means of which the learning machine is able to reject false positive matches is given by TN/(TN+FP); the Sensitivity, which is the ability of the machine to detect true positive matches is given by TP/(TP+FN) and the classification accuracy is given by (TP+TN)/(TP+TN+FP+FN). Higher classification accuracy means better performance. In the real world problem of transient stability assessment, (1 - Specificity) plays a crucial role. It is a measure of unstable states classified as stable, which is unacceptable. So, for better performance of the classifier it should be minimum.

Table 2

Results of SVC *with Feature Selection* (C = 100).

Sl. No.	σ	No. of SVs	Training Time (s)	Sensitivity	1-Specificitry	Classification Accuracy
1	10	1200	0.32	0.87	0.106	88.4%
2	600	890	0.24	0.91	0.100	91.5%
3	**1500**	**392**	**0.12**	**0.97**	**0.002**	**98.6%**
4	2000	350	0.10	0.90	0.097	92.2%
5	2500	350	0.10	0.86	0.072	94.4%

The results of SVC with proposed feature selection after training and testing phases with C as 100 are presented in **Table 2**.The results clearly show that the training of SVC is successful and the correct identification of power system stability has been achieved by SVC for previously unseen data.

D. *Comparison with feature extraction by kernel* PCA.

Dimensionality reduction techniques transform an input data set X of dimensionality n into a new data set X' with dimensionality d ($d < n$), while retaining the geometry of the data as much as possible. Then a test set can be classified with minimum expected number of misclassifications or the output for a test set can be estimated with minimum error. Kernel Principal Component Analysis [15], a new non linear dimensionality reduction technique has been employed for overcoming the problem of high input dimensionality. It performs non linear PCA by carrying out linear PCA in feature space. The key idea is to map the input patterns into the feature space fitted with dot products and computes the principal axis there. The KPCA projection of input patterns can then be used as feature for classification. The kernel PCA uses a Gaussian kernel with kernel parameter γ as 1, maximum number of eigenvectors as 30. After training the SVC is tested with test data. The results of training and testing with C equals 100 are reported in **Table 4**.

Table 3

Results of SVC *with Feature Extraction* (C = 100).

Sl. No.	σ	No. of SVs	Training Time (Sec.)	Sensitivit y	1-Specificitry	Classification Accuracy
1	10	1430	0.52	0.84	0.112	83.5%
2	600	1020	0.35	0.87	0.108	86.3%
3	**1500**	**564**	**0.21**	**0.93**	**0.096**	**93.8%**
4	2000	438	0.18	0.86	0.104	83.2%
5	2500	438	0.18	0.83	0.109	81.2%

From **Tables 2** and **3**, it is inferred that the best performance for both classifiers are obtained when σ equals 1500 and SVC combined with proposed feature selection methods achieve better generalization performance with lesser training time than the SVC with feature extraction by KPCA.

E. *Comparison with Weka classifiers*

Weka [17] is a machine-learning algorithm in Java developed at University of Waikato in NewZealand. Weka has been tested in all major operating systems like Linux, Windows and Macintosh and it is the presently available superior conventional classifiers. Our data in Matlab environment is converted into ARFF file format and fed into four learning schemes namely J48 (Trees), Zero R (Rules), Random Trees (Trees) and Nave Bayes (Bayes) in Weka-3-4-12 jre. The results obtained from Weka are compared with the SVC with proposed feature selection and extraction methods and presented in **Table 4**. It obviously depicts that the SVC with proposed feature selection method outperforms the superior conventional classifiers.

Table 4

Performance of Weka Classifiers.

Sl. No.	Classifier	Testing Accuracy
1	Trees-J48	92.02%
2	Rules-Zero R	54.94%
3	Trees-Random Tree	87.41%
4	Bayes-Nave Bayes	94.50%
5	**SVC with Feature Selection**	**98.60%**
6	SVC with Feature extraction	93.80%

5.2 Test System 2: IEEE 50 Generator equivalent North American System

This system consists of 50 generators, 145 buses and 453 transmission lines. Here a single, three phase short circuit fault is considered at the beginning end of transmission line connected between buses 63 and 118. The major line to be opened for maintenance is 75-91. Totally 150 operating states are created by considering changes in load level (100 for training and cross validation, 50 for testing) and each state is represented by 806 variables as mentioned in section II. Twelve significant generators namely, G_{60}, G_{67}, G_{80}, G_{100}, G_{104}, G_{112}, G_{128}, G_{135}, G_{138}, G_{140}, G_{79} and G_{96} are selected from the feature selection based on sensitivity index.

Table 5

Results of SVC *with Feature Selection* (C = 100).

Sl. No.	σ	No. of SVs	Training Time (s)	Sensitivity	1-Specificitry	Classification Accuracy
1	10	66	0.13	0.88	0.16	86.0 %
2	600	69	0.11	0.92	0.16	88.0 %
3	**1500**	**41**	**0.08**	**1.000**	**0.08**	**96.0 %**
4	2000	40	0.06	0..96	0.08	92.0%
5	2500	38	0.05	0..92	0.12	90.0%

The first few variables that have highest deterioration effect on the network performance during cross validation selected as input features to the SVC are as follows: P_{67}, P_{100}, P_{112}, P_{96}, P_{135}, Q_{80}, Q_{140}, Q_{100}, Q_{128}, Q_{104}, PF_{170}, PF_{172}, PF175,

PF_{180}, and PF182.The classification performance of the network for different values of σ are shown in **Table 5** that shows the consistency in the performance of the proposed SVC. Best performance is obtained when σ equals 1500, similar to the first test system.

The classification accuracies of the proposed SVC and SVC using KPCA with σ as 1500 are compared with WEKA classifiers in **Table 6**, which clearly shows the superiority of the SVCs over the other classifiers.

Table 6

Comparison with Weka Classifiers.

Sl. No.	Classifier	Testing Accuracy
1	Trees-J48	88%
2	Rules-Zero R	50%
3	Trees-Random Tree	88%
4	Bayes-Nave Bayes	92%
5	**SVC with Feature Selection**	**96%**
6	SVC using KPCA	90%

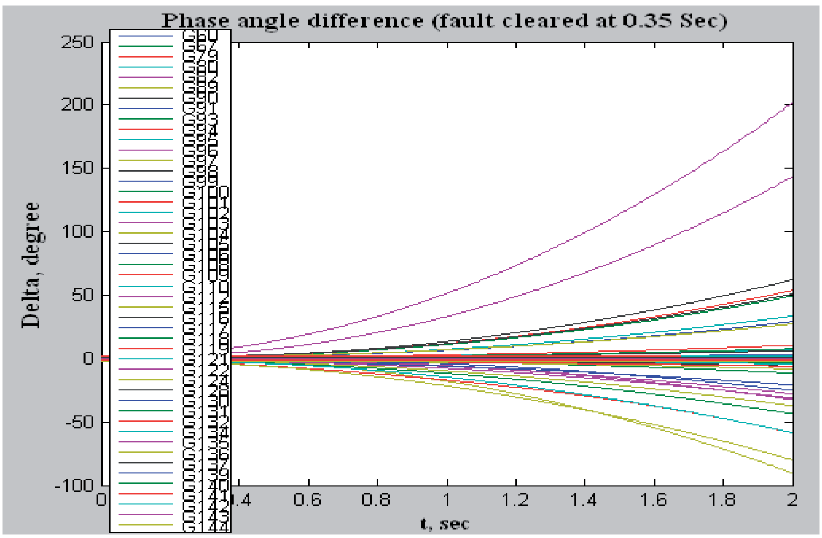

Fig. 2 – *Unstable Swing Curves.*

The fifty testing scenarios of this test system are subjected to Step by Step method of solving swing equations in time domain and swing curves of the generators are plotted to check the stability of the system. Forty eight out of the fifty states are correctly classified and only two unstable states are misclassified as stable. This makes the third row of **Table 5** as 100% sensitivity (No false negative states), 92% specificity (False positive states-2) and 96% classification accuracy (Misclassified states-2). Fig. 2 shows the swing curves of generators of a typical unstable state which is incorrectly classified by the proposed SVC as stable.

Thus there is a close agreement between the decision of the proposed SVC and the time domain solution of swing curves and hence the good potential of support vector classifiers in assessing the stability of power systems is proved.

6 Conclusion

The use of support vector classifier as a powerful tool for fast stability assessment is presented. The selection of appropriate features for classification has been carried out by enhanced feature selection based on sensitivity index and stepwise cross validation. The binary coding of fault location enables a single network to assess the stability of power systems for multiple faults. Simulation results on the IEEE 17 generator reduced Iowa system and IEEE 50 generator equivalent North American system show the proposed SVC based approach provides an accurate classification of stability of power systems for various operating conditions. When compared to SVC trained with feature set reduced by KPCA, the proposed approach has better generalization performance with minimum training time. The proposed SVC also achieves highest classification accuracy when compared to the *Weka* classifiers.

7 References

[1] P. Kundur: Power System Stability and Control, McGraw Hill, USA, 1994.

[2] A.A. Fouad, V. Vittal: Power System Transient Stability Analysis using the Transient Energy Function Method, Prentice Hall, 1992.

[3] Y. Xuo,T.V. Custem, M.R. Pavella: A Simple Direct Method for Fast Transient Stability Assessment of Large Power Systems, IEEE Transactions on Power Systems, Vol. 3, No. 2, 1988, pp. 40-412.

[4] S. Rovnyak, S. Kretsinger, J. Thorp, D. Brown: Decision Trees for Real-time Transient Stability Prediction, IEEE Transactions on Power Systems, Vol. 9, No. 3, 1994, pp. 1417-1426.

[5] G. Garcia, J. Bernussou, M. Berbiche: Pattern Recognition Applied to Transient Stability Analysis of Power Systems with Modeling including Voltage and Speed Regulation, IEE Proceedings of Electric Power Applications, Vol. 139, No. 4, 1991, pp. 321-335.

[6] D.J. Sobajic, Y.H. Pao: Artificial Neural Net Based Dynamic Security Assessment for Electric Power Systems, IEEE Transactions on Power Systems, Vol. 4, No. 1, 1989, pp. 220-228.

[7] L.S Moulin, A.P.A. Silva, M.A. El-Sharkawi, R.J. Marks: Support Vector Machines for Transient Stability Analysis of Large-scale Power Systems, IEEE Transactions on Power Systems, Vol. 19, No. 2, 2004, pp. 818-825.

[8] X.Wang, S. Wu, Q. Li, X. Wang: v-SVM for Transient Stability Assessment in Power System, ISADS 2005 Proceedings, 2005, pp. 356-363.

[9] C. Anderson, J.E. Solem: Classification of Power System Stability using Support Vector Machines, IEEE Power Engineering Society General Meeting, Vol. 1, 2005, pp. 650-655.

[10] C. Anderson, J.E. Solem: Improvements in Classification of Power System Security, IEEE Power Engineering Society General Meeting, 2006, pp. 1-6.

[11] A.E. Gaoyiannis, D.G. Vogiatzis, D.P. Georgiadis, N.D Hatziargyriou: Combined Support Vector Classifiers using Fuzzy Clustering for Dynamic Security Assessment, IEEE Power Engineering Society Summer Meeting, Vol. 2, 2001, pp. 1281-1286.

[12] L.S. Moulin, A.P.A. Silva, M.A. El-Sharkawi, R.J. Marks,: Support Vector and Multilayer Perceptron Neural Networks Applied to Power Systems Transient Stability Analysis with Input Dimensionality Reduction, IEEE Power Engineering Society Summer Meeting, Vol. 3, 2002 , pp. 1308-1313.

[13] S. Muknahallipatna, B.H. Chowdhury: Input Dimension Reduction in Neural Network Training-Case Study in Transient Stability Assessment of Large Systems, Proceedings of International Conference on Intelligent Systems Applications to Power Systems, 1996, pp. 50-54.

[14] I.A.W. Noor, M. Azah, Y. Iskandar: A New Method for Transient Stability Assessment in Power System using LS-SVM, 5th Students Conference on Research and Development, 2007, pp. 1-6.

[15] B. Scholkopf, A.J. Smola, K.R. Muller: Kernel Principal Component Analysis, Proceedings of International Conference on Artificial Neural Networks, 1997, pp. 583.