

# Transient Stability Assessment Using Fuzzy SVM and Modified Preventive Control

B. Dora Arul Selvi, N. Kamaraj

**Abstract**—Transient Stability is an important issue in power systems planning, operation and extension. The objective of transient stability analysis problem is not satisfied with mere transient instability detection or evaluation and it is most important to complement it by defining fast and efficient control measures in order to ensure system security. This paper presents a new Fuzzy Support Vector Machines (FSVM) to investigate the stability status of power systems and a modified generation rescheduling scheme to bring back the identified unstable cases to a more economical and stable operating point. FSVM improves the traditional SVM (Support Vector Machines) by adding fuzzy membership to each training sample to indicate the degree of membership of this sample to different classes. The preventive control based on economic generator rescheduling avoids the instability of the power systems with minimum change in operating cost under disturbed conditions. Numerical results on the New England 39 bus test system show the effectiveness of the proposed method.

**Keywords**—Fuzzy Support Vector Machine (FSVM), Incremental Cost, Preventive Control, Transient stability

## I. INTRODUCTION

POWER systems operation is constrained by stability limits. While these limits often cause congestion and thereby alter energy prizes in a deregulated market, they are vital to maintain the security of power system. Transient stability based limits constitute one of the major issues and a complete answer about security of power system requires evaluation of transient stability of the system following some credible contingencies. A Number of techniques such as time domain integration [1], direct methods based on energy function and extended equal area criterion [2], pattern recognition [3], decision trees [4] and artificial neural networks [5] has been adopted for Transient stability Assessment (TSA) during past years.

Support Vector Machines become the new research focus following pattern recognition and neural networks. Followed by the introduction of Support Vector Machines many Transient Stability Assessment applications based on SVM have been presented [6-10]. The authors of [6] presented a support vector classifier with polynomial kernel. In [7] an  $V$ -SVM with thirteen features is used. In [8-9] a linear SVM is

applied to classify the Stability of Power System using scaled variables. A combined Support Vector classifier based on Fuzzy -C- Means clustering is presented in [10]. In this paper to deal with the stability classification, we propose the fuzzy SVM [11] to make the classification more generalized and robust. We apply a fuzzy membership function to each data point of SVM such that the learning of decision heperplane is influenced by different data point with different degrees. This reduces the effect of noises and outliers in the data points and enhances the performance of SVM.

In a power system, maintaining an acceptable level of security is an important issue. When any potential instability is detected, some preventive control has to be applied to make the system secure. Generator rescheduling [13-16] is one of the mostly used techniques for preventive control of transient stability. This paper presents a new methodology for generation rescheduling using incremental fuel cost of generators.

Thus this paper presents an integrated scheme for investigation of transient stability and its preventive control. For assessing the transient stability of power system, fuzzy support vector machine, which is an extended version of support vector machine, is adopted. FSVM takes into account the fuzzy nature of the training samples during training. For rescheduling generators, a modified approach based on incremental cost characteristics of generators is presented. The resultant operating state of the power system is stable and at the same time more economical when compared to other rescheduling schemes.

The rest of the paper is organized as follows. In section 2 the outline idea of proposed approach is described. Section 3 provides a basic view of FSVM and the process of generating membership values for each input. Transient stability assessment using FSVM is presented in section 4. Section 5 deals with the preventive control measures derived from modified generator rescheduling scheme.

## II. THE PROPOSED METHOD

The objective of the unified approach is to assess system stability and provide operating guidelines for secure operation, during the detection of potential instabilities.

The overall approach is as follows.

1. Reading power system data.
2. Performing optimal power flow.
3. Application of Fuzzy Support Vector classifier to identify the stability status of power system.

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4. If the system is stable, the generators are dispatched as per the calculations in step 2.
5. If the system is unstable the generators are rescheduled by the modified generation rescheduling scheme.

Stability of new operating state is checked. If stable the generators are dispatched as per rescheduling and end otherwise update  $\gamma$  and go to step 5.

### III. FUZZY SUPPORT VECTOR MACHINES

Given a binary classification task with  $k$  samples:  $(x_1, y_1)$  ...  $(x_k, y_k)$  where  $x_i \in \mathbb{R}^N$  belongs to one of the classes  $y_i \in \{-1, +1\}$  for  $i=1 \dots k$ . To classify these samples, SVM first map the input points into a high dimensional feature space and finds a separating hyperplane that maximizes the margin between two classes in this space. Maximize the margin is a quadratic programming (QP) problem and can be solved from its dual problem by introducing Lagrangian multipliers. Without any knowledge of the mapping, the SVM find the optimal hyper plane by using the dot product functions in feature space that are called kernels. The solution of optimal hyper plane can be written as a combination of a few input points that are called Support Vectors.

Even though support vector machine is a powerful tool for solving classification problems, there are still some limitations of this theory. In SVM each training point is treated uniformly. In many cases, the effects of training points are different. In a classification problem, it is often happened that some training points are more important than others. Especially in classifying the stability status of power system, the state of the power system operating at the verge of stability is more important than other states. We would assure that the crucial training points must be classified correctly by defining a fuzzy factor  $0 < s_i < 1$  associated with each training point  $x_i$ . This fuzzy factor  $s_i$  can be regarded as the attitude of the corresponding training point towards one class in the classification problem and the value  $(1-s_i)$  can be regarded as the attitude of meaningless. Thus each training point  $x_i \in \mathbb{R}^n$  is given a label of  $y_i \in \{-1, 1\}$  and a fuzzy factor  $s_i$ . Now the set of training points becomes  $(x_1, y_1, s_1)$  ...  $(x_k, y_k, s_k)$  with associated fuzzy factor  $\delta < s_i < 1$  and sufficient small  $\delta > 0$ .

Basically, a linear hyperplane could be represented as  $x \cdot w + b = 0$  (Where  $x$  is training vector,  $w$  is weight vector and  $b$  is bias). This hyper plane can classify a sample point  $x_i$  according to the following function.

$$f(x_i) = \text{sign}(x_i \cdot w + b), i = 1 \dots k \quad (1)$$

If  $f(x_i) \geq 0$  then  $x_i$  belongs to positive class otherwise negative class. In order to maximize the margin for linear separable cases, the optimal separating maximal margin classifier is constructed using the smallest norm of weights. This is cast as an optimization problem as follows:

$$\text{Min } \frac{1}{2} \|w\|^2 \quad (2)$$

$$\text{Subject to } y_i(x_i \cdot w + b) \geq 1, \quad i = 1 \dots k \quad (3)$$

In the linearly non-separable case, the constraints in equation (1) cannot be satisfied for all data points. To account for the misclassified data, a soft margin is generated. This is incorporated into the optimal margin algorithm by introducing slack variables  $\xi_i, i = 1 \dots k, \xi_i \geq 0$ . An extra cost term is included into the objective function and it gets modified into the following form:

$$\text{Min } \frac{1}{2} \|w\|^2 + C \sum_{i=1}^k \xi_i \quad (4)$$

$$\text{Subject to } y_i(x_i \cdot w + b) \geq 1 - \xi_i, \quad i = 1 \dots k \quad (5)$$

$$\xi_i \geq 0, \quad i = 1 \dots k \quad (6)$$

Where,  $C$  is soft margin parameter that assigns a penalty to the misclassifications. With the introduction of fuzzy membership function  $s_i$  to each training datum, then the optimal hyperplane problem is regarded as a solution to the following equations:

$$\text{Min } \frac{1}{2} \|w\|^2 + C \sum_{i=1}^k s_i \xi_i \quad (7)$$

$$\text{Subject to } y_i(x_i \cdot w + b) \geq 1 - \xi_i, \quad i = 1 \dots k \quad (8)$$

$$\xi_i \geq 0, \quad i = 1 \dots k \quad (9)$$

A smaller  $s_i$  reduces the effect of parameter  $\xi_i$  in the above problem such that the corresponding point  $x_i$  is treated as less important, and the problem can be transformed into its dual problem as follows:

$$\text{Max } J(w, b, \alpha) = \sum_{i=1}^l \alpha_i - \frac{1}{2} \sum_{i=1}^l \sum_{j=1}^l \alpha_i \alpha_j y_i y_j k(x_i, x_j) \quad (10)$$

$$\text{Subject to } \sum_{i=1}^l y_i \alpha_i = 0, \quad 0 \leq \alpha_i \leq s_i C, \quad i = 1 \dots k \quad (11)$$

In SVM, a constant  $C$  bound the Upper bounds of  $\alpha_i$  while they are bounded by dynamical boundaries that are weight values  $s_i C$  in Fuzzy SVM.

#### A. Generating Fuzzy Membership Function

An important step in incorporating Fuzzy SVM is the determination of membership value. When using SVM the major cause for bad classification results is the noise and outliers present in the training data. To reduce the effect of

outliers, Lin and Wang [11] set the membership as a function of the distance between the point and its class centers. FSVM proposed in [12] solve the over-fitting problem by introducing the membership degrees for every data. Choosing an appropriate fuzzy membership function can be challenging. To reduce the effects of noise and outliers we have chosen the fuzzy membership  $s_i$ , as a function of mean and radius of each class. Let the mean of class 1 (Stable) be  $m_+$ , the mean of class -1 (Unstable) be  $m_-$ , the radius of class 1 be  $r_+$  and the radius of class -1 be  $r_-$ . Then the radii of the two classes are expressed by the following equations:

$$\begin{aligned} r_+ &= \max |m_+ - x_i| \quad (x_i : y=1) \\ r_- &= \max |m_- - x_i| \quad (x_i : y=-1) \end{aligned} \quad (12)$$

The fuzzy memberships function for any data point  $x_i$  from the above collected values to be:

$$s_i = \left\{ \begin{array}{ll} 1 - \frac{|m_+ - x_i|}{r_+ + \delta} & \text{if } y_i = +1 \\ 1 - \frac{|m_- - x_i|}{r_- + \delta} & \text{if } y_i = -1 \end{array} \right\} \quad (13)$$

Where  $\delta$  is a sufficient smaller value greater than zero to ensure  $s_i \neq 0$ . Since the fuzzy membership is a function of the mean and radius of each class, the distance of outliers to their corresponding mean is equal to the radius and they are regarded as less important in FSVM training such that there is a big difference between the hyperplanes of the SVM and FSVM. The only free parameter C in SVM controls the trade off between the maximization of margin and the amount of misclassification. In FSVM the soft margin parameter C can be set at a sufficient large value. Based on the value of  $s_i$ , the influence of C, on the training of SVM can be controlled. If all equals 1, it is the same as SVM that the system will get narrower margin and allow less misclassifications. A smaller value of  $s_i$ , makes the corresponding point  $x_i$  less important in the training. Thus, with different values of  $s_i$ , the tradeoff of the respective training point  $x_i$  in the system can be adjusted and hence the number of free parameters in FSVM equals the number of training data.

#### IV. APPLICATION OF FSVM TO TSA

To illustrate the applicability of FSVM, the New England 39 bus system [2] is used. The system consists of 46 transmission lines, 39 buses, 10 generators and 12 transformers. There the generators are represented by classical models and loads are represented as constant impedances.

#### A. Data Generation

The first step in TSA using FSVM is the generation of training and testing data. Totally 600 operating states have been created by adopting the following:

- 3 bolted faults are created at the beginning node of transmission lines, one at a time.
- For each fault, the loads on the individual load buses are varied randomly between 70 to 150 percentages of the base value.

The three transmission lines, where the three phase short circuit faults occurs are namely the transmission lines between bus 17 and bus 27, bus 23 and bus 24 and between bus 17 and bus 18. All faults occurred near the beginning end of the lines and the duration of disturbances are 0.34 seconds for fault at line 17-27 and 0.4 seconds for fault at lines 23-24 and 17-18. Opening the circuit breakers on both ends of the transmission line clears the fault.

Time domain simulation method is used for generating the data. The data generation involves the following procedure.

- 1) The load on a load bus is fixed at any one value between 70 to 150 percentages of the base value keeping the other loads at their normal value.
- 2) The created operating state is validated by an optimal power flow.
- 3) One of the contingencies from the contingency list has been simulated in time domain.
- 4) Based on the relative rotor angles of individual generators with respect to the reference generator, the given state is classified as stable or unstable.

For a given sample if the relative rotor angle of any one machine exceeds 100 degrees then the input state is considered as unstable otherwise it is stable. The complete input feature set consists of the active and reactive powers of each generator, total active and reactive loads of the system at the instant of fault, a 3 bit binary code indicating the location of disturbance and fuzzy membership value of each training point with a total of 25 inputs. The output feature set consists of only one output indicating the security class. Out of the 600 input states generated, 540 datasets are allotted for training and 60 for testing purpose.

#### B. Generation of Fuzzy membership Value

In the complete data set, the numbers of data belong to positive and negative classes are equal. As described in section 3, the mean and radii of each class and then the fuzzy membership value of each datum is computed. In calculating the fuzzy membership values, the first 22 input variables are considered. This is because that the 3 bit binary code is used just to indicate the location of fault and it is not a representative of the power systems operating point. The values of  $s_i$  and  $(1 - s_i)$  provide the degree of belongingness of the data for the two classes. If a datum belongs to positive

class by 86.7% then it belongs to negative class by 13.3%. In conclusion the data belongs to positive class.

### C. Training of Learning Machines

The SVM and FSVM with Gaussian RBF kernel are trained and tested in MATLAB environment. Table I shows the training details of both SVM and FSVM.

TABLE I: TRAINING DETAILS

Classifier	$\gamma$	No. of Support Vectors	Training Time (Sec)
SVM	1	504	0.343
	10	267	0.282
	100	066	0.274
FSVM	1	264	0.234
	10	240	0.211
	100	41	0.193

To illustrate the improvement in training in FSVM compared to normal SVM, the number of support vectors obtained by both the methods is compared. As can be seen from Table I, the number of support vectors yielded by FSVM is lesser than standard SVM. By reducing support vectors the training time of FSVM classifiers are improved. This clearly indicates the usefulness of fuzzification in the feature space.

### D. Performance Analysis.

Sensitivity, specificity and Classification accuracy are statistical measures of the performance of a binary classification test. 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 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)  
 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 accuracy is given by  $(TP+TN)/(TP+TN+FP+FN)$ . Table II, compares the functioning of SVM and FSVM with same values of kernel parameter. The SVM have large number of false positive states than the false negative states. So the sensitivity is lesser than the specificity. Here again the FSVM presents better performance. The classification accuracies acquired by the two machines are also presented. In Table III, the testing times of SVM and FSVM are given.

TABLE III: TESTING TIME

Classifier	Gaussian RBF Kernel ( $\gamma$ )	Testing Time (Sec)
SVM	1	0.034
	10	0.034
	100	0.034
FSVM	1	0.019
	10	0.019
	100	0.019

As can be seen from Tables I-III, the FSVM outperforms SVM. During the five folds cross validation in normal SVM, there was a lot of variation in the results of different folds and this was due to the presence of outliers. The selection of soft margin parameter C also causes lot of variation in the results even for same kernel function and kernel parameter. Then the FSVM with membership function based on the mean of two classes was constructed and tested. On the line of expectation, the results were higher for FSVM than normal SVM. For all cases listed in Table II the overall sensitivity and specificity of FSVM was higher than normal SVM and the classification accuracies of FSVM presented in Table III are also greater than SVM. FSVM achieves this with minimum training and testing times. This clearly demonstrates the superiority of the proposed FSVM for transient stability investigation.

Table IV shows the result of FSVM for four randomly selected operating states of the test system for each fault. From this we know that the result of FSVM coincides with the true operating status. Here no preventive control measures are needed for the stable cases C11, C21 and C31. The generators are scheduled as prescribed by Optimal Power Flow. The unstable cases C12, C22, and C32 should undergo the following modified generator-rescheduling scheme.

TABLE IV: RESULTS FROM FSVM CLASSIFIER

Faulted Line	Case No	Load Level	Actual Status	Results from FSVM
17-27	C11	Active load at bus 15 is reduced by 31%	Stable	+1 (Stable)
	C12	Active load at bus 24 is increased by 32.23 %	Un Stable	-1 (Unstable)
23-24	C21	Active load at bus 14 is increased by 15.62 %	Stable	+1 (Stable)
	C22	Active load at bus 3 is increased by 62.11% and Active load at bus 39 is increased by 25.36 %	Un Stable	-1 (Unstable)
17-18	C31	Active load at bus 39 is reduced by 9.06%	Stable	+1 (Stable)
	C32	Active load at bus 3 is increased by 19.53 % and Active load at bus 39 is increased by 18.11 %	Un Stable	-1 (Unstable)

TABLE II: PERFORMANCE COMPARISON

Classifier	$\gamma$	No. of Testing States	True Positive States	False Positive States	True Negative States	False Negative States	Correctly Classified States	Classification Accuracy	Sensitivity	Specificity
SVM	1	60	24	6	29	1	53	88.33	0.8000	0.9667
	10	60	26	4	29	1	55	91.67	0.8667	0.9667
	100	60	26	4	30	0	56	93.33	0.8667	0.1000
FSVM	1	60	30	1	29	0	59	98.33	0.967	1.000
	10	60	30	0	30	0	60	100	1.000	1.000
	100	60	30	0	30	0	60	100	1.000	1.000

V. PROPOSED PREVENTIVE CONTROL METHOD

The relative rotor angle of generators with respect to the reference generator has been used to detect the system's stability / instability status. When the relative rotor angle of any one of generator exceeds  $100^\circ$  it can be considered as an unstable case and it is given by equation (14).

$$:\delta_{ij} = \delta_i - \delta_j > 100^\circ \tag{14}$$

Where  $\delta_{ij}$  -Relative Rotor angle of generator i with respect to reference j,  $\delta_i, \delta_j$  -Rotor angle of most advanced generator and reference generator with respect to a synchronously rotating reference frame

Here 'i' refers to the most advanced generator and rests of the generator are considered as least advanced. To ensure system stability a small amount of real power ( $\gamma * \Delta P$ ) is to be shifted from the most advanced generator to any one of the generators in least advanced group. The generator whose realpower generation is to be increased is determined based on the incremental fuel cost characteristics.

Let

$P_k \dots P_n$  -Original real power generation of each unit

$\gamma$  -Acceleration factor

$\gamma * \Delta P$  -Amount of real power to be shifted

$\frac{dF_k}{dP_k} \dots \frac{dF_n}{dP_n}$  -Incremental fuel cost for each generator

The incremental fuel cost for the least advanced generators are calculated for the increase in real power  $\gamma \Delta P$ . The acceleration factor ( $\gamma$ ) lies between 0.25 and 1.The unit having minimum incremental fuel cost (m) has been taken as one candidate for rescheduling and the other candidate is the most advanced generator (i). Real power generations of the units are then given by equation (15).

$$\begin{aligned} P_{inew} &= P_i - \gamma * \Delta P \\ P_{mnew} &= P_m + \gamma * \Delta P \end{aligned} \tag{15}$$

With these generation values, system stability is checked. Even though we considered the system becomes unstable when the relative rotor angle of any one of generator exceeds

$100^\circ$ , by rescheduling generators the relative rotor angle of

most advanced generator is brought below  $90^\circ$  for the system to be stable. If the system is again unstable acceleration factor  $\gamma$  is decreased and the procedure is repeated until the system become stable. During the process, if the most economical generator hit the maximum limit then power is transferred to the second most economical generator for achieving system stability. Fig.1shows the flowchart of the rescheduling scheme.

For a better understanding of the rescheduling procedure, an illustrative example of the generation rescheduling is discussed. When the three phase short circuit occurs on the transmission line connecting bus 17 and bus 18 near bus 17, represented as case C32 in table 9 the system becomes unstable and the most advanced generator is G38. Fig.2 represents the unstable swing curves of the generators before generator rescheduling.

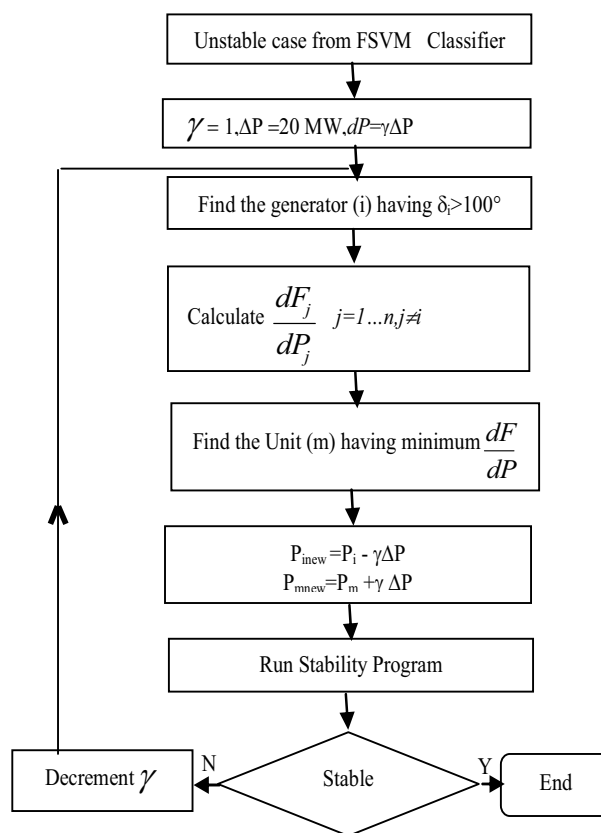


Fig. 1 Rescheduling Procedure

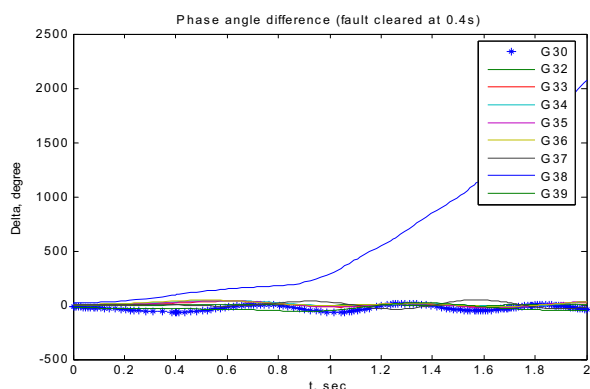


Fig. 2 Swing Curves-Before Rescheduling

Applying modified generation rescheduling scheme, the generator G33 is found to be the least advanced generator having minimum incremental fuel cost and 140 MW of power is shifted from most advanced generator (G38) to least advanced generator (G33). During the process, G33 reaches its maximum limit then the power is transferred to the next most economical generator G37. Thus 45 MW of power is shifted from G38 to G37. Totally 185 MW of power is shifted from G38 and its maximum rotor angle comes to 89.78°. Fig.3 shows the swing curves after rescheduling. It clearly states that the system is dynamically stable.

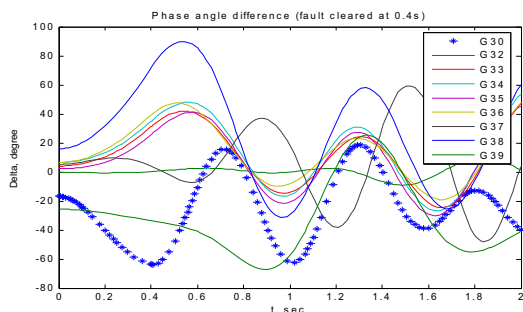


Fig. 3 Swing Curves-After Rescheduling

Table VI lists the details of rescheduling for all the unstable cases. Here PBR represents Power Before Rescheduling; PAR means Power After Rescheduling and PS means Power to be shifted.

TABLE VI RESCHEDULING DETAILS

Case No.	Most advanced generator			Most Economical Least advanced generator			PS (MW)
	Gn No	PBR (MW)	PAR (MW)	Gn. No.	PBR (MW)	PAR (MW)	
C12	38	913.98	838.98	33	567.93	642.93	75
C22	36	616.00	571.00	33	613.60	658.60	45
C32	38	930.00	745.00	33	589.00	729.00	140
				37	579.50	624.50	

During fault at lines 17-18 and 17-27 the most advanced generator is G38 and the most economical generator in the least advanced group is G33. When fault is presented in line 23-24 the most advanced generator is 36 and the least advanced generator remains the same. In order to obtain a stable system, specified amount of real power calculated by the rescheduling scheme is transferred from G38 to G33. In most of the generator rescheduling procedures, the reference generator has been considered as the least advanced generator. A cost comparison between the proposed scheme and the rescheduling scheme [14] based on reference generator has been presented in Table VII.

TABLE VII COST COMPARISONS

Fault ed Line	Case No	Production Cost in \$/hr		Saving in Cost \$/hr
		Most Economical Generator	Reference Generator	
17-27	C12	37497	37524	26.67
23-24	C22	42203	42224	20.72
17-18	C32	39895	40103	208.02

From Table VII, it is inferred that the proposed scheme achieves a stable operating point in a most economical way.

## VI. CONCLUSION

An integrated scheme for power system transient stability evaluation and its preventive control is proposed. Main requirements for online TSA methodologies are fast evaluation time and accuracy of results. The Fuzzy SVM presented in this paper achieves highest classification accuracy compared to pure SVM with minimum training and testing times. Thus it is highly suited for online TSA. To ensure secure operation of power system some preventive control actions are required when potential instabilities are detected. A modified generation rescheduling scheme is proposed which results in a stable and more economic operating state of power system. Numerical test demonstrates that the proposed approach is effective to assess the status and stabilize the unstable states of a multi machine power system.

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