International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 3 Issue 9, September- 2014

Static Security Analysis using Support Vector Machine

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***Abstract*— Security Analysis is the process of testing power system safety limits, up to what extent the system is safe. Power system security is divided into four classes' viz., secure, critically secure, insecure, and highly insecure, based on the value of security index. In this paper, a multi class support vector machine (SVM) classifier algorithm is used to classify the patterns. These patterns are generated for IEEE 6 bus and IEEE 14 bus by Newton-Raphson load flow method for line outage contingencies at different generating and loading conditions. The main objective is to give an indication of security level to the system operator which helps to initiate necessary control actions at the appropriate time, preventing system collapse.**

***Keywords* - Newton-Raphson, Load flow, Pattern generation, Classifier, Static security index, Support vector machine.**

I. INTRODUCTION

Power system security is the major electrical issue all over the world these days. Severe disturbances may cause the system to an undesirable state. Knowing the power system limits may help the security level system operator to take necessary action preventing the system collapse. Hence, potent control of power systems [13] is needed for expeditious security assessment [1]-[3]. Static security is the ability of the power system to withstand unexpected contingencies to reach steady state operating point without transgressing the system operating constraints [4]-[5]. A powerful tool is, therefore, required to classify and assess power system security level with high accuracy in less time.

Patterns are generated for IEEE 6 bus and IEEE 14 bus systems. To generate these patterns, it is necessary to run load flow of each system. Load flow analysis (also known as power flow analysis) may be solved by three methods which are the Newton-Raphson method, Fast-Decoupled method and Gauss-Seidel method. The most common power flow method is the Newton-Raphson due to the fact that it can converge very quickly as the iteration begins near the desired root.

After running load flow, the maximum and minimum voltage limits of each bus, and the maximum MVA limits of each line of each system are calculated. Maximum MVA limit will be the maximum value of the thermal limit which the line could withstand. The conventional method involves solving full ac load flow and rotor dynamics for each disturbance. This process is highly time consuming. Therefore, recently, many neural network [2] based techniques such as Artificial Neural Network [3] techniques have been proposed for security assessment problem.

Support vector machine (SVM) is one such tool, which is being used as a solution for pattern classification problem [4]. Today, Pattern classification is procuring more significance in solving multiple power system troubles [5]-[6]. The classification function is designed depending on the training set. This helps to know the security level of the power system in a short period of time.

II. POWER SYSTEM SECURITY ASSESSMENT

Security Analysis is the process of testing power system safety limits, up to what extent the system is secure. Security Assessment is broadly classified as Static security assessment (SSA) and Transient security assessment (TSA) [1], [3], [6], [8]. In this paper, the main concentration is on SSA. The security evaluation process include set of contingencies namely generator/line outage, system phase faults, sudden changes in the load etc. The line outage contingency is taken in this paper for testing the system security.

Power system security is divided into four classes' viz., secure, critically secure, insecure, and highly insecure, based on the value of security index [1]. The Static security level is defined based on the computation of a term called Static Security Index (SSI). The system is said to be static secure if the power generation and bus voltages are well within their limits.

The Static Security Index (SSI) is computed by calculating the Line Overload Index (LOI) for each branch and Voltage Deviation Index (VDI) for each bus. The equations of LOI, VDI and SSI are shown below which are represented as (1), (2) and (3) respectively.

$$LOI_{km} = \begin{cases} \dfrac{S_{km} - S_{km}^{\max}}{S_{km}} * 100, if & S_{km} > S_{km}^{\max} \\ 0, \quad if & S_{km} < S_{km}^{\max} \end{cases} \quad (1)$$

Where, S_{km} is the mega volt ampere flow representation of branch k-m and S_{km}^{max} is the representation of mega volt ampere flow that the branch k-m could withstand.

$$VDI_k = \begin{cases} \dfrac{\left|V_k^{min}\right| - \left|V_k\right|}{\left|V_k^{min}\right|} * 100, & if \quad \left|V_k\right| < \left|V_k^{min}\right| \\ \dfrac{\left|V_k\right| - \left|V_k^{max}\right|}{\left|V_k^{max}\right|} * 100, & if \quad \left|V_k\right| > \left|V_k^{max}\right| \\ 0, & Otherwise \end{cases} \qquad (2)$$

Where V_k^{min}, V_k^{max}, V_k are the minimum voltage limit, maximum voltage limit and bus voltage magnitude of bus k.

$$SSI = \frac{W_1 \sum_{i=1}^{N_l+N_t} LOI_i + W_2 \sum_{i=1}^{N_b} VDI_i}{N_l + N_t + N_b} \qquad (3)$$

Where N_l, N_t, N_b are the number of transmission lines, transformers and buses respectively.

III. PROPOSED SYSTEM

The proposed system consists of two stages namely A) Static Security Assessment [6] and B) SVM based pattern classification [5] as shown in Figure 1.

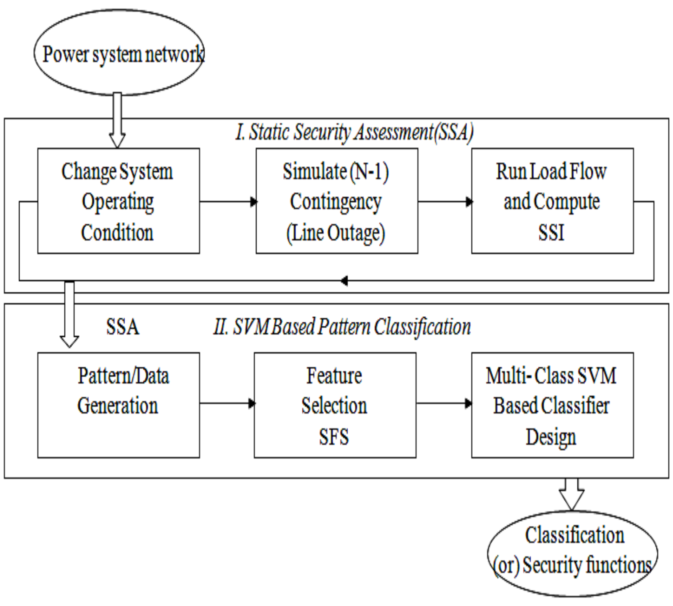

Fig 1. SVM classifier design for Static Security Assessment

A. Static Security Assessment

Static security is the capacity of a power system to reach a steady state operating point which is capable of withstanding the system operating constraints following a contingency. The violations of thermal limits of transmission lines and bus voltage limits are the main concerns for static security assessment. Feature Selection (FS) is the process of selecting a subset of pattern attributes called *'features'*, removing the redundant and irrelevant variables for building robust learning models [1]. The selected feature variables form the components of a vector called feature vector Z. A simple and quick procedure called *Sequential Forward Selection* (SFS), a wrapper model, is identified as a suitable FS method for the security assessment problem addressed herein. The feature selection block reduces the huge dimension of pattern vector. The classifier design block uses a suitable learning algorithm and develops the classifier model based on a training data set [9].

In this stage a power system network is taken and the operating conditions are changed to test the system. Each system consisting N lines, is applied to a line outage contingency, hence named as N-1 line outage contingency. Numbers of contingency conditions have been created, and each condition is applied to Newton-Raphson load flow method to obtain Static Security Index (SSI) at each condition. The class labels have been categorized depending on different values of SSI which is tabulated as shown below.

Class Category/Label	SSA
Class A: Static Secure	SSI = 0
Class B: Static Critically Secure	SSI > 0 & SSI ≤ 5
Class C: Static Insecure	SSI > 5 & SSI ≤ 15
Class D: Static Highly Insecure	SSI > 15

Table 1. Class labels for Static security assessment

The severity of each system is tested under normal conditions by creating a line outage. The line that is mostly affected by line outage can be identified by creating this contingency. Line outage of each line for an IEEE 6 bus system is tabulated below.

Line. No	Line outage	LOI	SSI
1	1-2	200.00	37.50
2	1-4	100.00	18.75
3	1-5	200.00	37.50
4	2-3	200.00	37.50
5	2-4	200.00	37.50
6	2-5	200.00	37.50
7	2-6	212.92	39.92
8	3-5	200.00	37.50
9	**3-6**	**243.43**	**45.64**
10	4-5	200.00	37.50
11	5-6	200.00	37.50

Table 2. Line outage for IEEE 6bus system

It is clear from the above table that the 6 bus system is much affected for a 3-6 line outage contingency. Number of lines in a 6 bus system is taken as 11. Similarly the Line outage contingency is applied to the IEEE 14 bus system, to know for which line outage contingency the system is mostly affected. The numbers of lines in 14 bus system are more and hence the line outage that affects the system is directly given below.

Line. No	Line outage	LOI	SSI
7	6-12	142.3662	31.82

Table 3. Line outage for IEEE 14bus system

B. SVM based Pattern classification

Patterns are generated for IEEE 6 bus and IEEE 14 bus systems by running at different line outage contingencies. To generate these patterns, Newton-Raphson load flow methods is applied to each system. Voltage deviation of each bus and thermal violation of each branch are calculated to find SSI.

These generated patters are classified by using SVM classifier. Classification in SVM [4] is an example of Supervised Learning. Known labels help indicate whether the system is performing in a right way or not. This information points to a desired response, validating the accuracy of the system, or be used to help the system learn to act correctly. A step in SVM classification involves identification as which are intimately connected to the known classes. This is called feature selection or feature extraction. Feature selection and SVM classification together have a use even when prediction of unknown samples is not necessary.

OBSERVATIONS

1. SSI is high for outage of line consisting generators.
2. SSI is less for outage of line consisting high load
3. Increasing the number of lines will reduce the overload of the line.

The single line diagram of IEEE 6 bus system and IEEE 14 bus system are shown below with the respected generated patterns. These patterns are categorized according to the class labels of SSI as shown in the Table 1.For IEEE 6 bus system 20 patterns and for IEEE 14 bus system 20 patterns are generated.

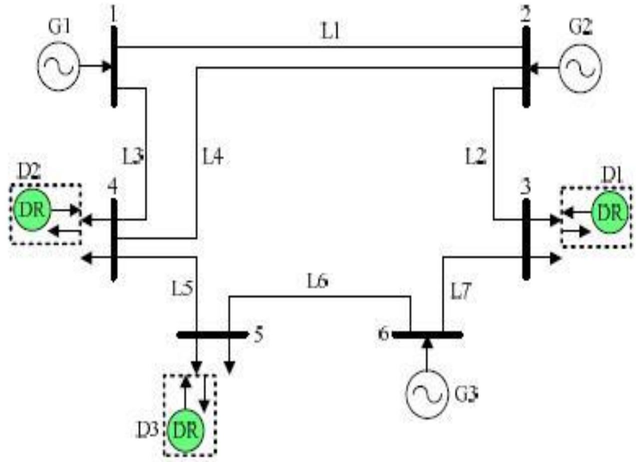

Fig 2. Single line diagram of IEEE-6 bus system

Class	VDI	LOI	SSI
Class A	0	0	0
Class A	0	0	0
Class A	0	0	0
Class A	0	0	0
Class A	0	0	0
Class B	5.4127	0	0.6388
Class B	8.6318	0	1.0155
Class B	0	17.9273	3.1636
Class B	0	12.6149	2.2262
Class B	0	28.1761	4.9722
Class C	0	31.2023	5.5063
Class C	0.2267	66.0729	12.417
Class C	6.5271	34.5286	14.0689
Class C	2.8216	82.1016	7.9073
Class C	0	100	13.6497
Class D	0	147.9216	27.7353
Class D	0.019	100	20.0025
Class D	0	138.3153	25.9341
Class D	0	100	20
Class D	0	100	17.6471

Table 5. SSI for IEEE-6bus system.

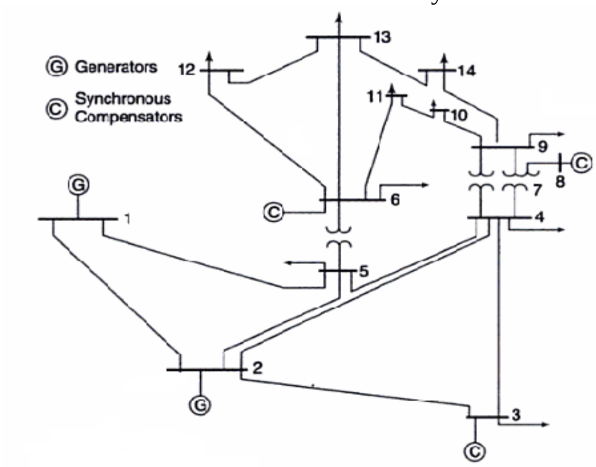

Fig 3. Single line diagram of IEEE 14 bus system

Class	VDI	LOI	SSI
Class A	0	0	0
Class A	0	0	0
Class A	0	0	0

Class A	**0**	**0**	**0**
Class A	**0**	**0**	**0**
Class B	**5.7143**	**0.0015**	**0.3363**
Class B	**6.6667**	**10.8196**	**1.3468**
Class B	**5.7143**	**20.6894**	**2.2272**
Class B	**6.6667**	**44.2842**	**4.4299**
Class B	**5.7143**	**41.0666**	**4.2071**
Class C	**100.4511**	**41.0666**	**10.1282**
Class C	**100.4511**	**20.6894**	**7.9688**
Class C	**20**	**141.9904**	**14.1203**
Class C	**15.2381**	**109.668**	**10.8933**
Class C	**9.5283**	**68.8937**	**6.6391**
Class D	**100.4511**	**294.6276**	**32.8723**
Class D	**77.1429**	**175.2476**	**20.6069**
Class D	**24.7619**	**154.3005**	**15.528**
Class D	**177.1429**	**178.2667**	**26.942**
Class D	**195.7143**	**290.4392**	**38.265**

Table 6. SSI for IEEE 14bus system

IV. SVM OVERVIEW

Support Vector Machine (SVM) is a supervised learning algorithm developed by Vladimir Vapnik and it was first heard in 1992. Support Vector Machines (SVM) is used to find a solution for the classification problem [10]-[12]. SVM has successful applications in many complex and real-world problems such as text and image classification, hand-writing recognition, face recognition, data mining, bioinformatics, medicine and bio sequence analysis and even stock market.

In many of these applications, SVM is the best choice. SVM performs minimization of error function called re-substitution process by an iterative training algorithm [9] to construct an optimal hyperplane. Support Vector Machine (SVM) has been used in this work for multi-classification task in security assessment model. Although SVM is basically intended for binary classification, the concept of multi-class SVM also exists.

Consider an example of set of n points (vectors):
$x_1, x_2, \ldots\ldots\ldots x_n$ such that x_i is a vector of length m , and each belong to one of two classes represented by "+1" and "-1".
So the training set is $(x_1,y_1), (x_2,y_2), \ldots\ldots\ldots(x_n,y_n)$, $x_i \in R^m$, $y_i \in \{+1,-1\}$.

Hence, the decision function will be $f(x) = \text{sign}(w.x + b)$. We want to find a separating hyper plane that separates these points into the two classes. The positives (class +1) and the negatives (class -1). (Assuming that they are linearly separable).

The separating hyper plane for the above considered input and output patterns, is shown in below figure which is represented as figure 4. But there are many possibilities for such hyper planes, is shown in figure which is represented as figure 5. The selection of optimal hyper plane by using SVM is also shown which is represented by figure 6.

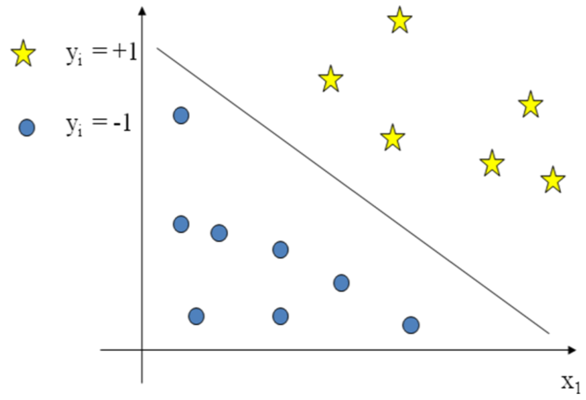

Fig 4. Hyper plane for linearly separable patterns

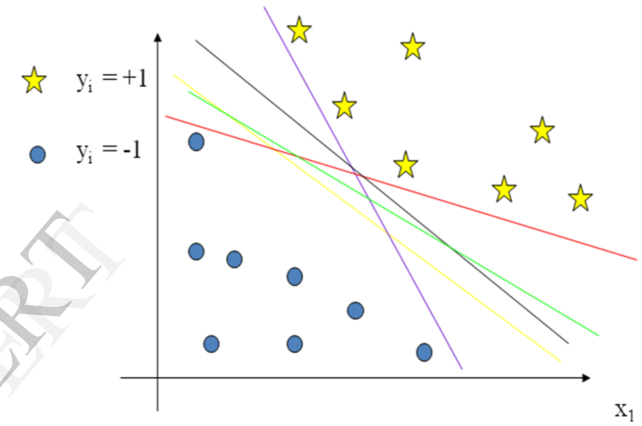

Fig 5. All possible Hyper planes

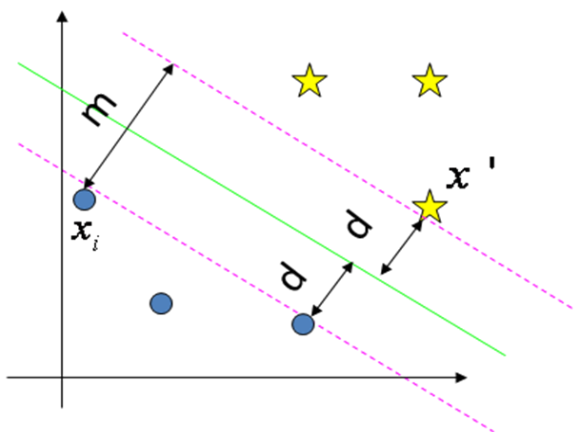

Fig 6. Choosing Optimal Hyper plane

V. RESULTS AND DISCUSSION

The generated patterns are classified by using SVM classifier. The SVM classifier classifies two classes at a time. The decision surface or hyper plane is obtained by using

SVM algorithm. The software used for this algorithm is MATLAB R2009a in Windows XP operating system. The results obtained are as follows.

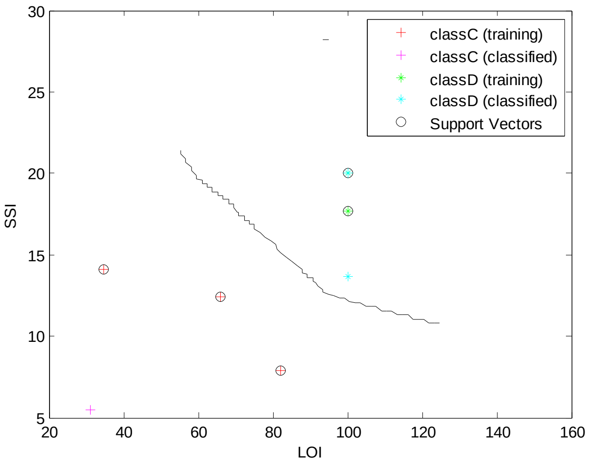

Fig 7. SVM classifier for IEEE 6 bus system

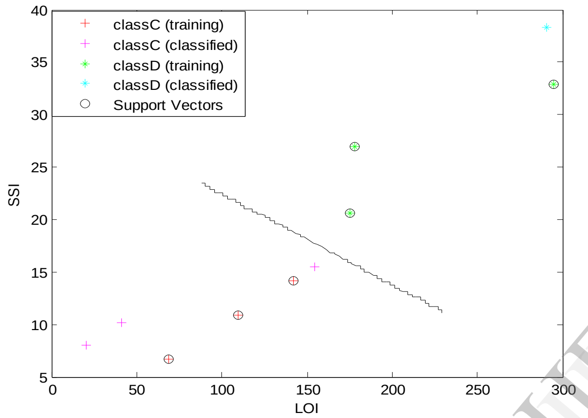

Fig 8. SVM classifier for IEEE 14 bus system

VI. CONCLUSION AND FUTURE SCOPE

Support Vector Machines (SVM) is the best solution of the classification problem. SVM technique is much effective when compared to Neural Network. Very low misclassification rate and high accuracy. The SVM-based pattern classification approach for power system security assessment in a multi class environment helps to initiate necessary control actions at the appropriate time preventing the system collapse. Future work will focus on online implementation of proposed system and application of facts controllers for reduction of risk, due to security.

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