Principle Component Analysis Based Data Mining for Contingency Analysis on IEEE 30 Bus Power System

Lekshmi M, M S Nagaraj

***Abstract:** This Paper is an attempt to develop a Data Mining tool for the contingency of the power system. By mining the big data in the power system and analyzing the early detection of the contingency in the power system a larger cost cutting can be planned. As Mining would reduce the computational complexity of the contingency analysis this attempt would lead to reduction in the hardware use. This paper uses Multiclass Relevance Vector Machine(MCRVM) and Multiclass Support vector machine(MCSVM) in order to mine the data which include the voltage, power generated , power angles , power demand in different lines of the power system. The Data mining would need a data transformation technique, which would reduce the dimensionality of the data introduced for mining. The combination of Data cleansing and the Principal Component Analysis would act as the data transformation technique in this paper. A Matlab based simulation is carried using the IEEE 30 bus system for the contingency analysis by incorporating the loading risk assessment strategy using the Multiclass SVM and RVM and the results are compared and the outputs are tabulated. Active power performance index and the reactive power performance index are used in contingency analysis of the IEEE 30 bus system thus used and the accuracy of classification and the speed of classification with the different methods and the contingency rankings are found and displayed.*

***Keywords** : Contingency Analysis, Principle Component Analysis, Artificial Neural Network, Support Vector Machine.*

I. INTRODUCTION

Smart Grid Implementation needs data from different sensors and meters to be collected from the power system and these data, which is collected, would be huge. The down time of any power system due to contingency would cause a loss to the power system economy. The Switzerland based Large Hadron Collider has developed a Big data experiment which would conduct experiments that would deliver data from 150 million sensors which samples its output at the rate of 40 million times per second. But only the 0.001% of the data is actually used for experiments carried out in the lab [1-3].

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The proposed work in this paper would gather the meter reading or the sensor data of power generated, power demand, power angles and the voltage firstly. Then the gathered data is applied with the Fast Fourier Transform as a preprocessing step[4-5]. Then the preprocessed data is feature extracted with Principle Component Analysis un order to get a feature of reduced dimension [6].

The feature thus extracted is used for training the MCRVM and the MCSVM for the different kinds of contingencies in the power system. A tradeoff between both RVM and The SVM methods are carried out in the IEEE 30 bus system. The idea developed in this paper is to avoid the load flow for contingency analysis by getting the real time data from the lines to be trained in the MCRVM and the MCSVM in order to get the contingency as a model to be used for further analysis for a system. The paper is organized as follows Section II talks about the proposed method of online contingency analysis, Section III discusses the implementation details of the contingency analysis carried out in the paper. Section IV would discuss the results and discussion of the proposed work, and the conclusion would follow with the references.

II. PROPOSED CONTINGENCY ANALYSIS-A CLASSIFCATION APPROACH

The implementation of the online contingency analysis of the system for a 30 bus IEEE bus system is carried out with loading contingency like the light load, medium load and heavy loading condition to be assessed. The inputs like the voltage, voltage angle, real power generated and the reactive power are introduced as the input which would be feature extracted in order to develop a contingency analysis model using two different learning models of MCRVM and MCSVM. Performance measures that would decide the adaptability of any of these methods for contingency analysis model is decided. The voltage, voltage angle, real power generated and the reactive power from the IEEE 30 bus power system under study thus obtained would be taken for feature extraction for training the MCRVM and the MCSVM training algorithms for making a intelligent model for online contingency analysis. The data cleansing analysis on the signals is carried out and the results are applied with Principle Component Analysis in order to give a reduced size input to the MCRVM and the MCSVM in order to have a reduced computational complexity.

The PCA analysis is the projection method that would project the complex system in to combination of the basis functions of Principle Components.

After applying the data cleansing methods on the inputs specified the PCA is applied on it in order to reduce the size of the data.

III. CLASSIFICATION

The performance measures that have to be predicted for the contingency analysis are the active power performance index and the reactive power performance index. The calculations of the performance indices can be described as defined in [7]. The orthogonal characteristics between the active and the reactive power which is a decoupled measurements on the power system can act as a parameter that would act as the measure for the contingency prediction. The active power performance index is given as ,

$$PI_p = \sum_{\alpha} w_p L(P_L / P_{L\lim})^2$$

where, P_L power in line L. w_p is the weight value for the line power $P_L, P_{L\lim}$ is the real power limit in the line L. α is the set of lines which has the power limit crossed .The reactive power performance index is dependent on the voltage variation in the buses that would cause the reactive power injection in the lines. The formula for the reactive power performance index is given as [7]

$$PI_v = \sum_{\beta} w_{vi}(|V_i - V_{i\lim}|) / V_{i\lim}$$

where V_i is the voltage magnitude at bus i, $V_{i\lim}$ is the voltage magnitude limit in line i, w_{vi} is the weight value for the line voltage, β is the set of buses that crosses the limits. The contingency ranking is carried out using the two methods of MCSVM and MCRVM in this paper.

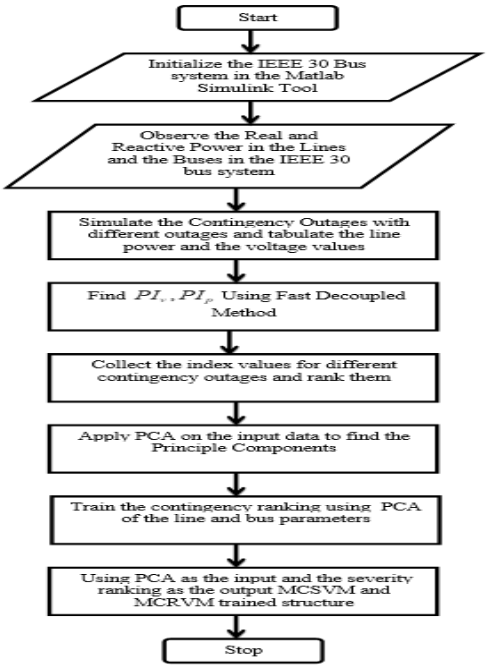

Fig. 1.MCSVM and MCRVM Training

The Training flow of the contingency ranking system for the IEEE 30 bus system is carried out as shown in the Figure1.During the testing phase the outages are made to occur in the buses randomly and the contingency severity ranking is classified using the MCSVM and the MCRVM method.

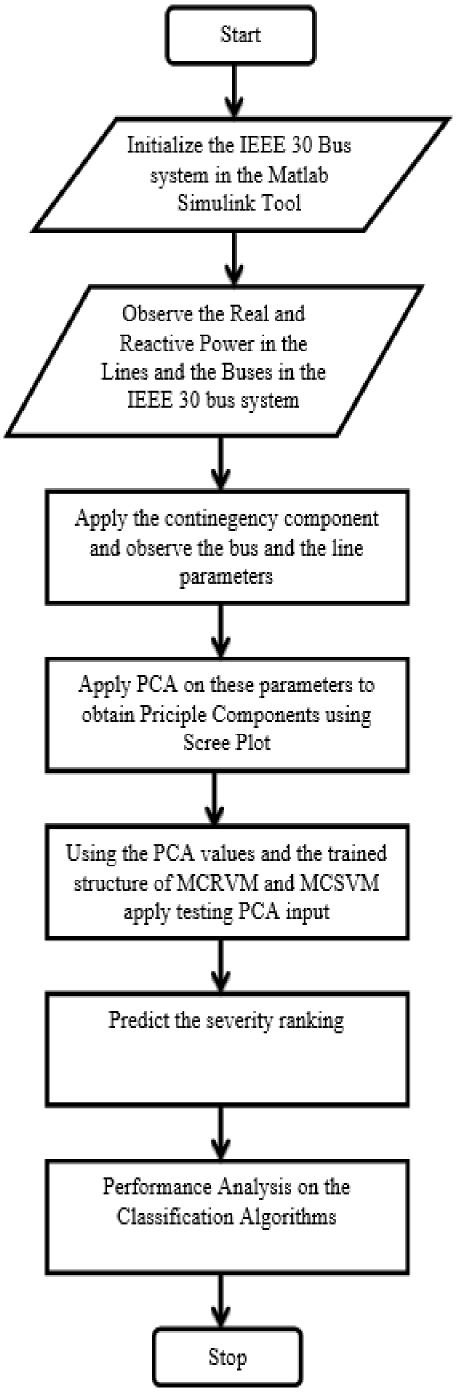

Fig. 2.MCSVM and MCRVM Testing

The testing phase of the contingency ranking classification is carried out as given in Figure 2.

The IEEE 30 bus system is applied with the contingency condition and for each condition the real and reactive power performance index is calculated and the data is collected for training. The voltage at each bus in the 30-bus system is taken as the input and the FFT is calculated for the voltage wave and the Principle Component Analysis using the Singular Value Decomposition (SVD).

The output of the SVM and the RVM training is taken as the composite performance index the PCA on the parameters of each bus is the input that is given for training.. The 30-bus input of all the line parameters with the PCA extracted and the corresponding ranking values as the output of the training data are given for the multiclass training. The multiclass training would correspond to the ranking of the bus in terms of the bus number, which is more severe.

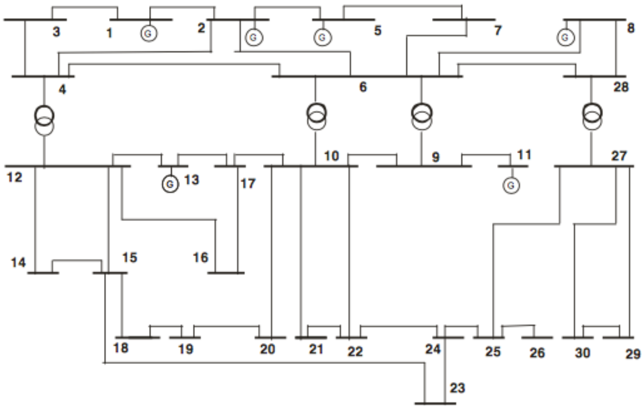

Fig. 3.IEEE 30 Bus System

The complete topology of the IEEE 39 bus system is as given in Figure 3.

IV. RESULTS AND ISCUSSION

Matlab Mfile based simulation is carried out on the IEEE 30 bus system as shown in the Figure 3. The IEEE 30 bus system is a 41 line power system which has the generators in the 2,5,8, 11 and 13 buses and slack bus is in the bus 1. The voltage profile of the 30 buses in per unit values while initializing is as given in Figure.4 as a plot of bus versus the voltage per unit value.

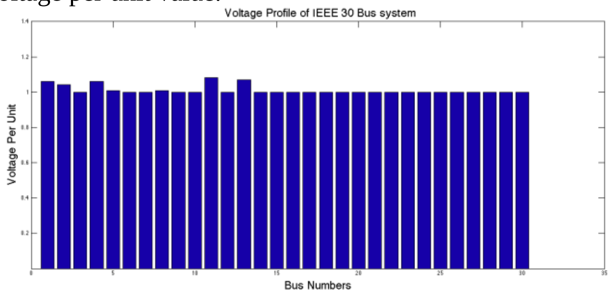

Figure 4.Voltage Profile of the IEEE 30 bus system

As the input for the training of the MCSVM and the MCRVM algorithm the real power performance index and the reactive power performance index using the Fast Decoupled method is carries out to get the contingency ranking for the different outages has to be tabulated. The contingency ranking values is predicted by means of applying a thresholding values on both the performance index values considered. The Table 1 depicts the performance index values calculated from the Fast Decoupled method, MCSVM and MCRVM on the IEEE 30 bus system. The MCSVM uses the Radial Basis Function for training and the MCRVM uses the probabilistic method for training. The input is the vector of 60 inputs that is the PCA extracted from the 30 buses for both the voltage and power waveforms.

The ranking obtained from the Fast Decoupled method

Table 1.Contingency Ranking

Line No.	Line outage	PI_v	PI_p	Fast Decoupled Rank	MCSVM Predicted Rank	MCRVM Predicted Rank
1	1-2	68.96	22.98	1	1	1
5	2-5	26.7	8.79	2	2	2
6	2-6	23.56	7.65	3	3	3
15	4-12	21.45	6.78	4	4	4
36	28-27	20.988	6.34	5	5	5
9	6-7	19.56	5.98	6	6	6
2	1-3	18.7	5.7	7	7	7

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18	12-15	18.34	5.55	8	8	8
4	3-4	18.26	5.34	9	9	9
3	2-4	18.1	5.23	10	10	10
38	27-30	17.89	5.1	11	11	11
37	27-29	17.78	4.87	12	12	12
25	10-20	17.65	4.56	13	13	13
27	10-11	17.56	4.45	14	14	14
19	12-16	17.45	4.40	15	15	15
17	12-14	17.42	4.35	16	16	16
22	15-18	17.40	4.32	17	17	17
24	19-20	17.35	4.31	18	18	18
41	6-28	17.33	4.27	19	19	19
12	6-10	17.30	4.195	20	20	20
30	15-23	17.28	4.0976	21	21	21
39	29-30	17.089	3.899	22	22	22
35	25-27	16.986	3.565	23	23	23
31	22-24	16.898	3.232	24	24	24
26	10-17	16.656	3.123	25	25	25
28	10-22	16.367	3.099	26	26	26
21	16-17	16.233	2.998	27	27	27
40	8-28	16.008	2.877	28	28	28
14	9-10	15.8787	2.645	29	29	29
23	18-19	15.766	2.564	30	30	30
32	23-24	15.667	2.449	31	31	31

20	14-15	15.0087	2.3354	32	32	32

The execution time for the contingency rank prediction using the fast decoupled method ,MCSVM and MCRVM methods are as given in Table-II.

Table- II: Comparison of execution time taken by various methods

Methods	Fast Decoupled methods	MCSVM	MCRVM
Execution Time	22.34 secs	12.34secs	11.45secs

While automating the contingency ranking of the lines the hardware needs and the algorithm reaction time are important aspects of the implementation. It is observed the time taken for prediction of the MCSVM and the MCRVM implementation takes lesser time facilitating the chances of obtaining the results quickly.

V. CONCLUSION

Matlab based implementation is carried out with the traditional method of Fast decoupled method and the proposed method of MCSVM and MCRVM. The results obtained from the proposed method matches the output obtained from the traditional method. The advantage of the proposed method is that the execution time of the proposed method is around 50% of the total time. This execution time of the proposed method suggests getting a best alternative to the traditional methods while online contingency ranking is a requirement. The hardware implementation of this proposed algorithm in the online contingency ranking algorithm would be most feasible as the execution time is optimal.

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