Critical Bus Ranking and Severity Prediction using Data Mining and ML Technique under n-1 Condition

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Abstract.

The load dispatch centre must identify critical or weak buses for each operational situation. It is now more important than ever due to the potential of voltage instability and voltage collapse. This article explore the application of data mining and machine learning techniques to identify and to predict the critical bus ranking under n-1 condition. In the process of static steady analysis, there will be a significant amount of data will generate during the contingency analysis process, and it is critical to figure out how to transfer that data to the system's value in order to evaluate the severity of the system. Data analysis through the use of data mining and machine learning techniques helps to predict the risk that bus services may suffer in a variety of load scenarios. The study is carried on IEEE 30 bus system; the data for the study is generated by computing VCPI for different load conditions. In the analysis, the MATLAB & WEKA Data Mining Software was employed.

Keywords. Contingency analysis, VCPI, Critical Bus, Data Mining, Machine Learning, severity prediction.

1. INTRODUCTION

The possible reasons for a power outage can range from major (with a huge impact) to minor (with a small impact). To properly control and ensure power system failures, impact assessments and system contingency rankings are essential. A system which compares the losses of one machine to the others' influence is utilized to conduct a general critical load bus identification (N-1 contingency criteria). There is often a consideration for the loss of a generator, a transformer, and a transmission line in the N-1 contingency analysis. [1-3]. Increasing use of stressed power systems creates voltage stability and system security challenges. A huge issue is the impact of a power outage. It's significant since one of the main problems is the frequency of a line outage, which has a drastic influence on the system's balance (pre-contingency case) electric power demand that allows for the utility provider to adjust the frequency without instability [4].

When a line outage occurs, the system is forced to function under the contingency state for an extended period of time. To avoid voltage collapse, a previous knowledge of the load bus voltage stability margins under various contingency situations is required. This may be acquired by monitoring and taking control action against any changes in those margins. One of the major causes of voltage collapse is the system's failure to provide reactive power, as a result of a growing load [5].

The likelihood of voltage collapse occurring is strongly influenced by the maximum load a certain bus can support. Trying to raise the load past this threshold would lead to the system falling out of control, which might cause the voltage to collapse. The massive overload would seem to prove that the main system's power capacity would be unable to handle it [4-5]. The maximum loadability of a load bus in the system is estimated using VCPI. The load buses are rated according to their maximum loadability, with the lowest maximum loadability being placed first. The bus has the least amount of strength, since its maximum load capacity is low, and the load has already overloaded the voltage to the point of failing.

Planning or operation engineers can utilize this information to ensure that the amount of equipment they install does not put the voltage stability limit at risk by beyond the maximum loadability of the system. Overloading a bus above a certain critical level leads the system to collapse unless the system is adjusted properly. The key voltage stability margin is what this study defines as the threshold for bus loading. Estimating the criticality of a bus may be done by calculating the voltage stability margin. It is important to know where to put the additional voltage support devices so as to minimize voltage instability, which is why figuring out where the key buses are is advantageous.

The planning power engineer must use this facts to correctly communicate. So, Big Data and machine learning approaches are providing a new framework that gives solutions to clean up poor data and support the power engineers in making informed decisions in the future about operation and planning [6-7]. The relevance and use of big data analytics in many areas is comprehensively discussed [8]. The simulation data is mined using a data mining tool with a j48 classification algorithm to estimate the transmission line severity [6-7] [9].

The VCPI is employed in this article to rank the buses. Data analytics tools are used to process the huge amount of data that is generated from simulation, and machine learning is used to evaluate the potential severity of the bus condition and identify conditions that could lead to it. Training data is evaluated by running the j48 classification algorithm and is fed to the machine learning, which identifies the potential risks that the bus could face.

This document has six parts. Section II describes the critical bus ranking technique. Section III introduces a data mining process. Section IV describes the proposed algorithm, whereas Section V discusses the Case Study and Results. Section VI concludes.

2. APPROACH OF CRITICAL BUS RANKING

The load dispatch centre must identify the crucial bus for a particular operational state. According to the operator's needs, these important buses will be prioritized based on load situations and voltages. Recent power systems' voltage instability and voltage collapse have made the bus ranking duty even more critical. The voltage collapse prediction indicator (VCPI) combines the voltage magnitude and voltage angle information at buses and the network admittance matrix to forecast voltage collapse [5] [10]. A successful approach of assigning importance to buses based on their capacity to tolerate voltage disturbances. The load restriction technique is used to create a ranking index for buses. The index identifies how bad things go in a bus (such as excessive voltage oscillations) if a particular situation occurs. The critical bus in the system is determined by an indication of voltage collapse [10]. The effectiveness of load monitoring may be achieved for all the load buses in the system utilizing VCPI. The model may be derived at bus k by using complex number identities, as stated in Eqn (1). When VCPI is equal to 1, the system is considered unstable [11].

$$VCPI_{kth,bus} = \left| 1 - \frac{\sum_{\substack{m=1 \\ m \neq k}}^{N} \left| V_m^{'} \right|}{V_k} \right| \quad \ldots\ldots.. \quad (1)$$

3. Critical Bus Analysis Using Data Processing and Data Mining

In the process of computing VCPI for various load condition, a huge volume of data will be generated dusting the steady state analysis. Handling the data is the huge problem of today because of the fast expansion of extracting data and transforming it into usable information. Data mining is a way of detecting patterns and valuable information using huge data sets. Even while organizations have seen more improvements in data management, their executives are still running into issues with scalability and automation [12]. This research analyses the relationship between data mining methods and support, and it will be possible to categorize the various methods into two distinct aims: either defining the target dataset or creating algorithms to make predictions [13].

The power engineers use data mining to identify significant information, connect patterns, and spot linkages. The typical sequence of Data mining includes four steps: establishing objectives, collecting and processing data, applying Data mining techniques, and assessing results. There are many simulations have to be done to learn the load flows of the system under different loading circumstances in order to better understand the results of contingency analysis. Many data processing steps will be needed in this process; data mining will be better suited to addressing the contingency analysis of power systems [3] [6-7].

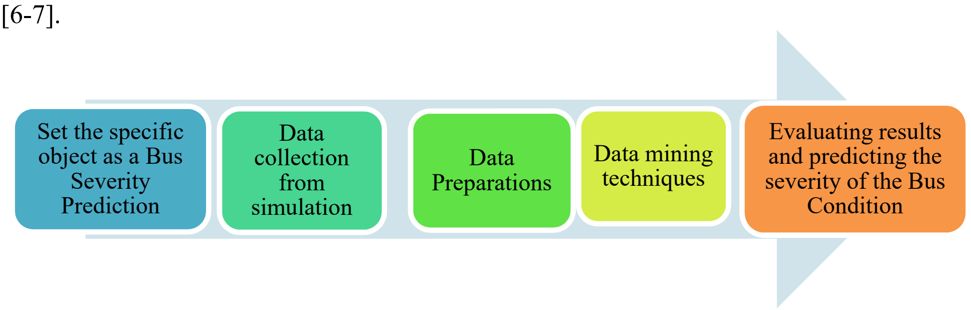

Figure 1. Data mining process applied to contingency study of power system

The schematic process flow of data mining techniques is presented in Figure 1, which illustrates the use of contingency analysis on the power system. Setting the specified object is the initial stage of data mining, and should take the least amount of time. First, data must be collected. This approach may vary depending on the system being used. Initially, three types of data are collected: Structured, unstructured, and semi-structured data.

To aid power engineers in addressing important issues, data mining collects and organizes data sets from simulation processes. Depending on the dataset, limiting the number of dimensions might further improve performance. While high frequency patterns have broader applications, data variances may be more fascinating to suggest probable severity forecasts. It is possible to apply classification algorithms based on the provided data at the fourth stage of data mining process. This is done by labelling the incoming data (supervised learning). The findings must be examined and comprehended when the data is aggregated. When finishing results, they should be valid, fresh, useful, and understandable. When these conditions are met, the suggested system may use this data to develop new techniques for successful severity prediction of bus.

4. Proposed Algorithm

The data mining approach was applied to the contingency analysis of the power system to rank the severity of the buses. The VCPI was calculated in accordance with eqn. (1). The following algorithm demonstrates the use of the constructed model; the model is shown to be effective.

Step No. 1: Read System Data.

Step No. 2: Compute the load flow solution by NR Method.

Step No. 3:	Calculate Voltage collapse proximity indicator for different load conditions.
Step No. 4:	Computed results to be saved.CSV file format.
Step No. 5:	Read the Voltage Collapse proximity indicator of each bus.
Step No. 6:	Data Processing Using Big Data Analytics tool.
Step No. 7:	Select Explorer in WEKA & Load the Data file saved in. CSV file format
Step No. 8:	Click on classification and save file in .arff format after selecting Select Classification-Tree-J48, and use training set and click on the start option to predict the severity and ranking of the each line.
Step No. 9:	Right Click for option of tree J48 which is shown on the Result List window.
Step No. 10	Print the severity and contingency ranking of bus.

Supervised learning is a machine learning technique that anticipates the input-output relationship. Supervised learning is used to determine transmission line severity under various load situations. Regression and classification models are among the most prominent groups of techniques used for control [6-7] [14]. A classification algorithm may be used in operational data mining to create models of both classification and regression. Decisions are made using a decision tree, the basis of which is a tree categorization [6-7] [15].

5. Case Study And Results

The suggested method's performance is tested by using IEEE-30's bus system to run a simulation. For the active and reactive power, the convergence limit is 0.00001. The basic MVA of the system is 100 MVA. The IEEE-30 bus system consists of 1-slack buses, 5-generator buses, 24 load buses, and 41 transmission lines [3]. When it comes to finding out the root cause of power system instability, critical bus is important. The identification of the most important bus occurs by prioritizing buses by importance. A transmission-line outage was the scenario taken into account. In this scenario, you take off one transmission line at a time. Critical buses are ranked by the usage of VCPI for IEEE-30. The case studies analysed are explained by considering two different loading condition under single line transmission out age conditions.

Table.1: List of Bus Ranking under n-1 of transmission line outage with base load condition.

Bus Rank No	Bus No. when line 4 outaged	Bus No. when line 18 outaged	Bus No. when line 24 outaged	Rank No	Bus No. when line 4 outaged	Bus No. when line 18 outaged	Bus No. when line 24 outaged
1	11	11	11	16	22	20	1
2	3	13	13	17	24	19	25
3	13	12	12	18	27	6	6
4	12	2	15	19	5	5	5
5	16	17	17	20	23	24	28
6	14	16	2	21	4	15	8
7	10	21	16	22	29	18	27
8	1	9	20	23	25	29	23
9	2	1	14	24	9	8	30
10	21	3	22	25	30	25	10
11	17	14	21	26	7	30	24
12	15	22	9	27	8	10	26
13	19	27	19	28	26	23	4
14	20	11	18	29	6	26	7

15	18	13	3	30	28	4	29

The ranking for the buses was based on the computation of VCPI. The rankings are as mentioned in table 1 for different line outages and it is observed very clearly from the table 1 the bus ranking is varied for different line outage scenario. The critical bus rankings are dependent on how severe the situation is. Critically severe ranges from 1 to 10, then from 11 to 20 and 21 to 30 for the lower levels of severity as mentioned in the table.

Table.2: Critical Bus Ranking Classification

Sl. No	Condition	Ranks
1	Critical	1 to 10
2	Semi- Critical	11 to 20
3	Non-critical	21 to 30

The same analysis was carried for different loading and observed it for top 10 contingency ranking is listed. The single line outages are considered into account separately to prepare the data for different loading conditions, in all three scenarios. The data produced is firstly pre-processed and categorized with j48 classification algorithms by ranging as critical, semi-critical and non-critical.

Table. 3: Trained Data set for Base Load Condition for different line outages.

Sl. No	C No.	VCPI	Condition	Sl. No	C No.	VCPI	Condition
1	C_No_3	0.1373	Critical	31	C_No_12	0.1674	Critical
2	C_No_3	0.1340	Critical	32	C_No_12	0.1596	Critical
3	C_No_3	0.1649	Critical	33	C_No_12	0.1598	Critical
4	C_No_3	0.1026	Non Critical	34	C_No_12	0.1154	Semi Critical
5	C_No_3	0.1054	Semi Critical	35	C_No_12	0.1043	Semi Critical
6	C_No_3	0.0522	Non Critical	36	C_No_12	0.1318	Critical
7	C_No_3	0.0879	Non Critical	37	C_No_12	0.1323	Critical
8	C_No_3	0.0866	Non Critical	38	C_No_12	0.1021	Semi Critical
9	C_No_3	0.0963	Non Critical	39	C_No_12	0.1094	Semi Critical
10	C_No_3	0.1420	Critical	40	C_No_12	0.1107	Semi Critical
11	C_No_3	0.1915	Critical	41	C_No_18	0.1099	Semi Critical
12	C_No_3	0.1551	Critical	42	C_No_18	0.1307	Critical
13	C_No_3	0.1644	Critical	43	C_No_18	0.1125	Semi Critical
14	C_No_3	0.1445	Critical	44	C_No_18	0.0513	Non Critical
15	C_No_3	0.1320	Semi Critical	45	C_No_18	0.1029	Semi Critical
16	C_No_3	0.1468	Critical	46	C_No_18	0.1041	Semi Critical
17	C_No_3	0.1324	Semi Critical	47	C_No_18	0.0469	Non Critical
18	C_No_3	0.1293	Semi Critical	48	C_No_18	0.0936	Non Critical
19	C_No_3	0.1315	Semi Critical	49	C_No_18	0.1196	Semi Critical
20	C_No_3	0.1297	Semi Critical	50	C_No_18	0.0819	Non Critical
21	C_No_12	0.1199	Critical	51	C_No_18	0.1636	Critical
22	C_No_12	0.1346	Critical	52	C_No_18	0.1542	Critical
23	C_No_12	0.1166	Critical	53	C_No_18	0.1560	Critical
24	C_No_12	0.0554	Non Critical	54	C_No_18	0.1252	Critical
25	C_No_12	0.1069	Semi Critical	55	C_No_18	0.1363	Critical
26	C_No_12	0.1077	Semi Critical	56	C_No_18	0.1288	Critical
27	C_No_12	0.0506	Non Critical	57	C_No_18	0.1313	Critical
28	C_No_12	0.0976	Non Critical	58	C_No_18	0.1172	Semi Critical
29	C_No_12	0.1214	Critical	59	C_No_18	0.1194	Semi Critical
30	C_No_12	0.0816	Non Critical	60	C_No_18	0.1264	Critical

The severity was predicted based on VCPI which was computed for different line outage condition, the data generated during this phenomenon was in high volume and was processed with the help of data analytic and machine learning tools. In this analysis 65% of the data is used for training to predict the severity of the line and 35% of the data is used to test based on the training data set. Table.3 shows the training data set for the different load condition.

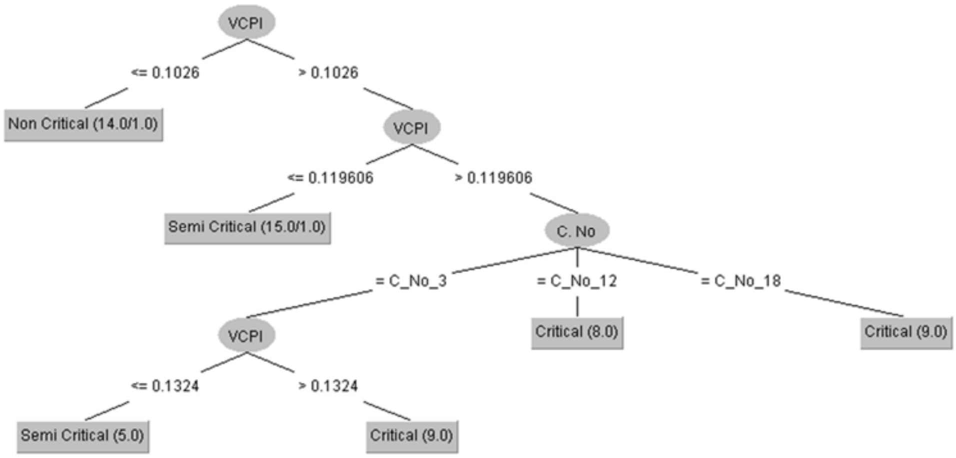

Figure 2. Decision tree for predicting the severity condition of the buses for different line outages.

Table. 4: Tested Data set for Base Load Condition for different line outages

Sl. No	C No.	VCPI	Condition	Sl. No	C No.	VCPI	Condition
1	C_No_3	0.1336	Critical	16	C_No_12	0.0705	'Non Critical'
2	C_No_3	0.126	'Semi Critical'	17	C_No_12	0.1133	'Semi Critical'
3	C_No_3	0.1034	'Semi Critical'	18	C_No_12	0.0164	'Non Critical'
4	C_No_3	0.1224	'Semi Critical'	19	C_No_12	0.0989	'Non Critical'
5	C_No_3	0.0984	'Non Critical'	20	C_No_12	0.0896	'Non Critical'
6	C_No_3	0.078	'Non Critical'	21	C_No_18	0.12	Critical
7	C_No_3	0.1173	'Semi Critical'	22	C_No_18	0.1218	Critical
8	C_No_3	0.0091	'Non Critical'	23	C_No_18	0.0894	'Non Critical'
9	C_No_3	0.1025	'Non Critical'	24	C_No_18	0.0797	'Non Critical'
10	C_No_3	0.0931	'Non Critical'	25	C_No_18	0.1057	'Semi Critical'
11	C_No_12	0.1222	Critical	26	C_No_18	0.0712	'Non Critical'
12	C_No_12	0.1146	'Semi Critical'	27	C_No_18	0.0929	'Non Critical'
13	C_No_12	0.0763	'Non Critical'	28	C_No_18	0.1003	'Non Critical'
14	C_No_12	0.1062	'Semi Critical'	29	C_No_18	0.0043	'Non Critical'
15	C_No_12	0.0905	'Non Critical'	30	C_No_18	0.0844	'Non Critical'

Figure.2 shows the decision tree chart for the basic loading condition for different line outages was illustrated. By considering the categorization, in table 4, the critical, semi-critical and non-critical ranges are tabulated and severity forecast for the buses based on the VCPI's are provided. The Figure 3 shows visualization classifier error for base load condition under different line outage. The data scattered visualization is obtained for different condition and analysed by using the visualization classifier errors. Based on the training data set, the sample missing data set conditions are predicted for the base load condition under single line outage is shown in Figure 4.

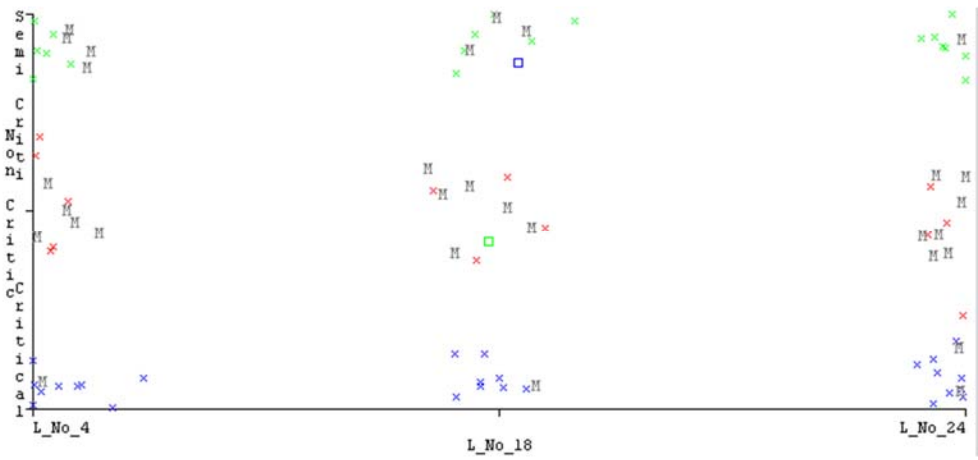

Figure 3. Visualization of Condition versus line number for base load condition for line outages

6. CONCLUSION

This study employs a classification approach to predict the critical buses by computing VCPI, and it does so depending on the ranking procedure. The J48 classification technique yielded nearly identical results to manual categorization. Using the top 10 rank index values, it was decided that rank-10 represents a serious issue, with rankings from 10 to 20 representing partially severe conditions, and ranks more than 20 representing typical conditions is achieved, the proposed method efficient to predict the severity of the busses by using the data mining technique, simulation data is processed and severity of the busses were predicted by using classification algorithm.

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