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VOLTAGE STABILITY ANALYSIS USING MACHINE LEARNING ALGORITHMS

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ABSTRACT: Voltage instability is a phenomenon that limits the operation and the transmission capacity of a power system. Sufficiently fast detection and appropriate remedial actions can prevent the system from undergoing a voltage collapse. These considerations motivate the development of methods to identify operating conditions that are near or within the region for which the system is voltage unstable, and to suggest remedial actions to bring back the system to a condition where it has sufficient margin to voltage collapse. This work presents a method that performs voltage stability assessment and voltage instability by using machine learning algorithms. However, assessment of voltage security margins is computationally challenging and can in most cases not be estimated in the time frame required by system operators in critical situations. To overcome this challenge, a machine learning-based method for fast and robust computing of the voltage security margin is proposed and tested. The main contribution of the proposed work is calculation of voltage stability indices using different machine learning algorithms. Finally, a method for voltage instability prediction is developed. This method is proposed to be used as an online tool for system operators to predict the system's near-future stability condition given the current operating state. The method uses KNN, Decision tree and SVM machine algorithms. The results from case studies using the IEEE 14-bus system and IEEE 30 bus systems show good performance and the network can accurately, within only a few seconds, predict voltage instability events in almost all test cases.

1. Introduction: In a three-phase AC power system, the active and reactive power move from the generating station to the load through various network buses and branches. This power flow, also known as load flow, is crucial for analyzing the steady state operation of the system. Power flow studies employ mathematical techniques to determine bus voltages, phase angles, and power flows (both active and reactive) through branches, generators, and loads. Power flow analysis plays a significant role in the planning and operation of power distribution systems. It enables power distribution professionals to evaluate the steady state conditions and make informed decisions. This analysis is particularly important when designing new networks or expanding existing ones, such as adding new generator sites, meeting increased load demands, or identifying optimal transmission sites. By solving the load flow equations, we obtain nodal voltages, phase angles, and power injections at all buses, as well as power flows through interconnected channels. This information is valuable for determining the best locations and optimal capacities of proposed generating stations, substations, and new transmission lines. Additionally, it helps maintain desired voltage levels at specific buses within acceptable tolerances, minimizes system transmission losses, and enables economic system operation by optimizing fuel costs for power generation. Furthermore, power flow analysis allows us to assess line flows and ensure they are not operating close to their stability or thermal limits. Overloading lines can lead to instability or thermal stress, which may compromise the reliability and safety of the power system. Therefore, load flow analysis helps identify potential issues and aids in making informed decisions to maintain a secure and efficient power distribution system.

Load Flow Analysis is the solution of an electric power system under the steady state operating conditions and is the first step for the solutions of several modern power utility. Results of the load flow equations are required for the system planning and the operational planning and control, state estimation and outage security assessment for large system and for the more complicated stability and optimization computations discussed Saxena et.al [1] and Vlachogiannis[2]. Load flow calculations provide power flows and voltages for a specified power system, subject to the regulating capability of generators, condensers, and tap changing under load transformers as well as specified net interchange between individual operating systems. This information is essential for the continuous evaluation of the performance of a power system and for analysing the effectiveness of alternative plans for system expansion to meet increased load demand AbdelMoamen et al [3].Modified Newton Raphson load flow method was suggested by Nagendra Rao et al [4]. In this method, the Jacobian is split into a constant part and a variable part. The constant part is symmetric and is factorized only once and stored. There is no need of triangularization of the Jacobian for every iteration. The memory requirement for this method is same as that of the Newton Raphson method.A constant matrix method in rectangular coordinates is proposed by Singh et al (1984). The matrix used is the same as that of the polar Fast Decoupled Load Flow (FDLF) method and therefore it is likely to have similar convergence problems for ill-conditioned systems. Prasad et al (1986) also proposed a constant matrix method in rectangular coordinates in which constant matrix is different from that of Singh et al (1984) and showed that the convergence is faster and more reliable in the sense that solution converges even from ill-conditioned systems. P. Kundur [7] defined voltage stability as "the ability of a power system to maintain steady and acceptable voltages at all buses in the system at normal operating conditions and after being subjected to a disturbance”. It is desired that the power system remains in an equilibrium state under normal conditions, and it is expected to react to restore the status of the system to acceptable conditions after a disturbance, i.e., the voltage after a disturbance is replace to a value close to the pre-disturbance situation.

In this paper to mitigate the voltage stability problems modern facts devices like STATCOM are used. These devices are expensive so must be located properly mostly at weak buses. The line stability indices like FVSI, Lmn play an important role. So, by using these indices the weak bus can be found and the devices can be placed. PSAT is a user-friendly MATLAB toolbox is used for the placement of STATCOM. Matlab code is written and implemented successfully Identification of critical bus plays an important role in placement of FACTS devices, like STATCOM.In this paper the voltage stability indices such as fast voltage stability index and line stability index and these are analysed for IEEE 14 bus these indices to identify critical lines in the system and can be evaluated by keeping buses at base as well as at different loading conditions. For each system, loading scenarios are varied i.e., base loading, load is increased by 30%, and load is increased by 50% etc. FVSI and Lmn indices are calculated for each loading condition at each line. From the results most critical line is decided.Nageshwar Rao [8] concerned with the review of the key methodologies usually used to find Voltage Stability Indices (VSI) in Potential of Electric System (PES). In voltage stability assessment, a number of voltage stability indices (VSIs) have been recommended for investigating and observing the system stability. More than a few VSIs have been listed to compute the voltage collapse proximity, voltage stability margin, identify weakest bus, contingency screening and ranking, identifying weak regions in terms of reactive power deficiency, reactive power margin, identifying and locating critical branch and areas, estimating and evaluating the system stability margin.

IEEE-14 bus system and IEEE-30 bus system are used at different loads to generate train data for the machine learning algorithms. To calculate Lmn and FVSI voltage stability indices to assess voltage stability of the power systems. To apply different machine learning algorithms like decision tree, KNN, Support vector machine (SVM) to find the voltage stability indices and to observe the status of the stability of the power system.

2. Load flow Analysis:

The mathematical model for the study of power flow is the set of non-linear algebraic equations. These equations can be expressed as real equations with voltages either in the rectangular or polar form. The loads and generations are continuously varying due to consumers. So, it is essential to solve the load flow problem. The load flow solution gives the information about voltage magnitudes, phase angles, power flow through the transmission lines, etc.

The Newton-Raphson method is a powerful method of solving nonlinear algebraic equations. The basis for the Newton-Raphson method of solving load flow problem is the Taylor series expansion. The real and reactive power at node 'i' is given by Equations 1and 2

$$Pi = \sum_{k=1}^{n} |Vi||Vk||Yik| \cos(\theta ik - \delta i + \delta k) \quad (1)$$

$$Qi = -\sum_{k=1}^{n} |Vi||Vk||Yik| \sin(\theta ik - \delta i + \delta k) \quad (2)$$

The correction vector matrix is given by Equation .3

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} J_1 & J_2 \\ J_3 & J_4 \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta|V| \end{bmatrix} \quad (3)$$

The elements of Jacobian matrix J1, J2, J3, J4 are obtained by differentiating the equations 2 and 3 with respect to δP and δQ . The algorithm is started by an initial guess value. The advantages of using this method are applicable for larger system, number of iterations required to converge is less, more reliable and more accurate results.

Voltage stability analysis:

Moghavvemi and Omar (1998) derived line stability index based on concept of single line two bus transmission system to find stability of a line.

The expression for the Lmn index is given in equation 4

$$Lmn = \frac{4XQr}{|Vs|^2 \sin^2(\theta-\delta)} \leq 1 \quad (4)$$

From the equation we can observe lmn is directly proportional to reactive power and indirectly related to active power. when the discriminant is less than zero then the root is imaginary and the system is unstable, If the value of lmn is near to 1 the system is said to be near to instability and if the value is near to 0 then the system said to be stable.

Musirin and Rahaman (2002), has proposed fvsi based on the concept of power flow through a single line two bus system The expression for FVSI index is given in equation 5

$$FVSI = \frac{4|Z|^2 Qr}{|Vs|^2 X} \quad (5)$$

Fvsi was developed using measurements of voltage and reactive power. if the value of FVSI IS NEAR to zero the system is stable and if the value near to 1 the will said to be unstable. Both Lmn ,FVSI indices used to find the weakest bus in the system.

3. Methodology:

The standard IEEE bus systems such as IEEE 14 bus and IEEE 30 bus are taken and the dataset generation details are also discussed along with the Machine Learning techniques, their algorithms and the programs used.

The dataset required for the analysis is generated by running the load flow analysis using Newton Raphson method in the MATLAB at different loads from 10% of load to 150% of load and the voltage stability indices like Lmn, FVSI are also calculated and trained to the regression models and the accuracy of the regression models are tested. Various regression techniques are applied to this set of features to potentially predict voltage stability indices.

Decision Tree Regression: When there are non-linear or complex relationships between features and targets, decision trees are a sort of method that uses a tree-like system of conditional control statements to form the machine learning model and therefore, can be more suitable for regression problems than other typical algorithms. The mean of the observations falling in that region is the value of terminal nodes in regression trees. As a result, if an unknown data point falls within that region, the mean value is used to make a prediction. To build the model scikit-learn is used, and Decision Tree Regressor is imported from sklearn.tree.

K Nearest Neighbors Regression:For regression task that predicts the actual numerical value of a new sample, this algorithm simply takes the mean of the nearest k neighbors. Optimal value of k is 1 (the number of neighbors) selected using the tool GridSearchCV. Each neighborhood's points are equally weighted. In comparison to other algorithms, this one has no or a very brief training phase, which means it does not generalise. Because of how kNN discovers the nearest neighbours, making predictions will take substantially longer. The distance calculated using default distance metric minkowski with p=1. kNN is also a non-parametric algorithm i.e., it does not have strict constraints on the shape and distribution of your data unlike linear regression, which assumes your features and target have a linear relationship. The create the model, regressor is readily available from sklearn.neighbors. KNeighborsRegressor.

Support Vector Machine Regressor: Support Vector Machine is able to generalize the characteristics that differentiate the training data that is provided to algorithm. This is achieved by checking for a boundary that differentiates the two classes by maximum margin. The boundary that separates the two classes is known as a hyperplane. Even if the name has a plane, if there are two features this hyperplane can be a line, in a 3D it will be a plane and so on. The basic idea behind SVR is to find the best fit line.

4. Mathematical Modelling of M.L techniques used:

The K-Nearest Neighbor fundamentally relies on a distance metric. The better that metric reflects label similarity, the better the result will be. The most common choice is the Minkowski distance given by equation 6

$$dist(x,y) = \left(\sum_{i=1}^{n} |xi - yi|^{p}\right)^{\frac{1}{p}} \qquad (6)$$

4.1. Mathematical Modeling of Decision Tree:

Attribute selection measures are also known as splitting rules because they define how the data points are to be split on a certain level in a decision tree.

Here are some major attribute selection measures:

Information Gain:

$$Info(D) = \sum^{m} pi \ \log_2(pi) \qquad (7)$$

We assume we have a training data D. pi is the probability that a value in dataset D belongs to class C.

Info(D) is simply the mean amount of information needed to identify the class/category of a data point in D.

$$Info\ A(D) = \sum_{j=1}^{v} \frac{|Dj|}{|D|} \times \log_2\left(\frac{|Dj|}{|D|}\right) \qquad (8)$$

Let Dj be the set of data in D satisfying outcome j.

Information Gain can also be calculated as:

$$Gain(A) = Info(D) - Info\,A(D) \quad (9)$$

$$SplitInfo\,A(D) = -\sum_{j=1}^{v} \frac{|Dj|}{|D|} \times \log_2 \frac{|Dj|}{|D|} \quad (10)$$

$$GainRatio(A) = \frac{Gain(A)}{SplitInfo(A)} \quad (11)$$

4.2. K-Nearest Neighbors Regressor Algorithm:

• Data is divided into training and test data. • K value is selected. • Select the distance function that is to be used. • Take a sample from the test data that needs to be classified and find the distance between it and the n training samples. • Sort the distances you've calculated and choose the k-nearest data samples. • Based on the majority vote of its k neighbours, assign the class to the test data sample.

4.3. Decision Tree Regressor Algorithm: Begin the tree with the root node which contains the complete dataset.Find the best attribute in the dataset using Attribute Selection Measure (ASM) i.e., by calculating information gain. Divide the S into subsets that contains possible values for the best attributes. Generate the decision tree node, which contains the best attribute. Recursively make new decision trees using the subsets of the dataset created in step3.Continue this process until a stage is reached where you cannot further classify the nodes and called the final node as leaf node.

4.4. Support Vector Machine Regressor Algorithm:

SVM takes all the data points in consideration and gives out a line that is called Hyperplane which divides the data into different classes.There can be many hyperplanes but the best hyper plane that divides the data into different classes would be the hyperplane having a large distance from the hyperplane from the classes.The motive of the SVM is to find such best hyperplane.

5. Results and Discussions:

5.1. IEEE-14 bus results:

Table1: Voltage Magnitude and phase angles of IEEE-14 bus using KNN, decision tree and SVM regressors.

Bus No.	Voltage magnitude by NR method	Voltage magnitude			Phase angle by NR method	Phase angle		
		predicted by KNN regressor	predicted by decision tree regressor	predicted by SVM regressor		predicted by KNN regressor	predicted by decision tree regressor	predicted by SVM regressor
1	1.06	1.06	1.06	1.031	0	0	0	-0.099
2	1.035	1.035	1.025	1.031	-5.876	-5.530	-5.530	-5.887
3	1	0.99	1	1.031	-15.068	-15.903	-14.284	-13.172
4	1.005	0.997	1.02	1.031	-12.156	-12.821	-12.821	-11.484
5	1.009	1.002	1.049	1.031	-10.355	-10.925	-9.8265	-8.143
6	1.07	1.07	1.07	1.031	-16.714	-17.656	-24.244	-11.286
7	1.064	1.101	1.075	1.031	-15.696	-0.6268	-10.644	-6.178
8	1.09	1.09	1.09	1.031	-15.696	-14.276	-12.644	-8.830
9	1.051	1.054	1.054	1.031	-17.516	-16.662	-16.662	-14.409
10	1.046	1.048	1.087	1.031	-17.703	-16.839	-16.839	-12.558

11	1.054	1.055	1.055	1.031	-17.358	-16.503	-18.307	-8.002
12	1.052	1.053	1.051	1.031	-17.699	-16.820	-16.820	-8.015
13	1.047	1.048	1.048	1.031	-17.789	-16.909	-18.772	-12.880
14	1.028	1.024	1.048	1.031	-18.796	-19.809	-17.876	-12.245

Table 2: Voltage magnitude and phase angle analysis of IEEE-30 bus using KNN, decision tree and SVM regressors.

Bus No	Voltage magnitude by NR method	Voltage magnitude			Phase angle by NR method	Phase angle		
		predicted by KNN regressor	predicted by decision tree regressor	predicted by SVM regressor		predicted by KNN regressor	predicted by decision tree regressor	Predicted by SVM regressor
1	1.06	1.06	1.06	1.002	0	0	0	-3.596
2	1.023	1.023	1.023	1.000	-6.382	-6.767	-5.988	-6.504
3	1.001	1.054	1.080	1.006	-9.422	-12.283	-5.919	-10.003
4	0.989	0.987	1.003	1.000	-11.408	-12.022	-12.022	-12.612
5	0.98	0.98	0.98	1.000	-17.091	-16.146	-16.143	-14.844
6	0.984	1.043	1.027	1.009	-13.462	-13.376	-11.550	-8.129
7	0.973	0.977	0.960	0.991	-15.590	-14.789	-14.789	-16.617
8	0.98	0.99	0.98	1.000	-14.292	-13.645	-15.100	-13.351
9	1.032	1.043	1.027	1.009	-17.118	-10.376	-11.550	-8.129
10	1.021	1.046	1.046	1.002	-19.023	-11.319	-14.424	-12.137
11	1.082	1.082	1.082	1.001	-17.118	-10.551	-11.547	-8.038
12	1.042	0.972	0.984	0.993	-18.243	-26.953	-19.201	-16.820
13	1.071	1.081	1.071	1.001	-18.243	-13.640	-12.282	-5.695
14	1.023	1.028	1.015	1.002	-19.297	-18.306	-20.308	-12.009
15	1.017	1.013	1.025	0.999	-19.379	-20.393	-17.051	-13.534
16	1.025	0.981	0.981	1.004	-18.893	-23.113	-17.933	-10.951
17	1.016	1.057	0.988	0.995	-19.231	-9.135	-12.135	-15.764
18	1.004	1.000	1.000	1.005	-20.088	-21.139	-4.144	-10.139
19	1.000	0.996	1.043	0.997	-20.280	-21.342	-21.342	-14.663
20	1.005	1.011	1.0416	1.006	-20.034	-19.018	-13.070	-9.548
21	1.006	1.002	1.002	0.992	-19.558	-20.583	-18.573	-16.801
22	1.007	1.043	1.027	1.009	-19.541	-1.3762	-14.550	-8.129
23	1.003	0.974	0.974	1.005	-19.816	-13.049	-13.049	-10.664
24	0.993	0.988	1.060	0.995	-19.987	-21.032	-15.930	-15.968
25	0.987	1.043	1.027	1.009	-19.497	-1.3762	-16.550	-8.129
26	0.966	0.960	0.976	1.004	-20.011	-21.073	-19.002	-11.330
27	0.994	1.043	1.027	1.009	-18.878	-16.376	-11.550	-8.129
28	0.982	1.043	1.027	1.009	-14.234	-13.376	-11.550	-8.129
29	0.970	1.080	1.080	1.006	-20.383	-4.144	-4.144	-9.782
30	0.956	0.967	0.950	0.997	-21.472	-20.367	-20.367	-14.019

Table 3: Line stability index (Lmn) analysis of IEEE-14 bus using KNN regressor, decision tree regressor, SVM regressor

Line.NO.	Indices predicted by NR method	Indices predicted by K-NN regressor	%Error	Indices predicted by Decision tree regressor	%Error	Indices predicted by SVM regressor	%Error
1	0.023	0.027	11.583	0.026	0.112	0.097	3.13E+00
2	0.029	0.032	0.179	0.026	-0.096	0.097	2.33E+00
3	0.034	0.040	-0.260	0.036	0.059	0.097	1.84E+00
4	0.029	0.027	0.503	0.028	-0.006	0.097	2.34E+00
5	0.012	0.012	2.624	0.012	0.009	0.097	7.08E+00
6	0.046	0.059	0.387	0.046	-0.007	0.097	1.09E+00
7	0.017	0.016	0.901	0.017	-0.021	0.097	4.54E+00
8	0.011	0.116	-0.048	0.116	-0.000	0.097	-1.66E-01
9	0.067	0.116	0.939	0.110	0.653	0.097	4.50E-01
10	0.169	0.174	0.172	0.171	0.008	0.097	-4.28E-01
11	0.027	0.032	2.193	0.028	0.054	0.097	2.59E+00
12	0.004	0.002	-0.806	0.004	-0.145	0.097	1.96E+01
13	0.003	0.000	-0.942	0.004	0.554	0.097	3.09E+01
14	0.004	0.011	-0.582	0.010	1.134	0.097	1.92E+01
15	0.009	0.005	-0.712	0.019	1.06	0.097	9.28E+00
16	0.021	0.021	0.063	0.020	-0.003	0.097	3.62E+00
17	0.050	0.049	0.003	0.050	0.003	0.097	9.42E-01
18	0.030	0.034	0.863	0.031	0.033	0.097	2.17E+00
19	0.004	0.005	6.761	0.004	0.105	0.097	2.24E+01
20	0.034	0.039	1.401	0.035	0.044	0.097	1.84E+00

Table 4: Fast voltage stability index (FVSI) analysis of IEEE-14 bus using KNN regressor, decision tree regressor and SVM regressor

Line.NO.	Indices predicted by NR method	Indices predicted by K-NN regressor	%Error	Indices predicted by Decision tree regressor	%Error	Indices predicted by SVM regressor	%Error
1	0.002	0.026	0.114	0.0032	0.254	0.097	3.13E+00
2	0.027	0.030	0.034	0.030	0.107	0.097	2.33E+00
3	0.054	0.036	0.061	0.013	-0.749	0.097	1.84E+00
4	0.018	0.028	-0.006	0.028	0.528	0.097	2.34E+00
5	0.003	0.012	0.008	0.009	1.906	0.097	7.08E+00
6	0.042	0.050	0.079	0.056	0.318	0.097	1.09E+00
7	0.018	0.017	-0.022	0.016	-0.087	0.097	4.54E+00
8	0.122	0.011	0	0.116	-0.048	0.097	-1.66E-01
9	0.060	0.122	0.826	0.110	0.845	0.097	4.50E-01
10	0.149	0.171	0.008	0.174	0.172	0.097	-4.28E-01
11	0.010	0.028	0.055	0.024	1.395	0.097	2.59E+00
12	0.011	0.004	-0.148	0.002	-0.806	0.097	1.96E+01
13	0.015	0.001	-0.366	0.001	-0.872	0.097	3.09E+01
14	0.027	0.010	1.125	0.011	-0.582	0.097	1.92E+01
15	0.020	0.008	-0.106	0.008	0.581	0.097	9.28E+00
16	0.019	0.020	-0.004	0.021	0.063	0.097	3.62E+00
17	0.049	0.049	-0.002	0.049	0.003	0.097	9.42E-01
18	0.018	0.031	0.032	0.034	0.863	0.097	2.17E+00
19	0.000	0.004	0.121	0.0006	-0.109	0.097	2.24E+01
20	0.016	0.035	0.043	0.039	1.401	0.097	1.84E+00

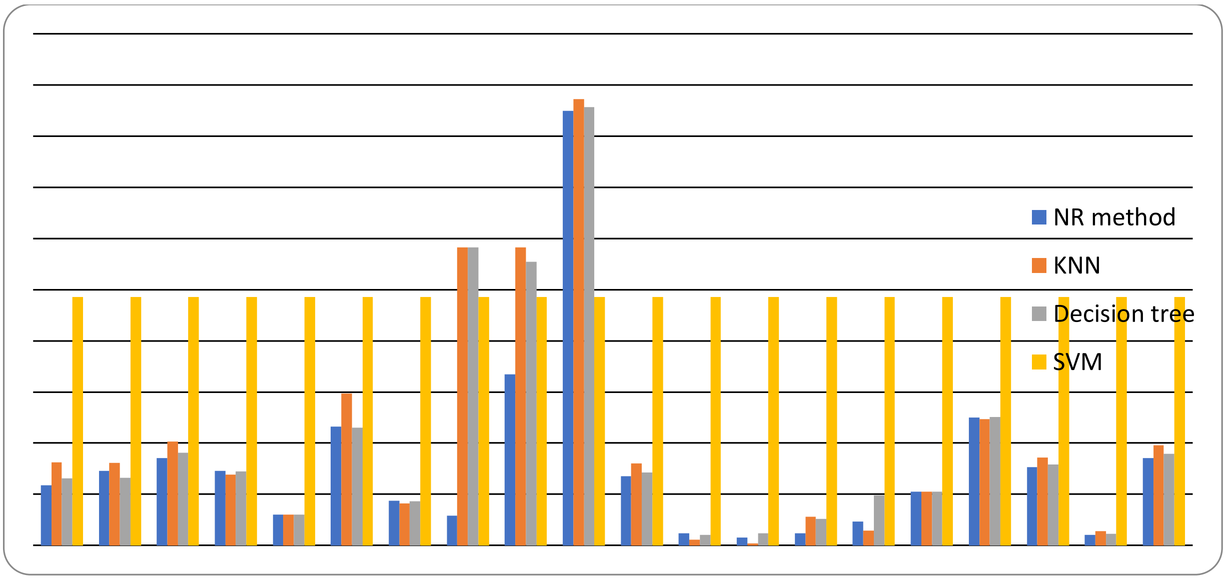

Fig 1: Comparison of Lmn stability indices for IEEE 14 bus system

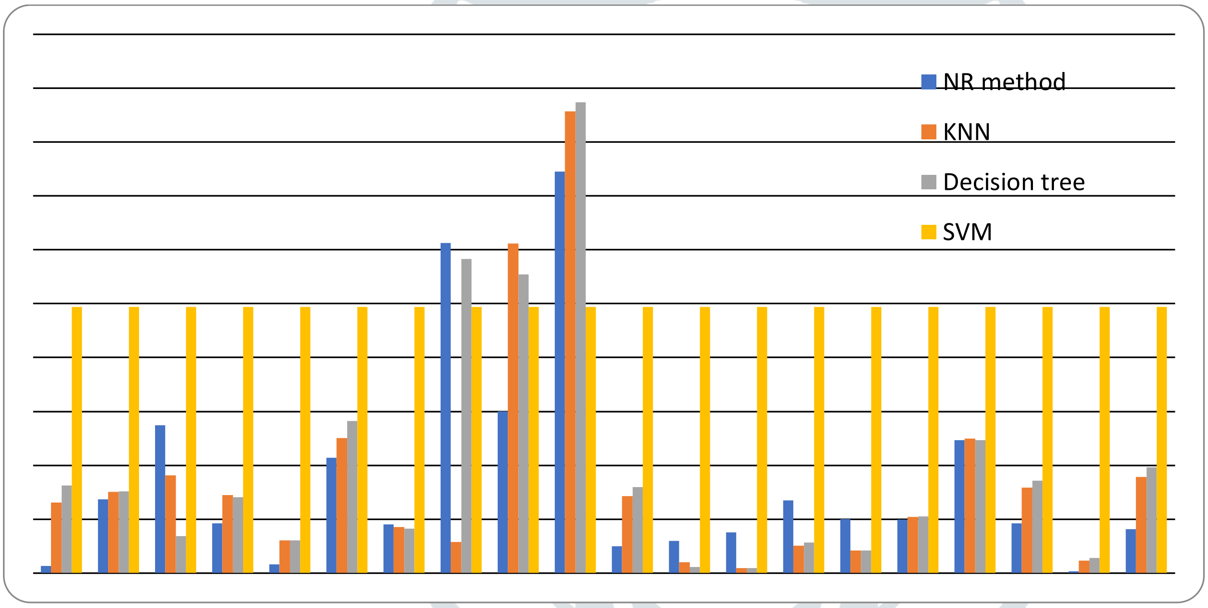

Fig 2: Comparison of FVSI voltage indices for IEEE 14 bus system

The fig 1 and fig 2 the graphical representations of the stability indices Lmn and FVSI of IEEE 14 bus system. The figures show the comparison of these indices with respect to the K-Nearest Neighbors, Decision Tree and Support Vector Machine to the load flow analysis using Newton Raphson method. From this we can infer that the K-Nearest Neighbors and Decision tree have showed better performing results whereas Support Vector Machines has given poor results.

Table 5: Line stability index (Lmn) analysis of IEEE-30 bus using KNN regressor

Line.NO	Indices predicted by NR method	Indices predicted by K-NN regressor	%Error	Indices predicted by Decision tree regressor	%Error	Indices predicted by SVM regressor	%Error
1	1.28E-02	3.57E-02	1.79E+00	2.47E-02	9.29E-02	0.07194	4.63E+00
2	2.71E-02	2.80E-02	3.29E-02	2.80E-02	3.29E-02	0.07194	1.66E+00
3	6.16E-03	6.18E-03	3.25E-03	6.18E-03	3.25E-03	0.07194	1.07E+01
4	8.03E-03	8.63E-03	7.47E-02	7.13E-03	-1.12E-01	0.07194	7.96E+00
5	5.27E-02	5.47E-02	3.84E-02	8.35E-03	-8.41E-01	0.07194	3.66E-01
6	1.68E-02	1.58E-02	-6.01E-02	1.58E-02	-6.01E-02	0.07194	3.28E+00
7	1.05E-02	9.44E-03	-1.01E-01	9.44E-03	-1.01E-01	0.07194	5.85E+00

8	1.82E-02	2.05E-02	1.26E-01	3.07E-02	6.85E-01	0.07194	2.95E+00
9	1.97E-02	2.04E-02	3.29E-02	2.04E-02	3.29E-02	0.07194	2.64E+00
10	1.93E-02	1.07E-01	4.54E+00	1.07E-04	4.44E-02	0.07194	2.72E+00
11	7.39E-02	7.49E-02	1.27E-02	7.25E-02	-1.93E-02	0.07194	-2.67E-02
12	4.63E-02	4.59E-02	-6.92E-03	4.59E-02	-6.92E-03	0.071	5.55E-01
13	5.03E-02	5.86E-02	1.64E-01	4.83E-02	-4.11E-02	0.071	4.29E-01
14	1.16E-02	2.41E-02	1.08E+00	5.50E-03	-5.26E-01	0.071	5.20E+00
15	1.24E-01	1.23E-02	-9.01E-01	2.47E-03	-9.80E-01	0.071	-4.22E-01
16	1.40E-02	9.33E-03	-3.35E-01	9.96E-03	-2.90E-01	0.071	4.13E+00
17	1.11E-02	2.02E-02	8.14E-01	2.02E-02	8.14E-01	0.071	5.46E+00
18	1.51E-02	1.42E-02	-6.16E-02	1.42E-02	-6.16E-02	0.071	3.77E+00
19	8.23E-03	1.05E-02	2.79E-01	4.75E-03	-4.23E-01	0.071	7.74E+00
20	2.24E-03	3.60E-03	6.07E-01	3.60E-03	6.07E-01	0.071	3.11E+01
21	9.00E-05	3.00E-05	-6.67E-01	3.00E-05	-6.67E-01	0.071	7.98E+02
22	4.95E-03	1.14E-02	1.31E+00	2.57E-03	4.81E-01	0.071	1.35E+01
23	1.70E-04	2.70E-04	5.88E-01	3.00E-05	-8.24E-01	0.071	4.22E+02
24	5.24E-03	5.10E-03	-2.67E-02	5.10E-03	-2.67E-02	0.071	1.27E+01
25	1.90E-02	1.85E-02	-3.05E-02	2.13E-02	1.18E-01	0.071	2.78E+00
26	1.02E-02	1.04E-02	1.67E-02	1.04E-02	1.67E-02	0.071	6.05E+00
27	1.54E-02	1.47E-02	-4.36E-02	1.47E-02	-4.36E-02	0.071	3.68E+00
28	1.40E-02	1.99E-02	4.26E-01	1.99E-02	4.26E-01	0.071	4.15E+00
29	1.09E-03	1.06E-03	-2.75E-02	1.06E-03	-2.75E-02	0.071	6.50E+01
30	7.62E-03	4.62E-03	-3.94E-01	6.87E-03	-9.84E-02	0.071	8.44E+00
31	9.61E-03	8.89E-03	-7.49E-02	8.37E-03	-1.29E-01	0.071	6.49E+00
32	1.60E-04	1.00E-04	-3.75E-01	2.90E-04	8.13E-01	0.071	4.40E+01
33	2.91E-02	2.95E-02	1.24E-02	2.95E-02	1.24E-02	0.071	1.47E+00
34	2.40E-02	1.49E-02	-3.80E-01	6.41E-03	-7.33E-01	0.071	1.99E+00
35	6.27E-03	6.65E-03	6.06E-02	6.97E-03	1.12E-01	0.071	1.05E+01
36	1.87E-02	1.61E-02	-1.36E-01	7.06E-03	-6.22E-01	0.071	2.85E+00
37	1.54E-02	8.37E-03	-4.58E-01	8.37E-03	-4.58E-01	0.071	3.66E+00
38	2.21E-02	2.11E-02	-4.43E-02	1.84E-03	-9.17E-01	0.071	2.25E+00
39	6.27E-03	5.99E-03	-4.47E-02	5.99E-03	-4.47E-02	0.071	1.05E+01
40	4.96E-02	4.95E-02	-3.63E-03	5.13E-02	3.28E-02	0.071	4.49E-01
41	2.71E-02	2.71E-02	-1.84E-03	2.71E-02	-1.84E-03	0.071	1.65E+00

Table 6: Fast voltage stability index (FVSI) analysis of IEEE-30 bus using KNN regressor

Line.no	Indices predicted by NR method	Indices predicted by K-NN regressor	%Error	Indices predicted by Decision tree regressor	%Error	Indices predicted by SVM regressor	%Error
1.	1.25E-02	3.82E-02	2.07E+00	2.82E-02	1.25E-02	0.081	5.56E+00
2.	2.61E-02	2.70E-02	3.52E-02	3.45E-02	3.2E-02	0.091	2.50E+00
3.	5.99E-03	6.01E-03	3.34E-03	6.01E-03	3.34E-03	0.085	1.32E+01
4.	7.96E-03	8.56E-03	7.54E-02	2.70E-03	-6.6E-03	0.092	1.06E+01
5.	5.05E-02	5.25E-02	4.04E-02	5.25E-02	4.04E-02	0.088	7.43E-01
6.	1.62E-02	1.52E-02	-5.88E-02	1.52E-02	-5.88E-02	0.083	4.15E+00
7.	1.04E-02	9.36E-03	-1.01E-01	9.36E-03	-1.01E-01	0.081	6.79E+00
8.	1.83E-02	2.06E-02	1.25E-01	2.06E-02	1.25E-01	0.081	3.43E+00
9.	1.96E-02	2.02E-02	3.32E-02	2.45E-02	2.51E-01	0.091	3.66E+00
10.	1.93E-02	1.07E-01	4.55E+00	2.70E-02	3.91E-02	0.051	1.66E+00

11.	7.39E-02	7.48E-02	1.29E-02	7.24E-02	-1.94E-02	0.080	9.31E-02
12.	4.62E-02	4.58E-02	-7.58E-03	4.58E-02	-7.58E-03	0.082	7.88E-01
13.	5.03E-02	5.85E-02	1.62E-01	4.83E-02	-4.11E-02	0.080	6.05E-01
14.	1.16E-02	2.37E-02	1.04E+00	1.31E-02	1.24E-01	0.082	6.10E+00
15.	1.24E-01	1.23E-01	-8.22E-03	1.23E-01	-8.22E-03	0.028	-7.66E-01
16.	1.40E-02	9.32E-03	-3.35E-01	1.62E-02	1.52E-01	0.084	5.04E+00
17.	1.11E-02	1.99E-02	8.04E-01	1.99E-02	8.04E-01	0.084	6.65E+00
18.	1.50E-02	1.40E-02	-6.09E-02	1.78E-02	1.88E-01	0.087	4.86E+00
19.	8.19E-03	1.05E-02	2.76E-01	4.73E-03	-4.22E-01	0.084	9.31E+00
20.	2.23E-03	3.59E-03	6.10E-01	2.15E-03	-3.59E-02	0.083	3.64E+01
21.	9.00E-05	3.00E-05	-6.67E-01	1.90E-04	1.11E-04	0.083	9.32E+02
22.	4.93E-03	3.96E-02	7.02E+00	4.26E-03	-1.3E-03	0.083	1.59E+01
23.	1.70E-04	2.70E-04	5.88E-01	3.00E-05	-8.24E-01	0.081	4.80E+02
24.	5.25E-03	5.11E-03	-2.67E-02	5.47E-03	4.19E-02	0.085	1.53E+01
25.	1.89E-01	1.83E-02	-9.03E-01	2.78E-02	-8.53E-01	0.085	-5.47E-01
26.	1.02E-02	1.04E-02	1.67E-02	9.95E-03	-2.45E-02	0.083	7.23E+00
27.	1.53E-02	1.47E-02	-4.31E-02	1.47E-02	-4.31E-02	0.083	4.44E+00
28.	1.39E-02	1.45E-03	-8.96E-01	1.45E-03	-8.96E-01	0.081	4.87E+00
29.	1.09E-03	1.06E-03	-2.75E-02	1.06E-03	-2.75E-02	0.085	7.77E+01
30.	7.60E-03	4.61E-03	-3.93E-01	1.51E-02	9.82E-01	0.085	1.03E+01
31.	9.57E-03	8.63E-03	-9.82E-02	8.63E-03	-9.82E-02	0.087	8.16E+00
32.	1.60E-04	1.00E-04	-3.75E-01	2.50E-04	5E-04	0.085	5.34E+02
33.	2.93E-02	2.97E-02	1.23E-02	2.97E-02	1.23E-02	0.082	1.81E+00
34.	2.39E-02	2.46E-02	2.93E-02	2.46E-02	2.93E-02	0.084	2.52E+00
35.	6.31E-03	6.69E-03	6.02E-02	6.69E-03	6.02E-02	0.084	1.24E+01
36.	1.87E-02	1.61E-02	-1.36E-01	2.25E-02	2.06E-01	0.086	3.62E+00
37.	1.53E-02	8.32E-03	-4.55E-01	8.32E-03	-4.55E-01	0.084	4.52E+00
38.	2.17E-02	2.07E-02	-4.38E-02	1.82E-02	-1.63E-01	0.084	2.89E+00
39.	6.22E-03	5.95E-03	-4.34E-02	5.95E-03	-4.34E-02	0.083	1.24E+01
40.	4.96E-02	4.94E-02	-3.63E-03	4.94E-02	-3.63E-03	0.080	6.31E-01
41.	2.70E-02	2.70E-02	-1.85E-03	2.70E-02	-1.85E-03	0.080	1.99E+00

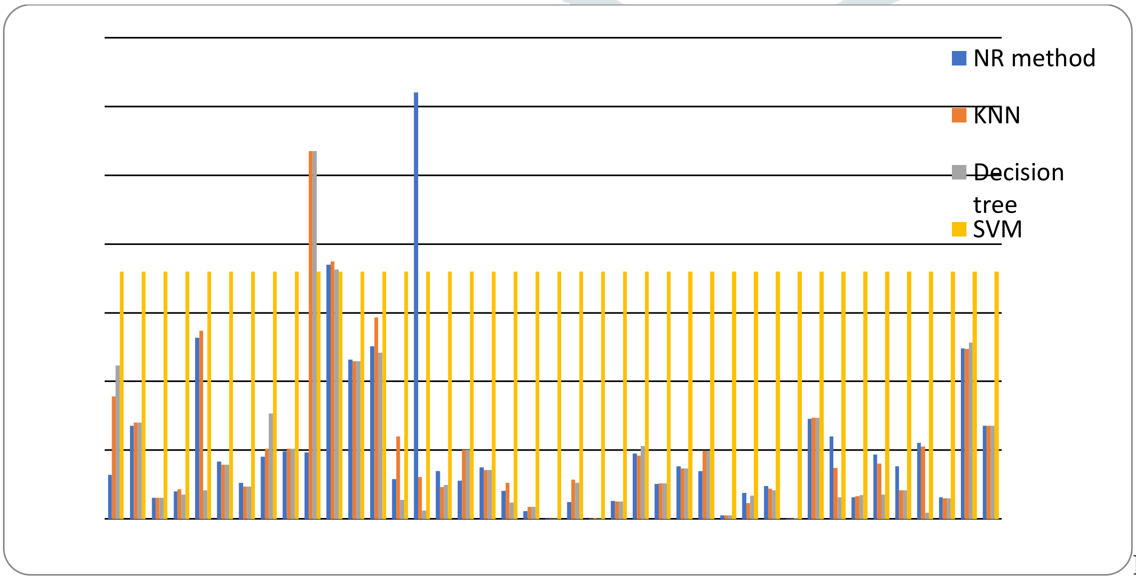

Fig 3: Comparison of Lmn stability indices for IEEE 30 bus system

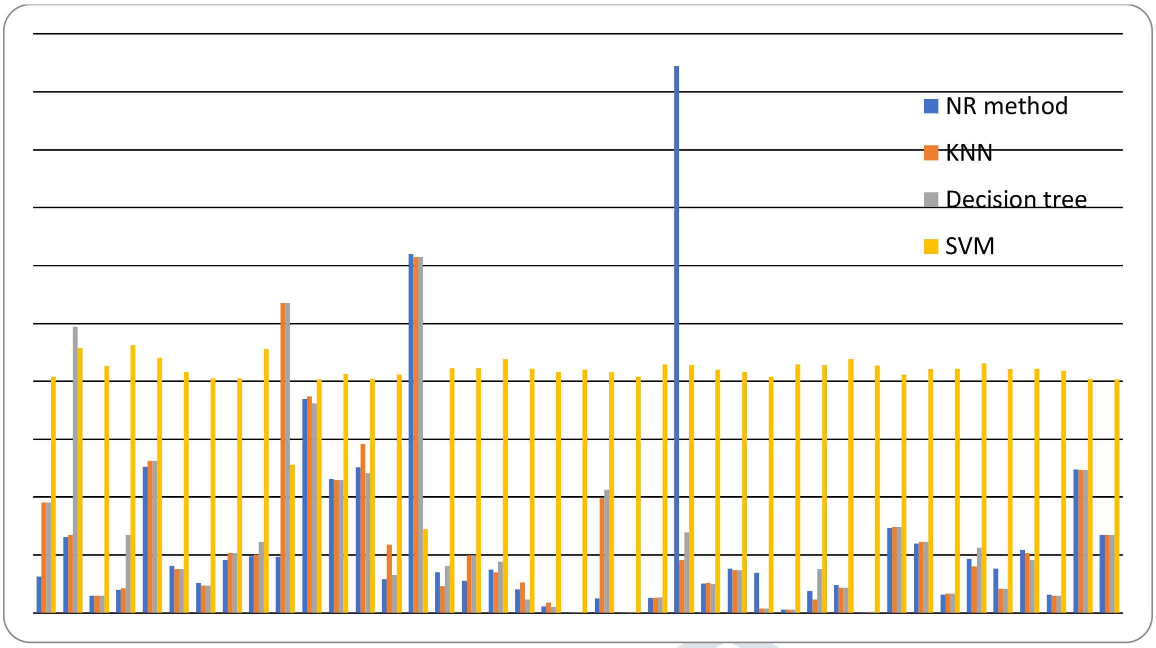

Fig 4: Comparison of FVSI stability indices for IEEE 30 bus system

The fig 3 and fig 4 the graphical representations of the stability indices Lmn and FVSI of IEEE 30 bus system. The figures show the comparison of these indices with respect to the K-Nearest Neighbors, Decision Tree and Support Vector Machine to the load flow analysis using Newton Raphson method. From this we can infer that the K-Nearest Neighbors and Decision tree have showed better performing results whereas Support Vector Machines has given poor results.

6. Conclusion:

The main aim of this work has been to develop a new real-time voltage stability assessment tool that can support system operators and allow more efficient utilization of the transmission grid. The thesis has demonstrated and tested machine learning algorithms for use in real-time voltage stability assessment.

First aimed to develop load flow NR method to generate data to calculate voltage stability indices and then to train different machine learning algorithms. The voltage tolerance of any stable bus system is +-5% i.e., 0.95 to 1.05. Once trained, the trained machines can allow system operators to continuously assess and predict whether the present system state is stable or if it will evolve into an alert or an emergency state in the near future. The trained machine is also adapted to be able to indicate where instability emerges, allowing system operators to perform more cost-effective control measures. The proposed machine learning algorithms are compared, and accuracy is tested on IEEE 14 and 30 bus systems. The dataset for training is taken from 10% of load to 150% of load and testing is done at a point where the system is not trained. The results are encouraging, and the proposed decision tree algorithm has shown good accuracy in predicting voltage instability and the KNN algorithm has shown average results, but the support vector machine is giving poor prediction for all the data.

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