# Decision Trees for Voltage Stability Assessment

V.S. Narasimham Arava
WAMS Centre of Excellence
GE Digital
Edinburgh, UK
Email: narasimham.arava@ge.com

Luigi Vanfretti
Department of Electrical, Computer and Systems Engineering
Rensselaer Polytechnic Institute
Troy, NY
Email: vanfrl@rpi.edu

***Abstract*—This paper proposes two different methods to train the DTs for voltage stability assessment, which in turn can aid in deriving preventive actions that can be given as recommendations to system operators or automatic load shedding schemes. In the voltage stability indices method, the DTs are trained on contingency cases that are classified based on voltage stability indices. In the region classification method, the DTs are trained on a new classification criterion that enlarges and generalizes the existing security boundary method of "stable" and "unstable" regions to a more granular operating space based on the distance from the nearest Saddle-Node Bifurcation. Case studies were performed using the Nordic 32 system for different contingency cases, several operating conditions and different network configurations. The ability to classify the degree of voltage stability of a multitude of operation conditions could be useful to aid operators in selecting and applying preventive measures to steer away the system from unstable conditions or conditions that are close to breaching operational requirements w.r.t. voltage stability.**

## I. Introduction

### A. Motivation

During the recent years the challenge brought by the ongoing energy transition has led electric utilities to operate closer to their operating-limits which has made voltage instability a major concern for power systems. One of the great challenges for electric utilities and regional transmission organization is being able to meet system-wide voltage security. Voltage stability is the ability of a power system to sustain acceptable voltage at all buses under the normal condition after being subjected to a disturbance [1]. Voltage instability usually occurs in power systems that are heavily loaded or that experience reactive power shortages.

Broadly speaking, two types of situations may lead to voltage instability. The first type is associated with the demand not being met by the available generation due to transmission or reactive power limitations. This situation may result from unexpected large load increase and/or an earlier weakening of the system, such as low voltages and increased losses. The second type of incident is a major event affecting the generation or transmission system in such a way that the demand, which is the pre-fault consumption, cannot be satisfied with the available generation or transmission capacity.

Voltage Stability Indices (VSI) were developed to deal with the first type of situation. These indices help to foresee unacceptable effects of load increments. Moreover, this anticipation capability along with inherent delay (in some cases) of load increments (because of the type of behaviour of certain loads) gives the operator some time to take remedial actions such as switching capacitor banks, changing the generator voltage set points, etc. However, the picture is quite different for voltage instabilities that can follow major incidents such as outage of a large capacity generator that is producing its maximum rated power or the disconnection of heavily loaded transmission lines. The time left to take remedial actions for this second type of situation is relatively shorter than the first. This short time is very important and early detection of a critical state can prevent the system from collapsing.

These above considerations motivate the development of approaches that can help in early identification of voltage instability and suggest remedial actions to bring back the system to stable state. Machine learning techniques like Decision Trees (DTs) can offer useful tools to handle the early identification of voltage instability by performing off-line analysis of thousands of potential operating conditions ahead of time.

### B. Literature Review

Identification of the voltage stability boundary (VSB) plays a vital role in the reliable operation of a power system. Although the voltage stability margin depends on numerous possible system conditions, in practical real-time applications, only several selected stress directions are computed and checked, especially, real-time static or dynamic security assessment (DSA) tools [3]. However, with the increasing variability and uncertainty in today's power systems, it is becoming increasingly clear that the stability margin assessment should be broadened to multiple types of system strain, covering various sources and ranges of uncertainty and variability. Therefore, an accurate and fast estimation of the available voltage stability margin is of paramount importance for the secure operation and control of electric power systems.

The voltage stability boundary surrounds the region of feasible and stable operating points in power system parameter space. These operating points cannot cross the VSB without losing their stability [4]. The voltage stability region (VSR) is a safe region for guaranteeing local stability at the equilibrium under slow parametric variations [5]. Voltage stability conditions are usually considered as power flow feasibility conditions; and the VSB is associated with singularity conditions of the power flow Jacobian matrix and saddle-node bifurcation (SNB). References [4] and [5] provide a comprehensive discussion on feasibility boundaries and regions in state and parameter space in the power system domain and summarize some recent development on the stability analysis of large-scale systems. Some publications that address the voltage stability problems include [6]–[9].

The conventional methods for calculating SNBs traditionally employ iterative procedures. An extensive review of these methods is provided in [10]. The two commonly used iterative methods are Continuation Power Flow (CPF) and Direct methods [11]. The purpose of CPF is to find a series of power flow solutions for a given load/generation change scenario [12]. The CPF method provides reliable convergence due to its predictor-corrector approach but is computationally intensive. Direct methods were proposed for assessing the VSB, in which augmented power flow equations are solved [13]–[16]. These methods provide the left or right eigenvectors corresponding to the zero Jacobian matrix eigenvalue at the point of voltage collapse. Direct methods are sensitive to the initial guess, i.e., the initial guess affects the speed of convergence and may even cause divergence of the iterative process [16]. This iterative process requires a considerable number of calculations to find a single VSB point. To obtain the full VSB, the computational effort becomes prohibitively significant for large-scale power systems. Computational time becomes critically important for real-time analyses, massive contingency screenings, and time-domain simulations.

Machine learning techniques, such as Decision Trees (DTs), clustering algorithms, neural networks and statistical methods have been considered for voltage stability assessment [17], [18]. These methods can create/use a model, which is based on the knowledge of the operator past decisions or historical data. The DT is a white-box model that can be applied when functioning/working of a system is unknown or complex, but there is plenty of data available. These models do not explicitly model the physical system but establish a mathematical relationship between many input-output pairs measured from the system. The mathematical relationship is a model of the system, which can be computed numerically from the measurements or simulated outputs. The accuracy of the model may vary depending on accuracy of the simulated outputs replicating the behaviour of original system. The investigation of DTs for voltage security assessment sparked interest in the early 90s. The DT based approach for power system security assessment was presented in [19], [20]. Due to the wide deployment of phasor measurement units (PMUs) in the recent years, real time security assessment combining DT and synchrophasor measurements became possible [21]–[27].

### C. Paper Contributions

This paper proposes two different methods to train the DTs for voltage stability assessment, which in turn can aid in deriving preventive actions that can be given as recommendations to system operators or automatic load shedding schemes. Two different methods are adopted and tested on the test system.

1) Voltage Stability Indices method: The idea behind this approach is to use voltage stability indices to classify the contingency cases to generate security rules using DTs that could provide recommendations to system operators. This approach is adopted from iTesla platform [28].
2) Region classification method: The idea behind this approach is to propose a new classification criterion that enlarges and generalizes the existing security boundary method of "stable" and "unstable" regions to classify the operating space based on the distance from the nearest Saddle-Node Bifurcation (SNB); thus, allowing to consider operational requirements w.r.t. voltage stability [35].

The remainder of the paper is organized as follows. Section II explains the details of the methodology, classification principal and sampling adopted for both the methods. Section III presents the simulation results of both the methods on a test system. Conclusions are drawn in Section IV.

## II. Voltage Stability Assessment using DTs

A Decision Tree (DT) is a form of inductive learning. For a given data set, the objective is to build a model that captures the mechanism that gave rise to the data. The process of constructing the model is a "Supervised learning" problem because the training is supervised by an outcome variable called the target. Decision Trees are grown through a systematic method known as recursive binary partitioning; where the successive questions with yes/no answers are asked in order to partition the sample space [19].

In this paper, two different methodologies adopted to train the DTs for voltage stability assessment are described next.

### A. Voltage Stability Indices method

In this method, the three-layer severity index from [29] is used to classify the output of the contingency cases. The workflow used to compute security rules follows the triptych anticipate – analyze – classify as shown in Fig. 1. This approach is adopted from iTesla offline workflow provided in [28].

**(i) Anticipate**: To compliment historical data, a large number of additional plausible network states is built (sampled), using the historical data. Uncertainties such as demand or wind power production are also modeled. **(ii) Analyze**: for each sampled network state, dynamic simulations are performed to quantify the impact of various contingencies (overloads,

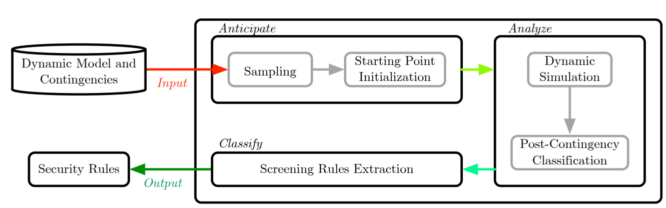


Fig. 1. Offline security assessment workflow, adapted from [28]

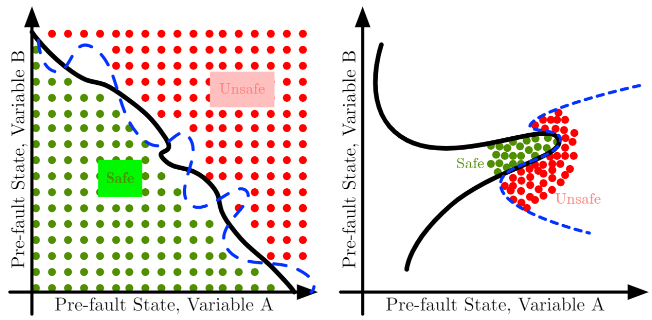


Fig. 2. Classification of operating points based on indexes

transient instability, etc.). **(iii) Classify**: machine learning algorithms are used to compress the results from the analysis stage into a set of security rules (threshold values) discriminating stable from unstable network states. These rules are used by the online platform to quickly classify unseen network states as safe/unsafe against a contingency.

The output simulations are classified by the voltage stability index as *safe* and *unsafe* as explained in [28]. These *safe* or *unsafe* cases are used to train the DTs to generate the security rules. Examples of a classification is shown in Fig. 2. Note that a security rule is obtained for each contingency and security phenomenon.

These security rules (boundary) are mapped against physical variables (active power, reactive power, voltage, etc.), which are predominantly influenced by the set of contingencies/security index pairs considered. Security rules are expressed as DTs [19], [30], which have the advantage of being easy to interpret and suitable for integration as linear constraints into optimization tools. In this work, DTs are generated by the "DataMaestro" software [31] that was integrated in the iTesla platform. These DTs help to characterize the power system security for pre-defined contingencies and minimize the amount of network simulations. Two approaches are used to generate DTs in the offline workflow for each contingency/security index pair. In the Worst-Case Approach (WCA), the set of candidate attributes of the DT can only be related with computed power variables. While in the Monte Carlo Like Approach (MCLA), the set of candidate attributes of the DT can also consider other type of network variables (e.g. voltage). Further details about these approaches is available in [28], [32].

### B. Region Classification method

In this method, the DTs are trained on the data from power system network models. The workflow (i.e. algorithm) proposed in this work to build a decision tree for the selected network is shown in Fig. 3. For each topology, such as the base case and for different contingency cases ($n$), a database is created with the power flow results for different load power consumption. These databases are then used to train the decision trees that are used to predict the voltage stability of the considered system using measured load powers and voltages.

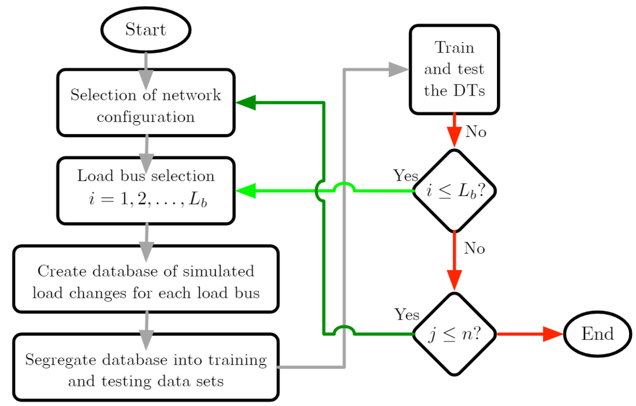


Fig. 3. Proposed workflow for the creation of decision trees

The DTs are created w.r.t. every load bus for different network configurations. The number of DTs created is therefore proportional to number of load buses and topologies considered. The number of branches for a tree increases with an increase in data. Creating one tree for a network configuration increases the size of the tree that further complicates interpretation. Moreover, creating one tree for a network configuration increases the computational burden and lookup time. For these reasons every network configuration will have a tree w.r.t. every load bus. Next, a Continuation Power Flow (CPF) is carried out for different network configurations with several load variations that are then used to train and test the decision tree for those network configurations.

Initially, SNB points are calculated using CPF [12]. The purpose of CPF is to find a series of power flow solutions for a given load/generation change scenario. The CPF method provides reliable convergence due to its predictor-corrector approach but is computationally intensive. Therefore, in order to lessen the computation burden, this paper proposes the use of a direct method to calculate the SNB points. Direct methods are sensitive to the initial guess [13], [14]. Consequently, the SNB direct method is initialized by running a CPF routine once to provide good initial guess [16]. Direct methods provide the left or right eigenvectors corresponding to the zero Jacobian matrix eigenvalue at the point of voltage collapse.

The conditions for a SNB point are as follows:

$$g\left(y,\lambda\right)=0,\ \ g\left(y,\lambda\right)=0 \text{ and } \ |v|=1 \tag{1}$$

or, alternatively,

$$g\left(y,\lambda\right)=0,\ \ g_y^T w=0,\ \text{ and } \ |w|=1 \tag{2}$$

where $v$ and $w$ are the right and left eigen vectors.

In this paper, instead of running CPF method for all the operating points to trace the unstable boundary, the CPF is executed to provide good initial guess for the direct method. The direction of load variations in CPF is fixed and it is along the load bus of interest (note that this would be repeated for every bus of interest). Initially, the CPF method is run for the load bus of interest (load $P_1$ as shown by the blue marker). The CPF method finds the SNB bifurcation point. The direct method uses this SNB and set direction as initial guess to

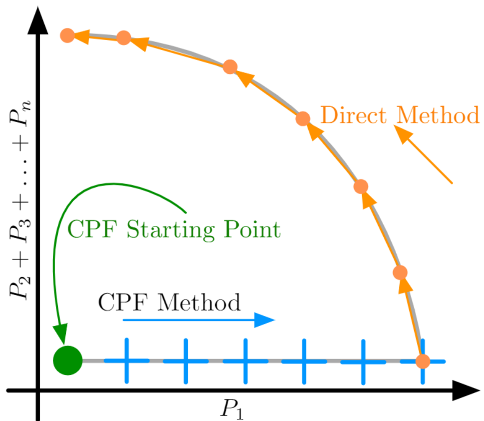


Fig. 4. Illustration of the applied method

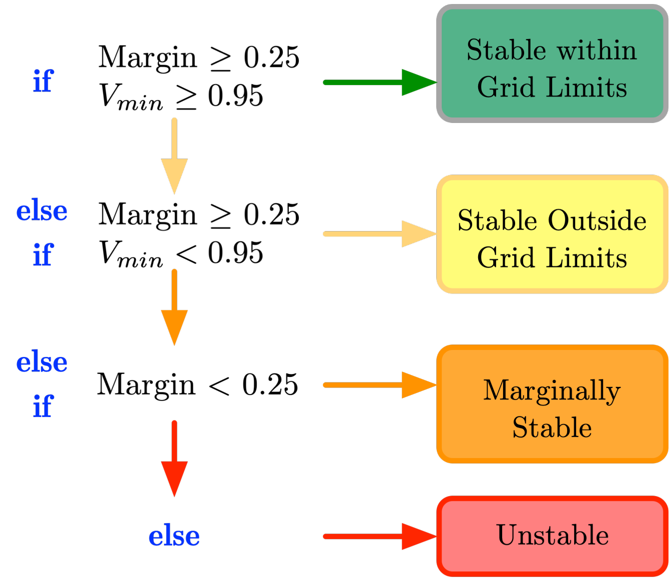


Fig. 5. Proposed Classification Criteria

calculate the eigen vectors (as shown by the blue arrows). From here, the direct method is applied sequentially in the same direction to calculate and trace the SNB boundary (as shown by the blue crosses and the orange dots). Thus, the direct method calculates the boundary of SNB points as shown in the Fig. 4. Using equations eqn3 and eqn4, the workflow Fig. 3 is modified to sample a reduced number of operation conditions are obtained when exploring the operational space used to train the decision trees, instead of using the entire space.

Initially, the Euclidean distance is calculated for the given load operating point *i* wrt load bus *a* (considering loads at bus *a*, *b*, *c*. . . *k*) ($Pa_i$, *Pbc*. . . $k_i$) from nearest unstable point ($Pa_{nSNB}$, *Pbc*. . . $k_{nSNB}$) using

$$d_i = \{(Pa_{nSNB} - Pa_i)^2 + (Pb_{nSNB} - Pb_i)^2 + \ldots + (Pk_{nSNB} - Pk_i)^2\}^{1/2} \quad (3)$$

The margin is calculated as given by

$$\text{Margin} = \frac{d_i}{Pa_i + Pb_i + ... + Pk_i} \quad (4)$$

The nearest unstable point ($Pa_{nSNB}$, *Pbc*. . . $k_{nSNB}$) is selected based on the distance calculated to all the unstable point on the boundary. If eqmargin is less than a given percentage (e.g. 25%), then the region of operation is classified as a "marginally stable" region. If the available margin is greater than or equal to the given percentage (e.g. 25%) with voltages at all the load buses being greater than a given threshold (e.g. 0.95 pu), then the region is classified as "stable within grid limits" region, otherwise it is classified as "stable outside grid limits" region. If the given load operating point is the saddle node bifurcation point or it exists further away from the given saddle node bifurcation point, then the region is classified as being in the "unstable" region.

The fact that the margins can be customized depending on the power system and how conservative an operator makes these criteria general. The classification criteria are visualized in Fig. 4. The given power flow outputs are classified into the regions based on the conditions explained above. The trained decision trees are tested with the test set and the accuracy of the classification is calculated.

## III. Case Studies and Results

The main objective of the studies herein was to demonstrate the use of decision trees for voltage stability assessment. The proposed workflows in Fig. 1 and Fig. 3 and the sampling method described in the previous sections was implemented. This proposed approach was tested on the KTH Nordic 32 bus system [33]. The KTH Nordic-32 Bus test system is an equivalent representation of the Nordic grid (Sweden, Norway and Finland) as shown in Fig. 6 and was originally implemented in PSAT [34]. It consists of 32 buses, 21 generators with various control systems (exciter, turbine, governor and stabilizer), 52 transmission lines (400kV, 200kV and 135kV) and 10 loads. The time domain simulations of 32 bus system were carried out for different loading conditions and network configurations using PSAT. The simulations in PSAT were automated by a Matlab script.

### A. Voltage Stability Indices method

In this method, 10 different contingencies were created and simulated using the KTH Nordic 32 bus system in the iTesla offline platform. These DTs are generated by the "Data-Maestro" software that was integrated in the iTesla platform. These DTs help to characterize the power system security for pre-defined contingencies and minimize the amount of network simulations. These contingencies were applied to 1000 snapshots and each snapshot indicates the operating point. The outputs from the contingencies were computed from a simulation program available in the platform. The selected contingencies contain transmission lines whose average loading is more than 65% of their nominal rating. The workflow is explained in detail with one contingency.

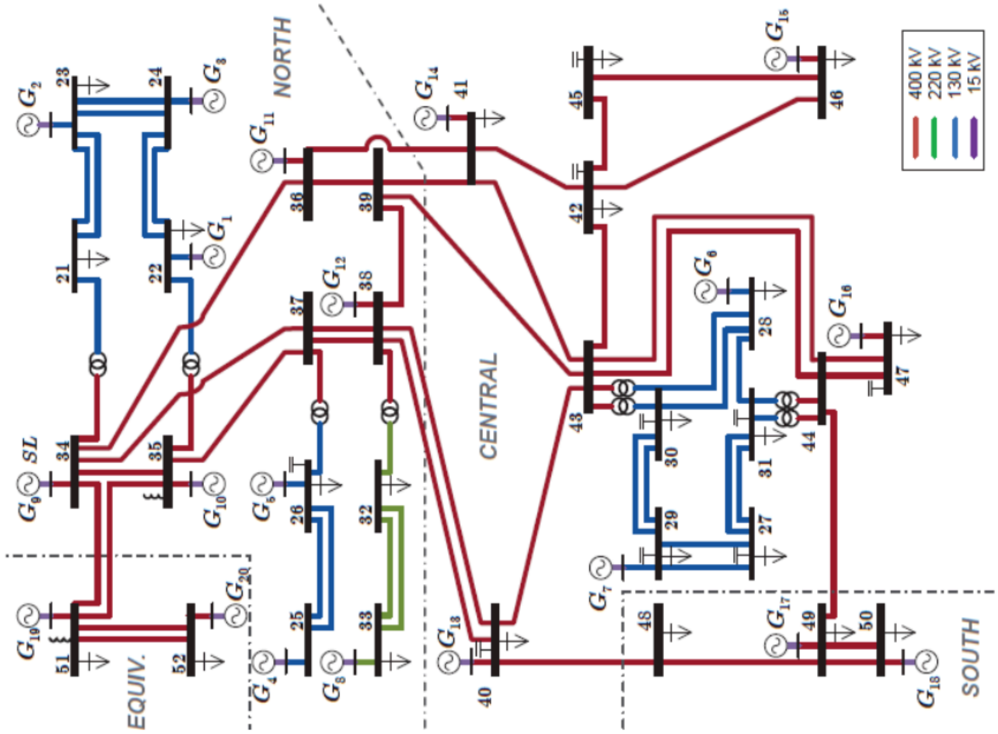


Fig. 6. Single Line Diagram of the KTH Nordic 32 Model [34]

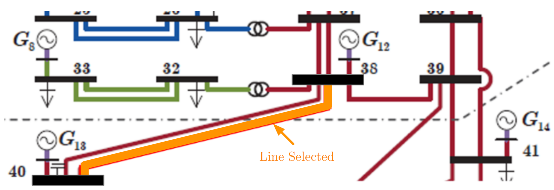


Fig. 7. Location of the selected transmission line (orange)

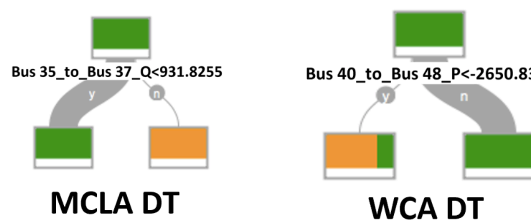


Fig. 8. Monte Carlo Like Approach (MCLA) DT and Worst Case Approach (WCA) DT

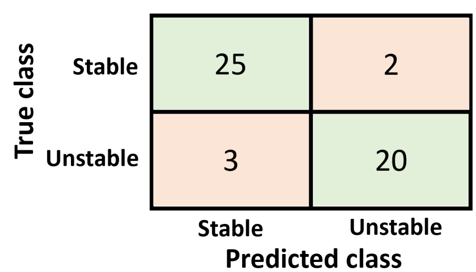


Fig. 9. Accuracy of the trained DTs w.r.t selected contingency

<u>*N-1 Bus 40 to Bus 38:*</u> This transmission line is in the central region of the network as shown in Fig. 7. For this contingency, the voltage stability index in the platform reported the voltage instability in 11 snapshots of the available 1000 snapshots. The DTs generated from the offline workflow is shown in Fig. 8. It can be observed from the figures that the size of DTs is same for both approaches, but the MCLA DT clearly differentiates *safe* and *unsafe* operating points; while the WCA DT classifies as *safe* operating points in the *unsafe* region (green shaded region in the orange box in Fig. 9). So, in the sequel, only the DT generated by the MCLA approach is considered.

This is consistent with the operational rule that shows that the power flow of the region is limited. This import flow is heavily correlated with this variable as long as the underlying 400kV topology does not change. The generated rule's performance is satisfactory when applied to the learning dataset, as shown in Fig.9 and Fig.10.

### *B. Region Classification method*

In this method, DTs are trained on the data generated by CPF and direct method as explained in section II. The simulations in PSAT were automated by a MATLAB script. Later, the machine learning toolbox available in MATLAB was used to train and test the decision trees on this simulation

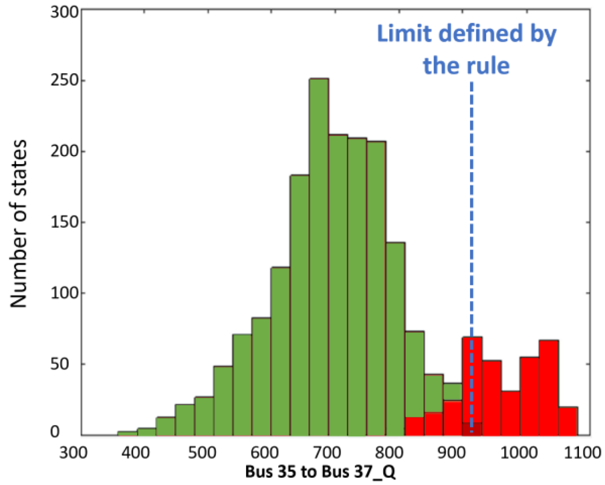


Fig. 10. Superimposed histograms of acceptable cases (green) and unacceptable cases (red) for the learning dataset

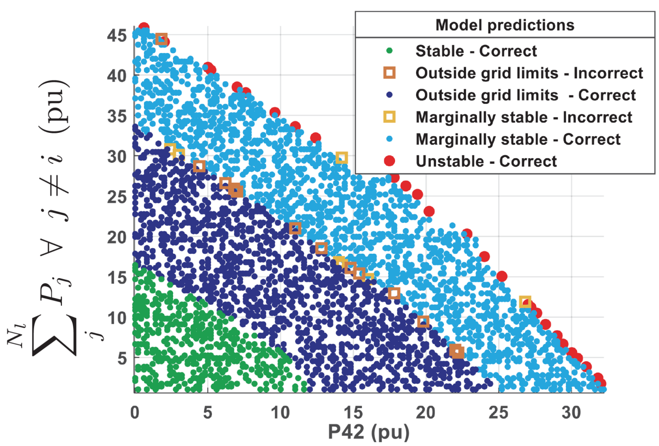


Fig. 11. Predicted states by the trained DTs w.r.t load bus $i$=42

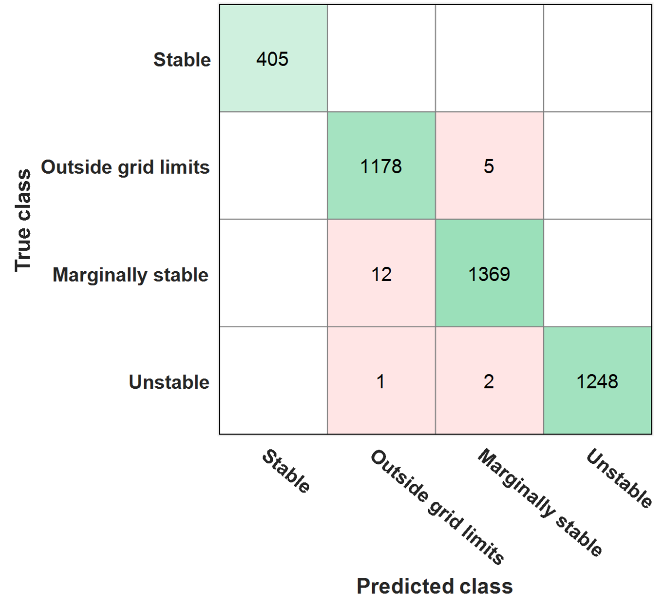


Fig. 12. Accuracy of the trained DTs w.r.t load bus $i$=42

results obtained from PSAT. Finally, a MATLAB script was written to validate the created decision trees by generating random load powers.

It can be observed that the trained DTs predicted the states of the operating points with 99% accuracy. It can be observed from Fig.10 that the DTs incorrect prediction is confined to boundary regions. Increasing the sampling of the data at the boundary region can reduce this problem but this will be the computational intense.

The performance of the trained DTs shown below in Fig.11. It can be observed that the operating points in "Stable" region are predicted with 100% accuracy but the operating points in "Outside grid limits" (99.58%), "Marginally stable" (99.14%) and "Unstable" (99.76%) regions are predicted with bit less accuracy. It can be observed from Fig. 10 that misclassification occurs in the boundary region because of the decimal values of the load powers and voltages. This misclassification can be reduced by increasing the sampling in the boundary region. Further details provided in [35].

## IV. Conclusions

This paper proposes two different methods to train the DTs for voltage stability assessment, which in turn can aid in deriving preventive actions that can be given as recommendations to system operators or as an input to automatic load shedding schemes. The main differences between the two methods are summarized in Table I, and discussed below.

TABLE I
COMPARISON OF THE TWO PROPOSED METHODS

| VSI Method | Region Classification Method |
|---|---|
| Computationally less intensive because it uses only the selected contingencies to train the model | Computational more intensive because it trains on all the network scenarios |
| Takes less time to train the model | Takes more time to train the model |
| The trained model is less accurate | The trained model is more accurate |
| The prediction accuracy of the trained model is lower for the fault on the sections of the network that are not considered in the training set | The prediction accuracy of the trained model is lower on the boundary of classification region |

For the VSI-based method, the results for a given set of contingencies applied to KTH Nordic 32 power system model and the generated DTs for different network operating conditions were verified. It was observed that the generated DT's are consistent for the given set of operating conditions. However, it should be noted that DT's can become more efficient and consistent if they are trained on diverse scenarios (i.e. well-defined contingencies and a large learning set). Hence, it would be beneficial to determine how the rules generated from DT's with less data vary from the rules generated with more data. This could help in validating the generalization capability of the generated trees.

For the region classification method, the average accuracy of classification by the created decision trees for random time domain simulations was 99.06 %. It was observed that most of the misclassified operating points lie on the boundary of regions. Therefore, more operating points are required in the boundaries of the regions when training the decision trees in order to reduce the misclassification of operating points at the boundary. The idea of this approach to use decision trees to classify the operating regions ("unstable", "outside grid limits", "marginally stable", "unstable") based on distance from the nearest SNB point has proved it to be fruitful in training the DTs, providing excellent prediction accuracy. The proposed time domain simulation-based verification can be of great value for DT accuracy verification in such cases.

## ACKNOWLEDGMENT

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## REFERENCES

[1] P. Kundur *et al.* "Definition and classification of power system stability IEEE/CIGRE joint task force on stability terms and definitions," in IEEE Transactions on Power Systems, vol. 19, no. 3, pp. 1387-1401, Aug. 2004.

[2] Y.V. Makarov *et al.* "Determining Static Stability Boundaries Using A Non-Iterative Method," in Power Engineering Society General Meeting, 2007. IEEE, 2007, pp. 1–9.

[3] Savu C. Savulescu, "Online Dynamic Security Assessment," in *Real-Time Stability in Power Systems,* $2^{nd}$ ed. Switzerland: Springer International Publishing, 2014, ch. 6, pp. 159-197.

[4] V. Venkatasubramanian *et al.* "Dynamics of large constrained nonlinear systems-a taxonomy theory," Proc. IEEE, vol. 83, no. 11, pp. 1530–1561, Nov. 1995.

[5] V. Venkatasubramanian *et al.* "Local bifurcations and feasibility regions in differential-algebraic systems," Autom. Control. IEEE Trans., vol. 40, no. 12, pp. 1992–2013, Dec. 1995.

[6] Y.S. Zhang and H.D. Chiang, "Local bifurcation boundary and steady-state security boundary in large electric power systems: Numerical studies," Int. J. Bifurc. Chaos, vol. 21, no. 03, pp. 647–662, Mar. 2011.

[7] X. Dong *et al.* "Computation of closest steady state voltage stability bifurcation using PSO approach," in 2012 IEEE ISGT Asia, 2012, pp. 1–4.

[8] T. V. Nguyen *et al.* "A new method for static voltage stability assessment based on the local loadability boundary," Int. J. Emerg. Elec. Power Sys., vol. 13, pp. 1–14, 2012.

[9] M. Perninge, "Approximating the loadability surface in the presence of SNB–SLL corner points," Int. J. Elec. Power Energy Sys., vol. 22, pp. 313–323, 2013.

[10] M. Parashar et al "Real-time Voltage Security Assessment (RTVSA) Algorithms & Framework," Consortium for Electric Reliability Technology Solutions, December 2007.

[11] J. H. Eto *et al.* "Real-time system operations (RTSO) 2006-2007," Consortium for Electric Reliability Technology Solutions (CERTS), 2008.

[12] A. Ibsais and V. Ajjarapu, "Voltage stability-limited interchange flow," Elec. Power Sys. Res., vol. 38, no. 2, pp. 91–95, 1996.

[13] I. Dobson and L. Lu, "Computing an optimum direction in control space to avoid stable node bifurcation and voltage collapse in electric power systems," Autom. Control. IEEE Trans., vol. 37, no. 10, pp. 1616–1620, Oct. 1992.

[14] I. Dobson and L. Lu, "New methods for computing a closest saddle node bifurcation and worst-case load power margin for voltage collapse," Power Syst. IEEE Trans., vol. 8, no. 3, pp. 905–913, Aug. 1993.

[15] H. G. Kwatny *et al.* "Local bifurcation in power systems: theory, computation, and application," Proc. IEEE, vol. 83, no. 11, pp. 1456–1483, Nov. 1995.

[16] Y. V Makarov *et al.* "Computation of bifurcation boundaries for power systems: a new Delta-plane method," IEEE Trans. Circuits Syst. I Fundam. Theory Appl., vol. 47, no. 4, pp. 536–544, Apr. 2000.

[17] L. Wehenkel and M. Pavella, *"Advances in decision trees applied to power system security assessment,"* IEE $2^{nd}$ International conference on Advances in Power System Control, Operation and Management, December 1993.

[18] L. Wehenkel *et al*, *"Machine Learning, Neural Networks and Statistical pattern recognition for voltage security: a comparative study,"* Engineering Intelligent Systems, vol. 2, December 1994.

[19] T. Van Cutsem *et al.* "Decision tree approach to voltage security assessment," IEEE Proceedings-C, vol. 140, no. 3, May 1993.

[20] L. Wehenkel, "Automatic learning techniques in power systems." Springer Science & Business Media, 2012.

[21] K. Sun *et al.* "An online dynamic security assessment scheme using phasor measurements and decision trees." *IEEE Trans. Power Syst.*., 2007, 22, pp. 1935-1943.

[22] R. Diao *et al.* "Decision tree-based online voltage security assessment using PMU measurements." *IEEE Trans. Power Syst.*., 2009, 24, pp. 832-839.

[23] R Diao *et al.* "Design of a real-time security assessment tool for situational awareness enhancement in modern power systems." *IEEE Trans. Power Syst.*., 2010, 25, pp. 957-965.

[24] I. Kamwa *et al.* "Development of rule-based classifiers for rapid stability assessment of wide-area post disturbance records." *IEEE Trans. Power Syst.*., 2009, 24, pp. 258-270.

[25] E.S. Karapidakis and N.D. Hatziargyriou "Online preventive dynamic security of isolated power systems using decision trees." *IEEE Trans. Power Syst.*, 2002, 17, pp:297-304.

[26] H.D. Hatziargyriou *et al.* "A decision tree method for on-line steady state security assessment." *IEEE Trans. Power Syst.*, 1994, 9, pp.: 1052-1061.

[27] Q. Gao and S.M. Rovnyak, "Decision trees using synchronized phasor measurements for wide-area response-based control." *IEEE Trans. Power Syst.*, 2011, 26, pp. 855-861.

[28] V.S.N. Arava and L. Vanfretti, "Analyzing the Static Security Functions of a Power System Dynamic Security Assessment Toolbox." *Int. J. Electr. Power Energy Syst*. 2018, 101, pp.: 323–330.

[29] V.S.N. Arava and L. Vanfretti, "A Method to estimate power system voltage stability margins using time-series from dynamic simulations with sequential load perturbations." *IEEE Access* 2018, 6, pp.: 43622–43632.

[30] L. Breiman *et al.*, Classification and Regression Trees, Wadsworth and Brooks, Monterey, CA, USA, 1984.

[31] PEPITe, "Tutorials - Datamaestro," Jun. 24, 2020. Online: https://www.pepite.com/datamaestro.html

[32] "iTesla - Innovative Tools for Electrical System Security within Large Areas", Project Final Report, March 2016. Online: https://bit.ly/2BLpWME.

[33] Y. Chompoobutrgool, W. Li, and L. Vanfretti, "Development and implementation of a Nordic grid model for power system small-signal and transient stability studies in a free and open source software," in Proc. IEEE PES Gen. Meeting, Jul. 2012, pp. 1–8.

[34] F. Milano, Power System Analysis Toolbox: Documentation for PSAT version 2.1.8, January 6, 2013.

[35] L. Vanfretti and V.S.N. Arava, "Decision tree-based classification of multiple operating conditions for power system voltage stability assessment", International Journal of Electrical Power  Energy Systems, Volume 123, 2020, 106251, ISSN 0142-0615.