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Dynamic Voltage Stability Analysis of the Kenya Power System Using Decision Trees

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Abstract
Dynamic Voltage stability analysis of any system is studied by considering load changes within the system and how voltage magnitudes at the load buses within the system are affected by the load changes. The analysis can be deepened further by considering probable contingencies within the system that could be line or generator outages. The dynamic nature of the load can be considered by using dynamic load models and evaluating the changes, with time, of the bus voltages. However, the model-driven voltages take time to compute which the system operator may not have as voltage collapse can be triggered within a very short period. Another way to analyse voltage stability is to consider many instances of system configuration in terms of varying loads and probable contingencies and then evaluating the bus voltages. This gives many snapshots of the dynamic load from which the dynamic tendency of the system can then be derived using artificial intelligence methods which can then build a time-sensitive model for online voltage stability estimation. This paper uses multiple iterations of system load configurations and a single contingency to simulate dynamic load conditions in the Kenyan system. The variables which are used to calculate the Voltage Collapse Proximity Indicator (VCPI) are captured for each load-contingency configuration. The resulting data is used to construct a Classification and Regression Trees (CART) for each bus which can then be used for online voltage estimation. The Decision Trees show the relationship between a particular bus's voltage magnitude and the contingency and power demand at other buses
Keywords: Voltage Stability, Online, VCPI, CART

I. INTRODUCTION

Voltage Stability in a power system can be defined as the tendency of the bus voltages at load buses to return to pre-disturbance equilibrium values after a disturbance has occurred within the system (IEEE Catalog, 2002). ANSI standard C84.1 defines the margin allowed for voltage magnitude to vary between ±4% or ±5% of the nominal bus voltage to allow for the slow load changes which are countered by governor action of the generators. Broadly speaking, voltage stability can be classified as either Static Voltage Stability or Dynamic Voltage Stability with the former concerned with bus voltage magnitudes resulting from one specific loading and contingency configuration. On the other hand, Dynamic Voltage Stability takes into account the dynamic nature of the load and how it affects bus voltage magnitudes from a given load and contingency configuration or a change in such a configuration. It is also broadly investigated from two angles (P. Kundur, 2004) ;

i. Mechanism of Voltage Collapse – which looks into the factors that would contribute to voltage instability and would therefore indicate the bus or system is headed to voltage instability and
ii. Distance to Instability – which is concerned with how close the system comes to becoming voltage unstable by looking at factors such as the level of loading, power factor at a critical bus or across a critical line or even the reactive power reserve across the entire system or a critical bus.

Previous research has focused on control aspects of a system to evaluate Voltage Stability e.g. (K. Ioannis and O. Konstadinos, 2006) using Multi-Variable Analysis, (L. Cai, and I. Erlich, 2007) using Singular Value Decomposition and (B. N. Soni, 2011) using bifurcation analysis. Many researchers have in the recent past also adopted Artificial Intelligence methods to study dynamic voltage stability of systems e.g. (R. A. Alammari, 2002) using Fuzzy models, (G. Balamurugan and P. Aravindhababu, 2010) using Artificial Neural Networks and (L. M. Ngoo et al, 2011) using a Neuro-Fuzzy Model of an inductive load.Decision Trees have also been used in online system security studies (E. Karapidakis and D. Hatziargyriou, 2002). The slow acting dynamics of the system allow for the use of many static snapshots of the system to simulate the dynamic nature of the system in evaluating Dynamic Voltage Stability.

II. METHODOLOGY

The Voltage Collapse Proximity Indicator (VCPI), also called the L-index, is used to show how close a bus is to voltage collapse (G.Haung and N. Kumar, 2002) and has been used in previous studies (S. Njoroge et al, 2014). The L-index is defined for a particular bus j as;

$$L_j = \left|\frac{S_{j+}^*}{Y_{jj+}V_j^2}\right| \quad (i.)$$

With

$$S_{j+} = S_j + S_{jcorr} \quad (ii.)$$

$$\text{where } S_{jcorr} = \left\{ \sum_{\substack{i \in Loads \\ i \neq j}} \frac{Z_{ji}^*}{Z_{jj}^*} \frac{S_i}{V_i} \right\} V_j \qquad (iii.)$$

To incorporate the effect of contingencies within the system, the Y-bus matrix is used where

$$Y_{jj} = \frac{1}{Z_{jj}} \qquad (iv)$$

With Z_{jj} being the jj^{th} element in the impedance matrix and the other variables defines as

L_j – $VCPI$ $index$; V_j – $Voltage$ at bus j ; S_j – $Complex$ $power$ at bus j

the L – index itself wasn't used in this research. Instead, the variables used in its calculation were recorded for each load-contingency configuration and after performing a load flow for each configuration, the resulting voltage magnitude matching the variables for the load-contingency configuration were also recorded. This was then repeated using a different load-contingency configuration and the results recorded. The variables chosen for a load bus $j$were;

$P_i - Real\ Power\ Matrix\ for\ configuration\ i$

$Q_i - Reactive\ Power\ Matrix\ for\ configuration\ i$

$Y_{jj} - The\ jj^{th} Element\ in\ the\ Y - bus$

$K_i - The\ load - contingency\ configuration$

$J_{1j} - the\ j^{th}\ element\ in\ the\ J_1\ matrix\ from\ the\ Jacobian$

$J_{3j} - the\ j^{th}\ element\ in\ the\ J_3\ matrix\ from\ the\ Jacobian$

The bus voltage obtained after the power flow iteration formed the target output for the Decision Tree.

Decision Trees have recently been used in data mining involving large groups of related data where the exact relationships between the input-output pairs isn't clear or takes a lot of computational power and time. (Kai Sun et al, 2007) used phasor measurements with decision trees in dynamic security assessment studies. The Decision Tree (DT) has the hierarchical form of a tree structured upside down. The construction of a DT is based on a knowledge base consisting of a large number of operating points covering all possible states of the power system. The goal is to create a model that predicts the bus voltage based on the input variables. The variables are successively split into a dichotomy at each step using a regression analysis relating that variable to the bus voltage at the bus in question. The variable with the greatest effect on the voltage is split first while the one with least observable effect is split last. The resulting Decision Tree indicates the variable with the greatest effect on the bus voltage at bus j and the subsequent variables as well as the corresponding range of variables for the variable at that particular node. For each leaf (terminal of the tree) corresponding to a bus voltage magnitude, the set of rules relating the voltage to the contributing variables was also obtained from the decision tree.

In this research, an algorithm was developed for construction of the decision trees. The algorithm was first tested on the IEEE 14-bus system before being applied on the Kenya Power System. First, the ideal system configuration is subjected to a power flow study iteration which shows the resulting bus voltages within the system. The input variables to the decision tree as well as the bus voltages are stored. Next, a single contingency is applied to the system, either a line outage or a random transformer tap variation of between ±10% of the nominal setting. The load buses within the system are then perturbed by between ±50% without maintaining power factor to simulate a dynamically varying load. A load flow iteration is then performed and the variables stored. For each contingency, 100 load configurations and load flow iterations are performed and the variables stored before moving to the next contingency, until all possible contingencies have been covered. The data collected then forms the basis for construction of the decision tree.

III. RESULTS AND ANALYSIS

The IEEE 14-bus system was first used in testing the algorithm to see the reliability of the decision tree generated. Previous studies (G. Balamurugan and P. Aravindhababu, 2010) found bus 14 to be the weakest and so a decision tree was constructed for bus 14. To determine the optimum number of nodes in the tree, the minimum cost of misclassification as a factor of the number of terminal nodes was evaluated by cross-validation and was found to occur with 2 terminal nodes as shown in Fig. 1

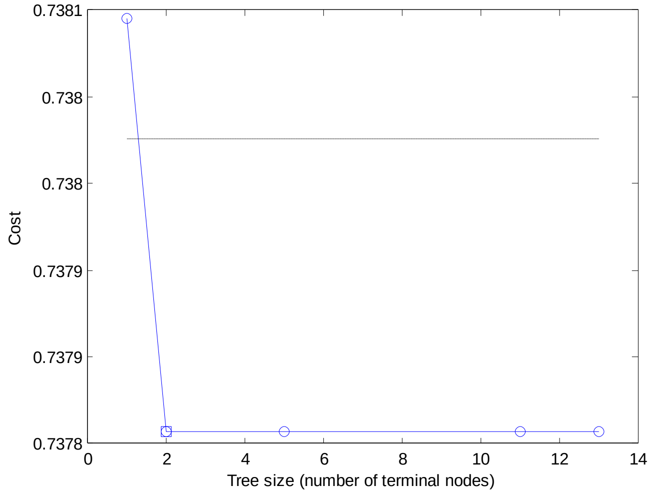


Fig. 1: IEEE Bus-14 Best Tree Evaluation - Bus-14

The corresponding decision tree is shown in Fig. 2. This showed clearly that the presence of a contingency within the system would lead to the voltage at bus 14 falling to 96% of its nominal value. Further analysis of the complete decision tree showed that considering a second level of pruning from the lowest cost tree produced the tree in Fig. 3. The contingency still carries the greatest weight followed by reactive power demand at buses 12 and 14 respectively, then real power demand at bus 11. The effect of Q_{12} on voltage at bus 14 is however low, given the voltage falls to 0.99pu when Q_{12} is greater than 1.4pu.$Q_{14}$is directly connected to the voltage at the same bus. P_{11} is the interesting variable having a great effect on voltage at bus 14. A possible explanation for this is the high percentage of the reactive load (1.8MVaR) at bus 14 as compared to the real load (3.5MW) showing a load with a poor pf, which would drain reactive power from other buses including bus 14.

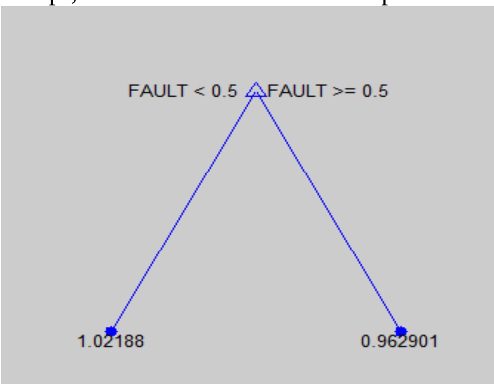


Fig. 2: Best-Tree Fit for IEEE 14Bus – Bus 14

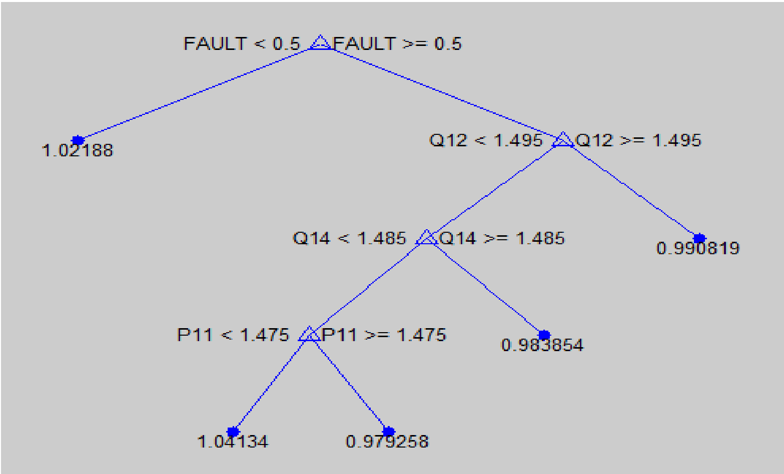


Fig. 3: 2nd Level Pruned Tree for IEEE 14 Bus - Bus-14

For the Kenya Power System, a previous study had identified buses 10,22,30,31as the weak buses (Muriithi C. M et al, 2009). Taking bus 10, the least cost tree has 3 nodes and is shown in Fig. 4. The tree still has the presence of a contingency as the most influential factor. Expanding the tree by one extra pruning level reveals the next level of contributing factors namely P_{17}, P_5, and P_3 as shown in Fig. 5.P_{17} is a remote location physically and electrically distant from bus 10 and it's low real power increases its impact on the regression analysis. P_5, andP_3 are both physically and electrically close to bus 10. In addition, they are both comparatively large load centers in comparison to the load at bus 10, which explains their impact on the voltage stability. $J_1$is the Jacobian matrix element. It's influence can be ignored since bus 1 is the slack bus without a generator or a load.

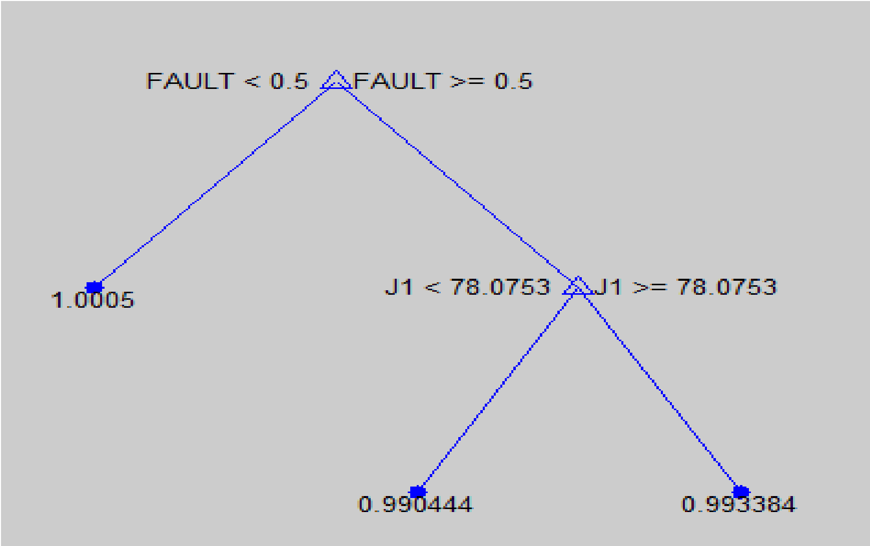


Fig. 4: Least Cost Tree for Kenya Power System Bus-10

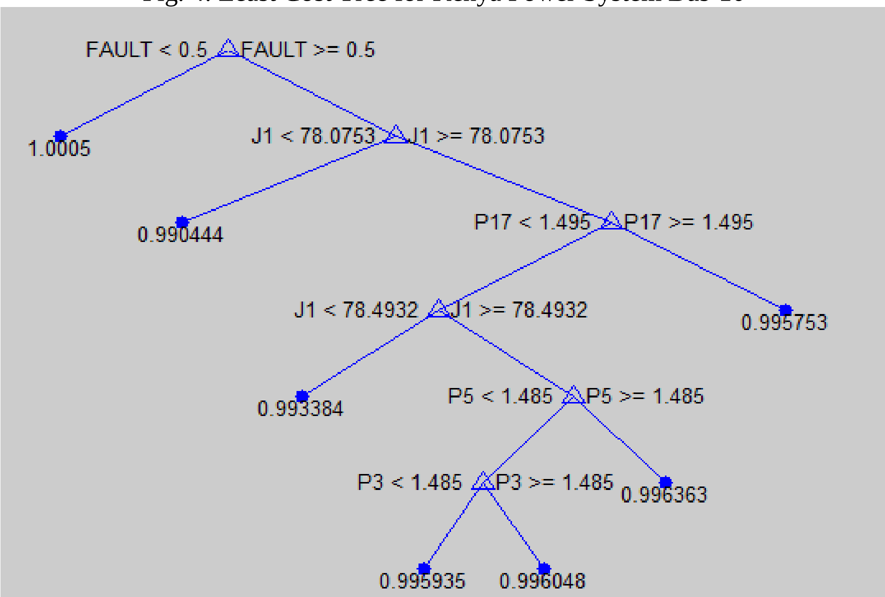


Fig. 5: 2nd Level Pruned Tree for Kenya Power System Bus-10

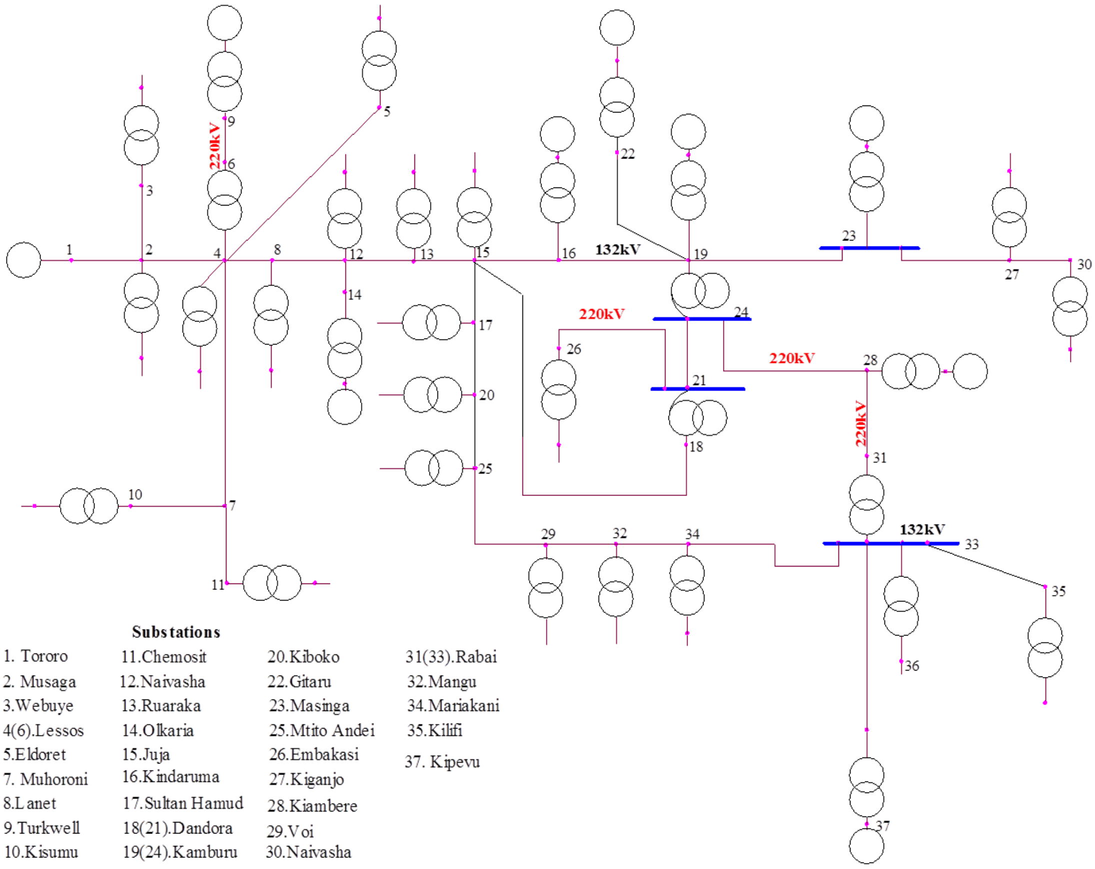
IV. CONCLUSION

From the results, it has been shown that decision trees can be constructed from static power-loading-contingency snapshots and used to predict the dynamic behavior of the system. Though the construction procedure for the decision trees is very intensive on computational requirements, the resulting decision tree makes for very reduced computation in providing an online tool that can be used in hard coding for system control or designing rules for Fuzzy systems for defensive online management of the Kenya Power System.

The Decision trees however have to be constructed individually for each bus and the variables to be considered for each bus have to be evaluated to avoid utilizing valuable computational time in predicting the voltage magnitude level instead of acting defensively to avoid voltage collapse.

V. APPENDIX

Appendix 1 : Kenyan



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