Dynamic Voltage Stability Analysis of the Kenya Power System Using VCPI Stability Index and Artificial Neural Networks

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Abstract

Dynamic voltage stability deals with the voltage levels and how they're affected by either faults or load changes within the system. Voltage instability has long been suspected in the voltage collapse and islanding of power systems. Identifications of operational conditions leading to voltage collapse is therefore critical in allowing for critical defensive measures by the system operator to avoid voltage collapse before it occurs. This paper examines the use of Voltage Collapse Proximity Indicator (VCPI) in conjunction with Artificial Neural Networks to predict conditions of voltage instability before they occur for load buses within the Kenya power system that can be used for online prediction of voltage stability within the system. The results show the validation of the VCPI index as an indicator of voltage stability when compared to previous studies on both the IEEE 9-bus system and IEEE 14-bus system and as an indicator of the point of voltage collapse. The application of Artificial Neural Networks to map the relationship between the power demand at a bus, total power demand in the system and the VCPI index to the Kenyan system shows a high level of accuracy leading to the conclusion that an online VCPI index prediction using an ANN can be used to predict voltage stability in the Kenya power system.

Keywords: Voltage Stability, VCPI, ANN

1. INTRODUCTION

A power system at a given operating state and subject to a given disturbance is voltage stable if voltages near loads approach post-disturbance equilibrium values (IEEE Catalog, 2002). Voltages of the buses within a power system are required to remain within 4% or 5% of the nominal bus voltage in line with ANSI standard C84.1. Voltage Stability can broadly be classified into Static Voltage Stability and Dynamic Voltage Stability. Static Voltage Stability evaluates the voltage magnitudes at all the buses in the system for a given loading and system configuration. The result only applies to that network topology and loading condition. Dynamic Voltage Stability is concerned with 2 aspects of voltage stability (P. Kundur, 2004)

i. Distance to instability – this measures how close the system is to being voltage unstable. The distance is given in terms of system parameters like loading, power flow across a critical line or reactive power reserve.
ii. Mechanism of Voltage Instability – this investigates what system factors contribute to voltage instability and what indicates that the system is heading towards instability.

Previous studies on Dynamic Voltage Stability have used singular value decomposition, multi-variable control theory and bifurcation analysis. (L. Cai, and I. Erlich, 2007) used singular value decomposition in the evaluation of dynamic voltage stability on the IEEE 9-bus system. (B. N. Soni, 2011) employed bifurcation analysis while (K. Ioannis and O. Konstadinos, 2006) used multi-variable analysis in dynamic voltage stability analysis.Since voltage stability is affected by slow acting system dynamics which allows for the use of many static points to analyze Dynamic Voltage Stability.

2. METHODOLOGY

To evaluate how voltage-stable a bus is, the Voltage Collapse Proximity Indicator (VCPI) is one of the tools employed recently. It incorporates elements of the Y-bus matrix to capture the network topology as well as the real and reactive power configurations both at the reference bus and within the system as a whole. The VCPI can be calculated at each bus for each loading and contingency condition (G. M. Haung and N. Kumar, 2002). It is calculated at bus j as

$$L_j = \left|\frac{S_{j+}^*}{Y_{jj+}V_j^2}\right| \tag{1}$$

Where

$$L_j - VCPI\ index\ ; \quad V_j - Voltage\ at\ bus\ j\ ; \quad S_j - Complex\ power\ at\ bus\ j$$

$$S_{j+} = S_j + S_{jcorr} \tag{2}$$

$$S_{jcorr} = \left\{\sum_{\substack{i\in Loads \\ i\neq j}} \frac{Z_{ji}^*}{Z_{jj}^*}\frac{S_i}{V_i}\right\} V_j \tag{3}$$

and

$$Y_{jj} = \frac{1}{Z_{jj}} \tag{4}$$

Where $Z_{jj} - Impedance\ matrix\ element\ jj$

S_{jcorr} is a component of all the other loads in the system incorporated into the index at bus j. The VCPI is calculated for the load buses within the system. It has a value of 0 for stability and 1 for complete instability. The VCPI can however only be calculated for static conditions and in this paper minute load changes are used to simulate dynamic loading and contingency conditions.

Artificial intelligence techniques have also been used for a while to reduce the computation times in the power flow solution which is an iterative procedure. Artificial Neural Networks (ANN) are used to mimic human brain cognitive properties and can be trained to read patterns in related data that may be too complex to capture in mathematical terms. They have previously been used for identifying weak buses within a system (Muriithi C. M et al, 2009). ANNs learn the pattern on which they are trained. An artificial neuron consist of synapses which apply weights to the inputs, an adder that sums the weighted inputs and an activation function that maps the sum to the output function of the neuron. ANNs are formed by arranging neurons in layers.

In this research, we aim to develop an algorithm for training an Artificial Neural Network using calculated VCPI index values and corresponding real and reactive power values. The algorithm is first validated on IEEE test systems (9-bus and 14-bus) before being applied to the Kenya power system.

The algorithm involved calculation of a power flow solution for the ideal system then increasing the load in steps of 0.001pu while maintaining power factor. At each load configuration, the load flow solution is obtained using the Newton Raphson iteration method with a 100 iterations limit and the corresponding voltage magnitude and VCPI index is calculated for the bus in question. The loading is increased until the load flow solution fails to converge, with the value of the VCPI index, voltage magnitude and real and reactive power at each load configuration recorded. The values of the powers and VCPI index are then used to train an ANN. Some of the power values are then used to evaluate the VCPI index using the ANN and the output of the ANN compared with the calculated values from the load flow to evaluate the accuracy of the ANN in predicting the VCPI values. This is first done on the IEEE 9-bus system and 14-bus systems to validate the algorithm before its used on the Kenya Power System.

3. RESULTS AND ANALYSIS

The 9-bus WSCC system was used to test the accuracy of the VCPI calculations using static load increments. The loading on Bus 5 was increased in steps of 0.001pu while maintaining pf until when the power flow solution did not converge. This occurred at 2.971pu loading and the corresponding plot of the VCPI and voltage magnitude was as in Fig 1.

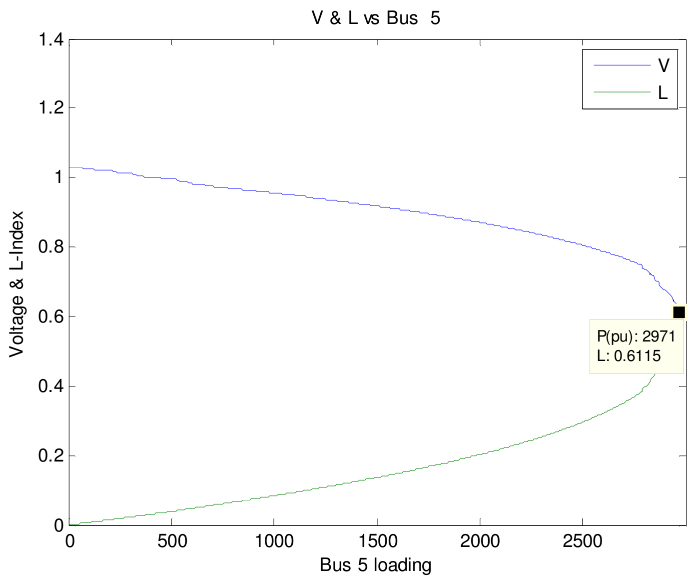


Fig. 1 : Bus 5 V & L (WSCC 9-bus system)

This result matched previous studies using the VCPI (I. Kumarswamy et al, 2012) with the collapse point for Bus 5 occurring at 2.971pu (371+j149MVA).

Next the IEEE 14-bus system was studied. This involved iterations for the ideal case and with n-1 contingency. The contingencies were selected as line contingences and for transformers the tap settings were varied between 90% and 110% of the nominal tap setting. At each iteration, 100 random loading configurations of between 30% and 200% at each load bus without maintaining pf. Within each of theseiterations, a load flow study was run with the single contingency and load configuration. From the loadflow, the voltage magnitudes, real and reactive power at each bus and for the whole system were recorded. Also, the L-index was calculated for that configuration. This data was then used to train an ANN with 100 neurons in the hidden layer. Previous studies (G. Balamurugan and P. Aravindhababu, 2010) found bus 14 is the weakest bus in the system. A comparison of the VCPI calculated from the Power Flow and that predicted by the ANN is shown in Table 1

All Values in pu				**n-1**		
P_{14}	Q_{14}	P_{tot}	Q_{tot}		**Method**	**VCPI**
1	1	1	1	0	**Calculated**	0.0279
					ANN	0.0259
0.98	0.71	0.91	0.90	2	**Calculated**	0.0303
					ANN	0.0277
1.15	1.45	0.99	1.11	10	**Calculated**	0.0394
					ANN	0.0263
0.55	0.8	1.04	0.87	18	**Calculated**	0.0466
					ANN	0.0449
1.31	1.44	1.07	1.16	18	**Calculated**	0.0207
					ANN	0.0090

Table 1: VCPI for IEEE 14 bus System

From Table 1, it is clear that as the total system load increases, the VCPI value increases. Similarly, increased loading on bus 14 increases the VCPI value, indicating increased instability. The ANN values also follow the power flow calculated values. Since the VCPI varies from 0-1, the relative error is very minimal.
The same algorithm was then used on the 37-bus Kenyan system. Previous studies (C. Muriithi and S. Njoroge, 2010) identified buses 10,22,30,31 as the weakest buses in the system. The VCPI for the 3 buses using power flow and ANNs are shown in tables 2, 3 and 4.

All Values in pu				**n-1**		
P_{10}	Q_{10}	P_{tot}	Q_{tot}		**Method**	**VCPI**
1	1	1	1	0	**Calculated**	0.007928
					ANN	0.007935
1.04	1.50	0.86	1.08	20	**Calculated**	0.008729
					ANN	0.008658
1.40	1.15	1.02	0.86	20	**Calculated**	0.011047
					ANN	0.011137
0.57	0.53	1.01	1.05	1	**Calculated**	0.004443
					ANN	0.004390
0.71	0.73	0.88	0.91	33	**Calculated**	0.005663
					ANN	0.005570

Table 2: VCPI Values for Kenyan System Bus 10

The VCPI values in Table 2 indicate that in all the randomly selected cases the bus is stable even with the selected single contingencies. The ANN generated values also closely follow the power flow values to a very great extent. A comparison of a contingency on line 20 shows bus 10 stability drops with a relatively small increase in the total system real power loading even when the reactive power demand at the bus is reduced. This reinforces its classification as a weak bus.

All Values in pu				**n-1**		
P_{30}	**Q_{30}**	**P_{tot}**	**Q_{tot}**		**Method**	**VCPI**
1	1	1	1	0	**Calculated**	0.0059142
					ANN	0.0059142
0.76	1.13	0.81	0.97	8	**Calculated**	0.0049734
					ANN	0.0049744
0.95	1.05	1.19	0.94	34	**Calculated**	0.0057342
					ANN	0.005734
0.97	0.80	1.06	0.84	34	**Calculated**	0.005555
					ANN	0.005555
0.90	1.09	1.09	1.18	21	**Calculated**	0.005548
					ANN	0.0055493

Table 3:VCPI Values for Kenyan System Bus 30

From Table 3, a contingency on line 34 with 2 separate values of loading on bus 30 show slight drop in the stability of bus 30 with a similar slight increase in reactive power. This shows it is a weak bus though it doesn't evaluate the maximum reactive power the bus can support without voltage collapse. The VCPI values from the ANN are almost identical to the ones from the power flow.

All Values in pu				**n-1**		
P_{22}	**Q_{22}**	**P_{tot}**	**Q_{tot}**		**Method**	**VCPI**
					Calculated	0.112534
1	1	1	1	0	**ANN**	0.112534
					Calculated	0.112534
0.00	0.00	1.16	0.94	11	**ANN**	0.112534
					Calculated	0.112534
0.00	0.00	0.99	0.89	11	**ANN**	0.112534
					Calculated	0.112534
0.00	0.00	0.92	0.73	7	**ANN**	0.112534
					Calculated	0.112534
0.00	0.00	1.01	0.91	33	**ANN**	0.112534

Table 4: VCPI Values for Kenyan System Bus 22

Table 4 shows the unique case of bus 22 which is a node in the system without a direct load. The VCPI values for both the ANN and the power flow are identical. The stability index doesn't vary with the change in total system demand showing the sensitivity of the VCPI index to the load on a bus. This case is similar to bus 31 which is also a node.

A simulation of the VCPI using the load flow for buses 10 and 30 was done with increasing loading till the voltage got to 0.95pu. It showed the VCPI being 0.02292 at 267% loading for bus 10 single loading (Fig. 2) and 0.04975 at 769% loading for bus 30 single loading (Fig. 3). While the loading may seem extreme, the buses are increasingly loaded alone while the rest of the system is maintained at the nominal values without any contingency. This shows the sensitivity of the VCPI index to the voltage magnitude of the buses.

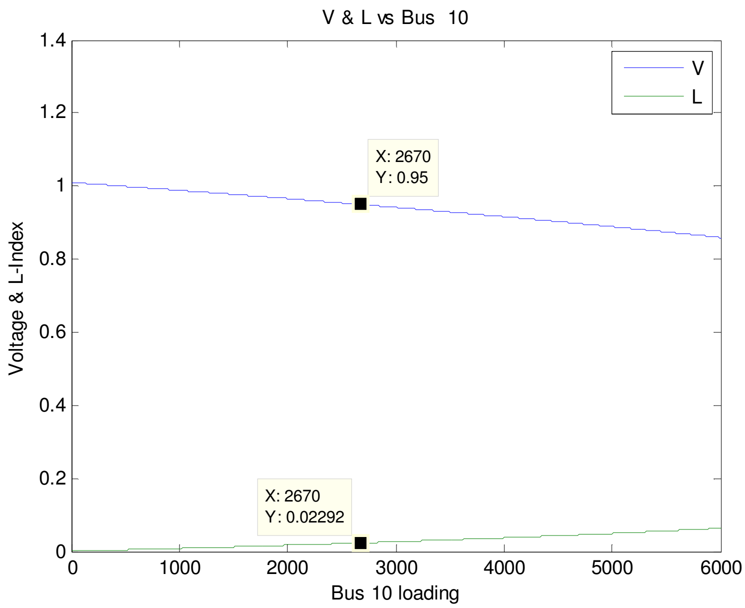


Fig. 2: VCPI for Bus 10 Kenyan System

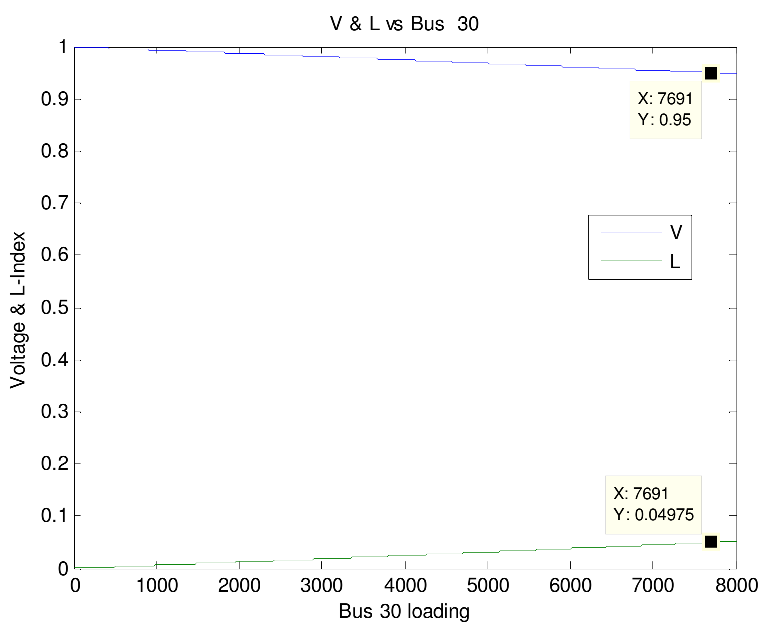


Fig. 3: VCPI for Bus 30 Kenyan System

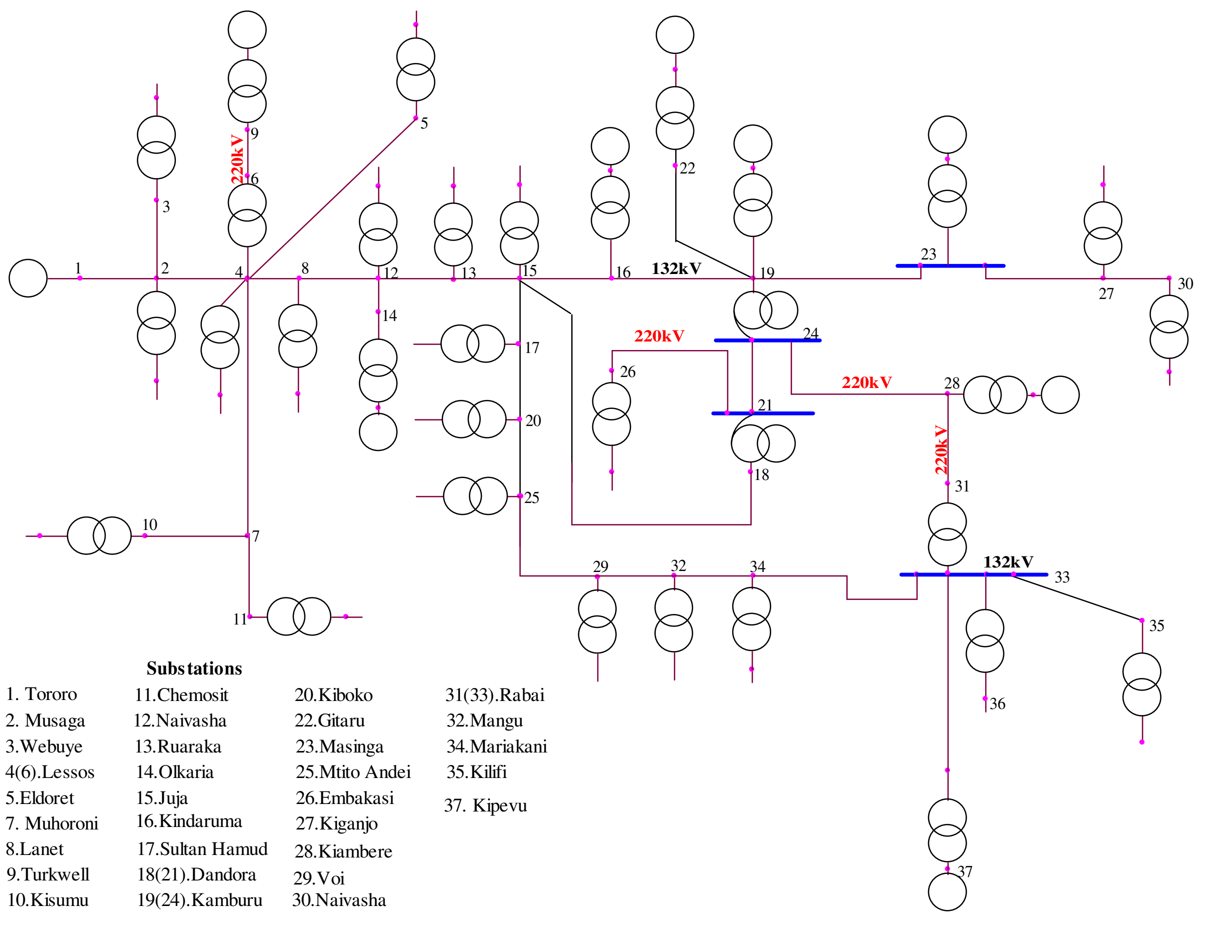
4. CONCLUSION

From the results, it has been shown that the VCPI index can be used as an accurate measure of voltage stability. The relationship between the VCPI values generated by the ANN and the actual values generated by carrying out load flows shows that ANNs can be trained for a bus which can then give a real time approximation of the stability of the bus using only 4 power measurements that are easy to read using a SCADA system which can lead to an on-line estimation of the stability at all the buses within the system using the VCPI. The VCPI for the weak buses within the Kenya Power system were also evaluated and the ANN values for VCPI found to very accurately track the actual values calculated using the power flow.

A major short coming of the VCPI is that while it may indicate increasing instability, it doesn't indicate the distance to instability. This is an area that can be studied further.

APPENDIX

Appendix 1 : Kenyan Power System



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