DEVELOPMENT OF EARLY WARNING METHODS FOR VOLTAGE INSTABILITY IN ELECTRIC POWER SYSTEM

TAI CHIA WUEN

A project report submitted in partial
fulfillment of the requirement for the award of the
Degree of Master of Electrical Engineering

Faculty of Electrical and Electronic Engineering
Universiti Tun Hussein Onn Malaysia

JUNE 2013

ABSTRACT

Voltage collapse is still the biggest threat to the transmission system. It will involve large disturbance, non-linear and discontinuous dynamics. There are many approaches that have been explored to predict the distance of the point of voltage collapse. However, it is still lack of information that related to current system state. With the latest Phasor Measurement Units (PMU) technology, it can provide an alternate pathway to improve the current power system state estimation. Hence, it was of interest to develop better methods that could give an early warning for voltage collapse. This project report concerns the development of methods that can provide in a real time system monitoring from PMU for an early warning of voltage collapse in the electric power systems. The algorithm to predict the distance of the points of collapse is based on the assumption that voltage instability is closely related to maximum loadability of a transmission network, thus the Thevenin impedance is equal to the apparent load impedance at the points of collapse. Few methods were being implemented to track the Thevenin equivalent parameters in order to get the Thevenin impedance and its voltage. Performance of the methods used in this project is based on the analyzed results for the points of voltage collapse.

ABSTRAK

Penurunan voltan merupakan ancaman yang amat besar kepada sistem penghantaran data. Ia akan melibatkan gangguan secara besar-besaran, tidak sekata dan keadaan yang dinamik secara berterusan. Terdapat banyak pendekatan yang telah diterokai untuk meramal kadar kejatuhan voltan. Walau bagaimanapun, masih ada lagi kekurangan tentang maklumat yang berkaitan dengan keadaan sistem arus elektrik. Dengan teknologi terkini, *Phasor Measurement Units* (PMU) ini dapat memberi laluan alternatif untuk memperbaiki anggaran kuasa arus pada keadaan semasa. Oleh yang demikian, ia adalah menjadi agak perlu untuk membangunkan kaedah yang lebih baik supaya dapat memberi amaran secara awal pada kejatuhan voltan. Kertas kerja ini melibatkan pembangunan kaedah yang boleh memberi maklumat mengenai sistem pemantauan semasa dalam keadaan sebenar daripada PMU untuk membagi amaran awal tentang kejatuhan voltan dalam sistem kuasa elektrik. Kaedah yang digunakan untuk meramal jarak penurunan voltan adalah berdasarkan andaian bahawa ketidakstabilan voltan dan ianya berkait rapat dengan keupayaan kepada beban secara maksimum dalam rangkaian penghantaran. Dengan itu, impedans Thevenin adalah sama dengan impedans ketara pada titik kejatuhan voltan. Beberapa kaedah telah dilaksanakan untuk mengesan parameter yang setara Thevenin untuk mendapatkan impedans Thevenin dan nilai voltan. Kaedah prestasi yang digunakan dalam projek ini adalah berdasarkan keputusan yang dianalisis untuk titik kejatuhan voltan.

CONTENTS

	TITLE	**i**
	DECLARATION	**ii**
	DEDICATION	**iii**
	ACKNOWLEDGEMENT	**iv**
	ABSTRACT	**v**
	CONTENTS	**vii**
	LIST OF TABLE	**xi**
	LIST OF FIGURES	**xii**
	LIST OF SYMBOLS AND ABBREVIATIONS	**xvi**
CHAPTER 1	**INTRODUCTION**	**1**
	1.1 Project title	1
	1.2 Introduction	1
	1.3 Objective and scope of study	2

CHAPTER 2	**LITERATURE REVIEW**	**4**
	2.1 Definition	4
	2.2 Case study for pervious work based on Phasor Measurement Units (PMUs) applications	4
	2.2.1 Wide area measurement system (WAMS) based applications	5
	2.2.2 Application and analysis of optimum PMU placement methods	9
	2.3 Voltage stability overview	10
	2.3.1 Factors affecting voltage stability	11
	2.3.2 Point of collapse	14
	2.3.3 Conventional power flow	14
	2.4 A Hilbert-Huang based approach for on-line extraction of modal behavior from PMU data	16
	2.5 Case study on previous works that related to the Kalman filter, extended Kalman filter and unscented Kalman filter	17
	2.5.1 Voltage stability margin identification using local measurements and linear Kalman filter	17
	2.5.2 Case study for pervious work on the extended Kalman filter	18
	2.5.3 Case study for pervious work on the unscented Kalman filter	19

CHAPTER 3	**RESEARCH METHODOLOGY**	**22**
	3.1 Definition	22
	3.2 Voltage instability predictor (VIP)	22
	3.3 Use of radial equivalent independent (REI) network	24
	3.4 Application to TNB 132 kV network	26
	3.5 Methods of tracking Thevenin equivalent parameters for online estimation	27
	3.5.1 The Kalman filter algorithm	29
	3.5.2 The extended Kalman filter algorithm	30
	3.5.3 The unscented Kalman filter algorithm	33
CHAPTER 4	**RESULTS AND DISCUSSION**	**35**
	4.1 Definition	35
	4.2 Results and analysis for two bus system	35
	4.2.1 Results by using Kalman filter algorithm	37
	4.2.2 Results by using extended Kalman filter algorithm	39
	4.2.3 Results by using unscented Kalman filter algorithm	40
	4.2.4 Discussion for the results in two buses system	41
	4.3 Results and analysis for ten bus system	43
	4.3.1 Results by using Kalman filter algorithm	45
	4.3.2 Results by using extended Kalman filter algorithm	46
	4.3.3 Results by using unscented Kalman filter algorithm	48

	4.3.4 Discussion for the results in ten buses system	49
	4.5 Overall discussion	50
CHAPTER 5	**CONCLUSIONS AND RECOMMENDATIONS**	**52**
	5.1 CONCLUSION	52
	5.2 RECOMMENDATIONS	53
	REFERENCES	54

LIST OF TABLE

4. 1	Changes of voltage and apparent power at specific time	36
4. 2	Value of the index from different method	41
4. 3	Value of voltage and apparent power at time 0.16 seconds	42
4. 4	Value of the index from different method	47

LIST OF FIGURES

2.1	TNB WAMS System Architecture	6
2.2	TNB real-time Human Machine Interface Visualization Display	6
2.3	PMU location at Transmission Grid System in Peninsular Malaysia	7
2.4	GUI Power system oscillation and spectrum analyzer	8
2.5	Examples of power disturbance captured	9
2.6	Role of State Estimation in power system control and operation	10
2.7	Voltage stability phenomena and time responses	11
2.8	Two bus system	12
2.9	P-V curve for two bus system	13
2.10	A continuation power-flow analysis	15
3.1	Local bus and the rest of the system treated as a Thevenin equivalent	23
3.2	WAPS and the simplified network	24
3.3	General circuit for REI network	25
3.4	Detail of TNB 132 kV load area under investigation	26
3.5	The ongoing discrete Kalman Filter cycle	29
3.6	A complete picture of the operation of the Kalman Filter	30
3.7	A complete picture of the operation of the Extended Kalman Filter	32
3.8	A complete picture of the operation of the Unscented	34
4.1	Voltage at each bus and the REI network	37

4.2	The apparent power at each bus and the REI network	37
4.3	Graph of load voltage with Thevenin voltage and load impedance with Thevenin impedance by KF	38
4.4	The point of collapse traced by using KF algorithm	38
4.5	Graph of load voltage with Thevenin voltage and load impedance with Thevenin impedance by EKF	39
4.6	The point of collapse traced by using EKF algorithm with Thevenin impedance by UKF	39
4.7	Graph of load voltage with Thevenin voltage and load impedance	40
4.8	The point of collapse traced by using UKF algorithm	40
4.9	Graph of real power profile for two buses system	42
4.10	Voltage at each bus and the REI network	44
4.11	The apparent power at each bus and the REI network	45
4.12	Graph of load voltage with Thevenin voltage and load impedance with Thevenin impedance by KF	46
4.13	The point of collapse traced by using KF algorithm	46
4.14	Graph of load voltage with Thevenin voltage and load impedance with Thevenin impedance by EKF	47
4.15	The point of collapse traced by using EKF algorithm	47
4.16	Graph of load voltage with Thevenin voltage and load impedance with Thevenin impedance by UKF	48
4.17	The point of collapse traced by using UKF algorithm	49
4.18	Graph of real power profile for ten buses system	50

LIST OF SYMBOLS AND ABBREVIATIONS

Active power	-	P
Admittance	-	Y
Apparent impedance	-	Z_{app}
Apparent power	-	S
Current	-	I
Imaginary Thevenin voltage	-	E_i
Kalman filter measurement vector	-	z_k
Kalman filter state vector	-	x_k
Kalman gain	-	K_k
Load impedance	-	Z_{load}
Measurement noise covariance	-	R
Measurement noise	-	v_k
Process noise covariance	-	Q
Process noise	-	w_k
Reactance	-	jX
Reactive power	-	Q
Real Thevenin voltage	-	E_r
Thevenin impedance	-	Z_{th}
Thevenin reactance	-	X_{th}
Thevenin resistance	-	R_{th}
Voltage angle	-	δ
Voltage magnitude	-	V

CHAPTER 1

INTRODUCTION

1.1 Project title

The title of this project is *"Development of Early Warning Methods for Voltage Instability in Electric Power System."*

1.2 Introduction

With the growing of demand in power system, voltage instability problem has become a challenge to power system operator. Load growth without a corresponding increase of transmission capacity has brought many power systems closer to their voltage stability boundaries, which leads to voltage instability problems increase. Moreover the stable system contributes to reliability and reduction in system loss. Hence the voltage instability problem has received a lot of attention not only from researchers but also from the industry. Thus, a continuous real-time voltage margin monitoring system is required to predict the distance to the point of voltage collapse.

The Malaysia power system is equipped with Phasor Measurement Units (PMUs). The implementation of the technology of PMU in real power systems is under the process currently. PMU technology is able to get a snapshot of the current system state by measuring such parameters as positive sequence voltage and current magnitude and angel and frequency. By referring to the announcement on the increase in electricity tariff from [1], the continually increasing in load demand and fuel cost leads to an urgent needs to improve operational efficiencies utilization of transmission and distribution assets and reduction of losses. Therefore, Tenaga Nasional Berhad-Transmission (TNB-T) and TNB-Research (TNB-R) have joint collaboration in a 5-years research and development project on Wide-Area Intelligent Systems (WAIS) to enhance security and reliability of the power system network, and hence to provide system operators with real-time information on proximity of the system to voltage collapse [2].

1.3 Objective and scope of study

There are three main objectives of conducting research on the methods for early warning of voltage instability in electric power system.

- To investigate the countermeasures available in order to advise prevention purpose.
- To develop and implement early warning methods on voltage instability.
- To predict the point of voltage collapse and improve the methods for prevention purpose.

The scope of the study is basically based on the analyzing data collected from PMUs system and few methods for voltage stability analysis. The actual data from the applied PMUs in the system will never find any voltage collapse. This is because the existing transmission lines already equip with the protection and countermeasure systems to make an early prevention from collapse. Therefore, voltage collapse such as fault occurrence or tripping on the bus will be created with the simulation in order to obtain the data from the Real-Time Digital Simulator (RTDS). The PMUs simulated data obtained from TNB-R are in the form of voltage and current Phasor which refer to its magnitude and angle. For the time being, TNB-R is using the latest PMUs technology that able to measure 50 samples per second. The experimental performance of simulation was conducted at TNB-R with the 132 kV load area under investigation.

The limitation of this project is due to the communication channels at some TNB substations of interest are not fully configured, thus the measurements based on actual data streams are still not possible at the moment. Therefore, the results shown are based on input from simulations.

CHAPTER 2

LITERATURE REVIEW

2.1 Definition

This chapter consists of the literature review and case study on the applications of PMUs and pervious researchers' methods for voltage stability study and analysis. It is directly related to the project, providing information on theories, models, materials and techniques used in the research.

2.2 Case study for pervious work based on Phasor Measurement Units (PMUs) applications

PMUs are time-synchronized tool used by power engineers and system operators for Wide-Area Measurement (WAMS) applications [3]. The PMUs measure time-synchronized voltage and current phasors that are time-stamped with high precision. PMUs are equipped with Global Positioning Systems (GPS) receivers that allow for the synchronization of the several readings taken at distant points. They rely on recursive algorithm for calculating symmetrical components of voltages and currents. In recent years, significant attention has been given to the methods that use direct parametric (load) dependence to estimate the proximity of a power system to the voltage collapse. Some authors propose PMU-based algorithms to determine voltage collapse proximity. PMU-based measurements support real-time measurements of voltage and incident current phasors at observable system buses. The voltage phasors contain enough information to detect voltage-stability margin directly from their measurements [4].

2.2.1 Wide area measurement system (WAMS) based applications

Sheikh Abdullah currently a senior research engineer at TNB-R and Nik Yusuf, a senior Technical Expert (Wide Area Protection) at TNB-T, Engineering Department are both at year 2008 introduced the Wide Area Measurement System (WAMS) project using synchrophasor. In-house development of the synchrophasor based system is currently being implemented as a pilot project under the research initiative. The synchrophasor applications are part of Wide Area Intelligent System (WAIS) initiative being proposed under TNB 20 years Technological Road Map II program. The WAMS project was started in July 2005 and in April 2006 the TNB WAMS prototype was installed in the TNB power system network. The objective of the project is to build a reliable and accurate WAMS for Wide-Area Monitoring, Control and Protection Research and Development (R&D) program to assist TNB to improve and secure the grid.

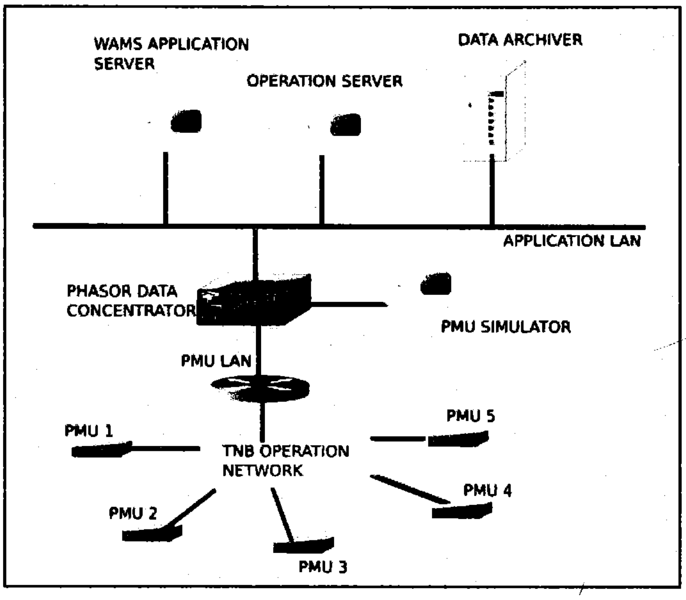

Figure 2. 1 TNB WAMS System Architecture [5]

The real-time monitoring system application development by TNB-R has completed the development of real-time voltages phase angle/magnitude and system frequencies visualization display, power oscillation, dynamic thermal circuit rating and generator dynamic parameter monitoring system applications and historical analysis tools.

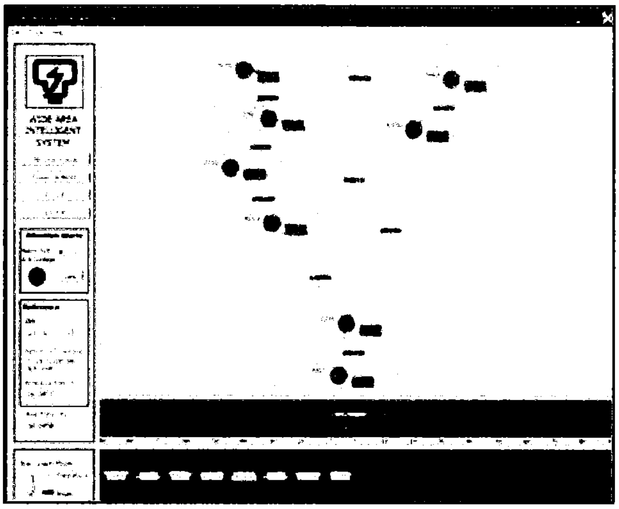

Figure 2. 2 TNB real-time Human Machine Interface Visualization Display [5]

Instantly, there are eight units of PMUs have been installed at TNB 275kV Main Intake substations which located at the four corners of the TNB grid system as shown in Figure 2.3. The installation basically to allow maximum observation of the TNB transmission power system under real operational conditions. The PMUs installation locations of are:-

i. PLPS & JJNG [northern]
ii. PAKA & KAWA [eastern]
iii. ATWR & KULW [central]
iv. YGPE & PMJY [southern region]

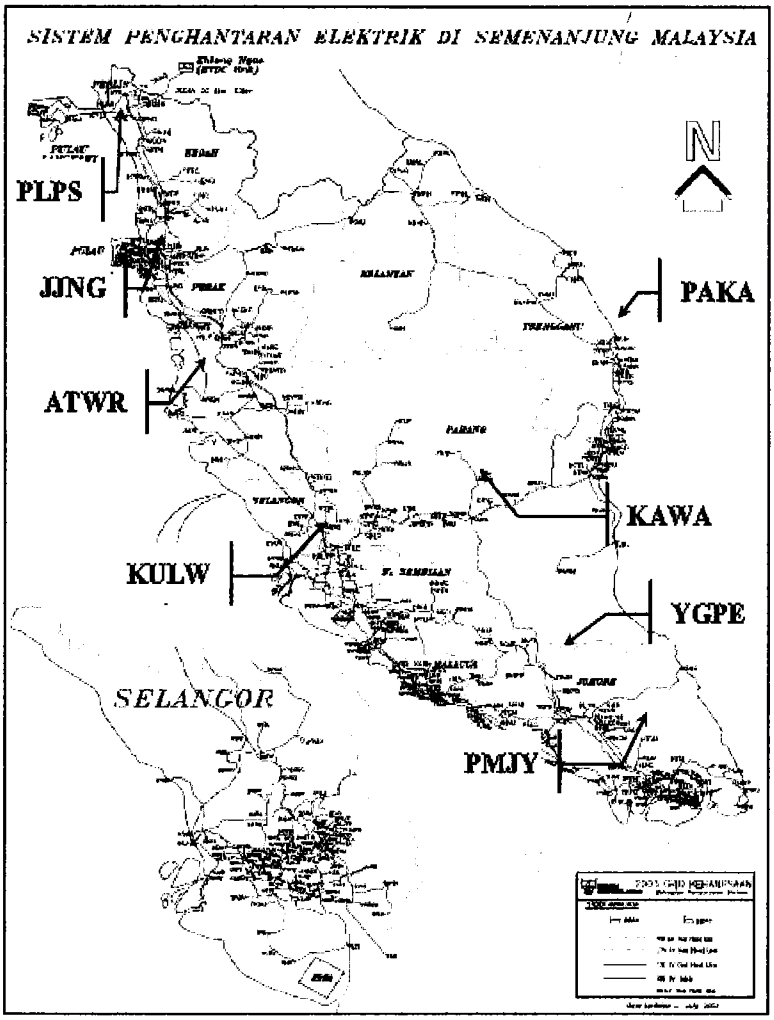

Figure 2. 3 PMU location at Transmission Grid System in Peninsular Malaysia [5]

Power System Oscillation Monitoring System provides the information on dynamic characteristics of inter-area oscillation, together with information on oscillation frequency and damping coefficient. With this application, it will increase the knowledge of the operator with regards to the dynamic behavior of the grid, and for better Power System Stabilizer tuning.

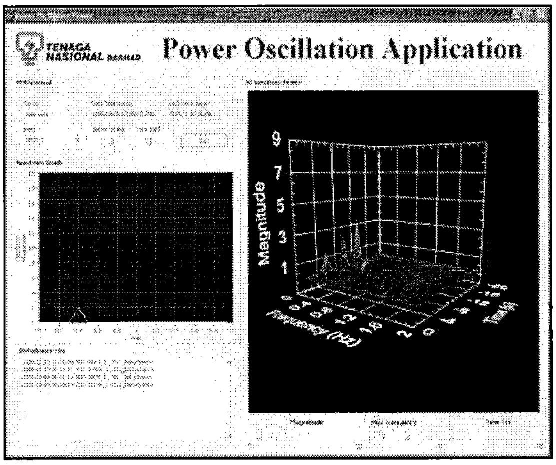

Figure 2. 4 GUI Power system oscillation and spectrum analyzer [5]

Wide area historical analysis tool is used for reviewing the system performance in the previous one month and for post-disturbance assessment. Thus, it enables operator/engineer to analyze phasor data and disturbance recorded. There are few events that have been captured by the WAMS system during the initial research and development stage. First was the circuit breaker tripping at 275kV PKLG substation where had caused a voltage dip to that selected region. Second was power system oscillation caused by double tripping on 275kV OHL between Temenggor and Pergau substations where the phase angle for PAKA substation originally at 11 degree had increased by 16 degrees to 27 degree and finally stable at 22 degree [5].

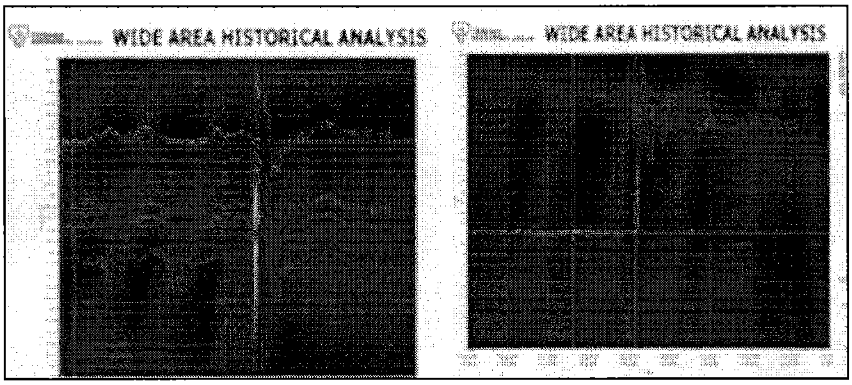

Figure 2. 5 Examples of power disturbance captured [5]

2.2.2 Application and analysis of optimum PMU placement methods

Kun, Lars, and Lennart (2009), had considered the optimum PUM placement methods with applications to state estimation accuracy. They considered geographic location of the PMUs within the power system naturally affects the value added by PMUs to one specific application in power grid control and operation. The analysis shows that there are considerable gains to be made in estimator accuracy if the PMUs are placed in accordance with this method when compared to the current placement strategy. It could be observed when the PMU monitored buses reaches a certain number in the entire network, the further introduction of phasor measurements will not be as effective in estimation accuracy improvement.

The estimator determines a best estimate of the current power system states, usually including the voltage phasors, transformer tap positions and circuit breaker status, given the stream of telemetry that has been collected from the system's sensors, current network model and information from other data sources. In the modern control centre, estimates are the major input for many grid supervision applications. Thus, state estimator is commonly referred as the "boarding ticket" to many other power system monitoring and control applications [6].

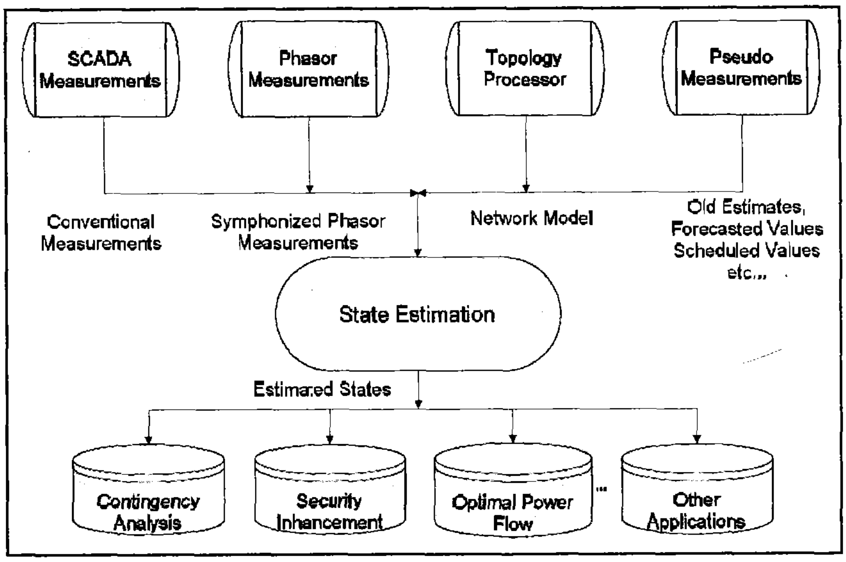

Figure 2. 6 Role of State Estimation in power system control and operation [7]

The study of optimum PMU placement methods with application to state estimation accuracy gives a significant gain in accuracy, especially for the angle estimates, if the PMUs are placed with priority given to estimation accuracy improvement. However, in reality the decision of PMU placement is a compromise of many issues spanning from technology level up to enterprise vision which will be made based on comprehensive research.

2.3 Voltage stability overview

This sub-title gives a description of voltage stability and together with factors causing voltage instability such as mechanisms for load restoration. An overview of voltage stability indices and the methods for voltage stability analysis also included. These indices are used to predict the proximity to voltage collapse. Power system voltage stability is a dynamic phenomenon involving power generation, transmission and distribution. Voltage stability is closely associated with other aspects of power system steady-state and dynamic performance [8].

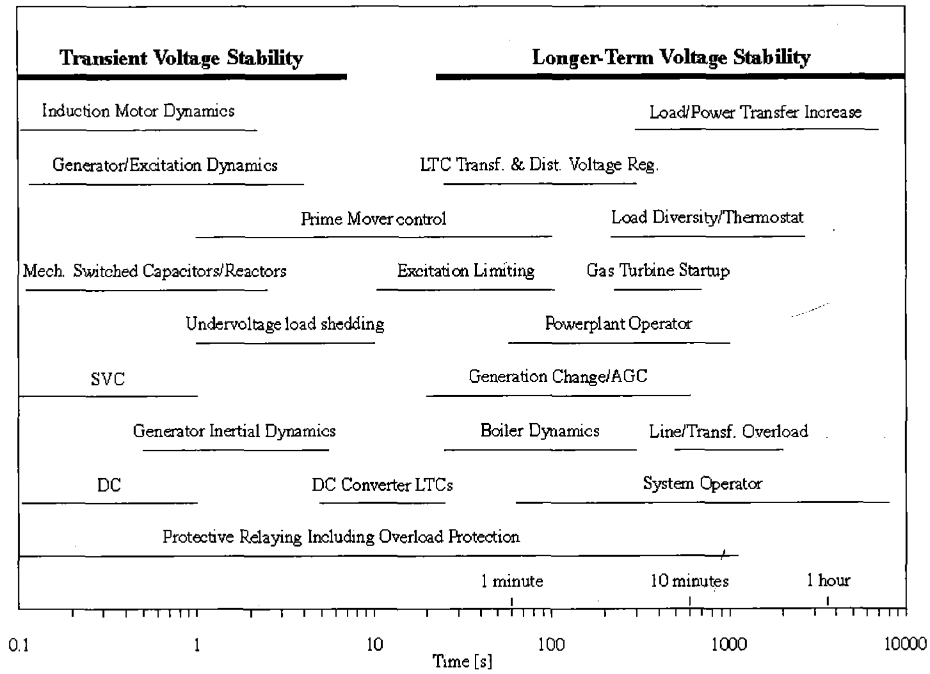

Figure 2. 7 Voltage stability phenomena and time responses [9]

2.3.1 Factors affecting voltage stability

Voltage instability and collapse are dynamic and normally large disturbance phenomena, involving load, transmission and generation subsystems of large power systems. There are three key aspects of voltage stability. First is the reactive power support either through power transfer, or at loading point. The second is the load characteristics as seen from the bulk power network. The last is the available means for voltage control at generators and in the network [8]. In the main grid there is a strong connection between voltage magnitude, V and the reactive power, Q and similar between voltage angle, δ and active power, P. Using the two-bus system as shown in Figure 2.8, the characteristics of voltage stability can be studied.

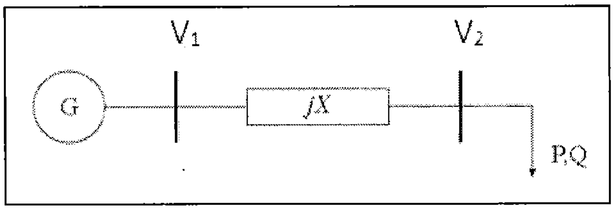

Figure 2. 8 Two bus system

The generator is represented by an infinite bus supplying both reactive and active load, keeping the voltage at 1.0 p.u. The transmission line is represented by a reactance, *jX* and the load is constant power, both reactive power, *Q* and real power, *P*. Generally, voltages are solved using the Newton-Raphson algorithm in a load-flow program, but the load voltage can be calculated analytically in this simple example. The solution of Equation (2.1) is the load voltage for the load-flow equations of the example, when the voltage angle is eliminated.

$$V_2 = \sqrt{\frac{(V_1^2-2QX)\pm\sqrt{V_1^4-4QXV_1^2-4P^2X^2}}{2}} \qquad (2.1)$$

P-V curve presents load voltages as a function of load or sum of loads. Equation (2.1) yields two solutions of voltages to any set of load flow, represented by the upper and lower parts of the P-V curve.

Power systems are operated in the upper part of the P-V curve. This part of the P-V curve is statically and dynamically stable. The tip of the "nose curve" is called the maximum loading point. Figure 2.9 presented five P-V curves for the system given in the two bus system with the value of X is 100 Ω and V_1 is 400 kV. Since inductive line losses make it inefficient to supply a large amount of reactive power over long transmission lines, the reactive power loads must be supported locally.

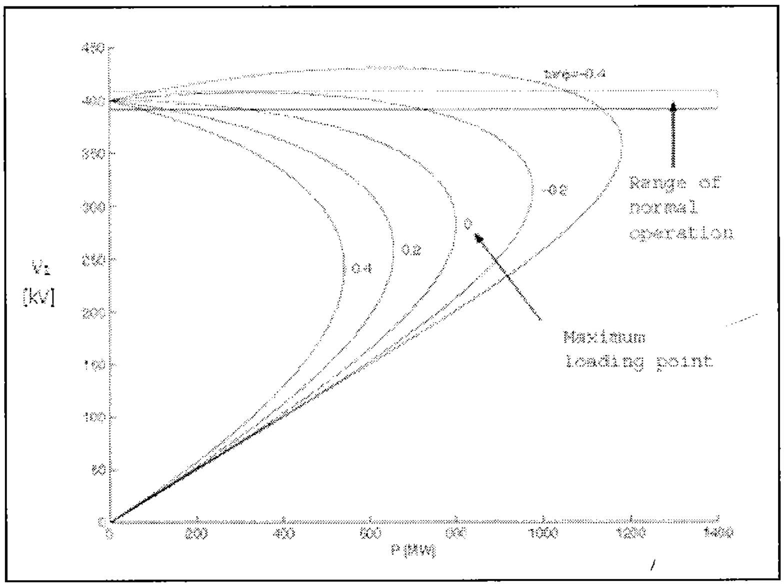

Figure 2. 9 P-V curve for two bus system [8]

The description of the voltage stability phenomenon has been limited to a radial system because it presents a simple and clear picture of the problem. In practical power systems, many factors affect the progress of voltage collapse due to voltage instability. However, the major disadvantages of the power flow situation will diverge near the nose or maximum power point on the curve. Also, generation must be rescheduled as the area load is increased in reality. Hence, the curves are dynamics in real time and will not to static.

The load compensation makes it possible to increase the loading of the power system according to voltage stability. Thus, the monitoring of power system security becomes more complicated because the critical voltage might be close to voltages in the normal operation range. The opportunity to increase power system loading by load and line compensation is valuable nowadays. Compensation investments are usually much less expensive and more environmentally friendly than line investments. Furthermore, the construction of new lines has become time-consuming and even impossible in some cases. At the same time new generation plants are being constructed further away from load centers, fossil-fired power plants are being shut down in the cities and more electricity is being exported and imported. This trend inevitably requires addition of transmission capacity in the long run.

2.3.2 Point of collapse

The point of collapse method [10] solves the conditions for the bifurcation point.

$$\begin{aligned} f(x,\lambda) &= 0 \\ D_x f(x,\lambda) &= 0 \\ \|v\| &\neq 0 \end{aligned} \qquad \text{OR} \qquad \begin{aligned} f(x,\lambda) &= 0 \\ D_x^T f(x,\lambda) &= 0 \\ \|w\| &\neq 0 \end{aligned} \tag{2.2}$$

Where, the $D_x f(x, \lambda)$ is the system Jacobian and the w and v are the left and right eigenvectors. The bifurcation point is characterized by the steady-state Jacobian, denoted by $D_L f(z, \lambda)$ having a single and unique zero eigenvalue, with non-zero left and right eigenvectors. These conditions can be summarized by Equation (2.2). This method has the advantage of producing left and right eigenvector information. The left eigenvector can be used to compute an optimal control strategy to avoid saddle-node bifurcations, whereas the right eigenvector can be used to detect variables (areas) in the network prone to voltage collapse.

2.3.3 Conventional power flow

The conventional power flow algorithms are prone to convergence problems at operating points near the stability limit. The continuation power-flow [11] analysis overcomes this problem by reformulating the power flow equations so that they remain well conditioned at all possible loading conditions. This allows the solution of the power flow problem for stable as well as unstable equilibrium points. The continuation power flow analysis uses an iterative process involving predictor and corrector steps as depicted in Figure 2.10.

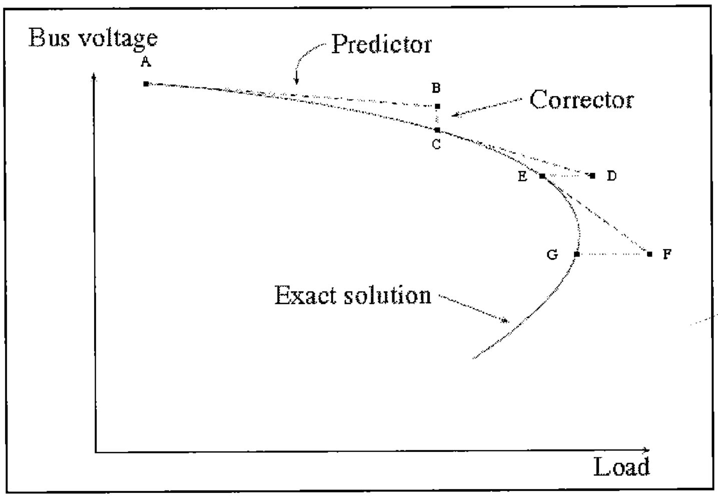

Figure 2. 10 A continuation power-flow analysis [8]

From a known initial solution (A), a tangent predictor is used to estimate the solution (B) for a specified pattern of load increase. The corrector step then determines the exact solution (C) using a conventional power-flow analysis with the system load assumed to be fixed. The voltages for a further increase in load are then predicted based on a new tangent predictor. If the new estimate load (D) is now beyond the maximum load on the exact solution, a corrector step with fixed loads would not converge; therefore, a corrector step with a fixed voltage at the monitored bus is applied to find the exact solution (E). As the voltage stability limit is reached, the size of load increase has to be reduced gradually during the successive predictor steps to determine the exact maximum load.

2.4 A Hilbert-Huang based approach for on-line extraction of modal behavior from PMU data

Zarraga, F. L., A. L. Rios, et al. in 2009, had proposed on Hilbert Huang based approach for the on-line extraction of modal behavior from PMU data. They found that the Hilbert Huang Transform (HHT) and empirical mode decomposition (EMD) was an efficient method for analyzing the local dynamics of transient oscillations. Two novel approaches are investigated to characterize non-stationary issues.

The first method is a local implementation of the EMD technique. The second technique is an algorithm to compute the Hilbert transform using variable window filters. By combining a sliding window of finite length with the sifting process by blocks, a local implementation of the empirical mode decomposition is proposed. Approaches to extending Hilbert-Huang analysis to analyze the local properties of general non-stationary signals are then explored based on finite-impulse-response (FIR) designed using Kaiser Window. This approach enables the Hilbert-Huang technique to be a truly online analysis technique for measured data. The application of these techniques is tested on time-synchronized phasor measurements collected by Phasor Measurement Units [12]. In this paper an efficient method for analyzing the local dynamics of transient oscillations using a local EMD and the Hilbert transform is presented. The results at the early stage of the applications using this technique imply that the method is accurate, and capable of identifying multiple modal characteristics.

The Hilbert–Huang transform (HHT) is an empirically based data-analysis method. Its basis of expansion is adaptive, so that it can produce physically meaningful representations of data from nonlinear and non-stationary processes. HHT consists of two parts, one is the empirical mode decomposition (EMD) and the other is the Hilbert spectral analysis (HSA). The core of the HHT is the EMD, which decomposed the complicated data into a set of finite intrinsic mode functions (IMF) that admit well-behaved Hilbert transforms. This decomposition method is adaptive and highly efficient. The decomposition is based on the local time scale characteristic of the data, thus it is applicable to nonlinear and non-stationary data [13].

2.5 Case study on previous works that related to the Kalman filter, extended Kalman filter and unscented Kalman filter

This section include case study for the related methods which are suitable for the application in tracking the Thevenin equivalent parameters. The Thevenin equivalent networks are connected to a bus and a load. Tracking the Thevenin equivalent is the essential of the voltage collapse detection. There are many methods to track the Thevenin parameters. The methods being used in this project are the Kalman Filter, Extended Kalman Filter and the Unscented Kalman Filter. The more detail information for these methods will be discussed in Chapter 3. An analysis of the results from these three methods will be compare and discuss in and Chapter 4.

2.5.1 Voltage stability margin identification using local measurements and linear Kalman filter

Alammari, R. A. in 2002, had proposed a new algorithm for identification of voltage instability in a specified load bus in a power system. It is based on the linear Kalman filtering algorithm and the maximum power transfer principle. The proposed technique is used to identify Thevenin's equivalent circuit at a bus for different loading conditions, either when the total system loads changes at the same rate (long-term voltage stability problem) or when a load on a certain bus changes. The proposed algorithm uses the real measurements at the bus to calculate the load impedance. These measurements are the load voltage and current. Thus, it can be implemented on-line on the control centers to investigate the voltage stability. The proposed algorithm is implemented to the standard IEEE 30-bus system [14]. Kalman filtering algorithm is being used to implement to identify the critical point beyond which voltage instability may occur. The results obtained in this paper show that Kalman filter algorithm is an effective algorithm for measuring Thevenin's impedance for short-term and long-term voltage stability studies.

2.5.2 Case study for pervious work on the extended Kalman filter

Hongwen, Rui et al. (2011) had introduced the State-of-Charge Estimation of the Lithium-Ion Battery Using an Adaptive Extended Kalman Filter (EKF). EKF algorithm is able to obtain a better convergent and robust result that can greatly improve the dependence of the traditional filter algorithm on the battery model. The typical characteristics of the lithium-ion battery are analyzed by experiment. An improved Thevenin battery model is achieved and model parameters are identified by using the EKF algorithm. There is a comparison between the EKF algorithm and the adaptive EKF and yet the results for adaptive EKF which present that the estimation algorithm has higher accuracy compared with the EKF algorithm. Normally, the EKF algorithm possesses certain stability; however, it easily causes divergence due to the error existing in the model and the noise statistics, particularly the noise statistics evaluated by the trial-and-error method [15].

Sayadi, O. and M. B. Shamsollahi (2008) had introduced the efficient denoising and lossy compression schemes for electrocardiogram (ECG) signals based on a modified EKF structure. They have chosen the EKF for its simplicity and more numerical stability. However, the overall filtering performance is expected to be better with Extended Kalman Smoother or Unscented Kalman Filter [16].

Pera, x, et al. (2007) stated that the Kalman filter and its extensions has been widely studied and applied in positioning, in part because its low computational complexity is well suited to small mobile devices. While these filters are accurate for problems with small nonlinearities and nearly Gaussian noise statistics, they can perform very badly when these conditions do not prevail. In these paper "Robust Extended Kalman Filtering in Hybrid Positioning Applications", there are two methods to robustify the Kalman filter are presented. Six robust EKF together with the classical EKF and the second order EKF (EKF2) are tested in numerical simulations. Based on the simulations, the proposed methods seem to outperform EKF and EKF2 in contaminated cases and do almost as well in normal cases [17].

The summary of the studies for the EKF methods can be conclude that it can be viewed as providing "first-order" approximations, however, it can introduced a large errors in the true posterior mean and covariance of the transformed Gaussian random variables, which may sometimes lead to divergence of the filter.

2.5.3 Case study for pervious work on the unscented Kalman filter

Wan and Van der Merwe (2000) had investigated on the Unscented Kalman Filter (UKF) for Nonlinear Estimation. They points out the flaws in using the EKF, and introduces an improvement which is the UKF. A central and fundamental operation performed in the Kalman Filter is the propagation of a Gaussian random variable (GRV) through the system dynamics. The EKF state distribution is approximated by a GRV, which will propagate analytically through the first-order linearization of the nonlinear system. This can caused large errors in the true posterior mean and covariance of the transformed GRV, which may lead to sub-optimal performance and sometimes divergence of the filter. The UKF addresses this problem by using a deterministic sampling approach. The state distribution is again approximated by a GRV [18]. In this paper, comparison has been made between the results by using the EKF and UKF. The UKF consistently achieves a better level of accuracy than the EKF at a comparable level of complexity.

Partovibakhsh, M. and L. Guangjun (2012) had published an American control conference paper which entitled "Online Estimation of Model Parameters and State-of-Charge of Lithium-Ion Battery using Unscented Kalman Filter". In this paper, based on the equivalent circuit model of the Lithium-Ion battery, the UKF algorithm has been employed for online estimation of model parameters. As many factors affect the battery performance during charge and discharge, by this method the validity of the battery model has been increased and the obtained results have shown good consistency with offline calculations [19]. Experiments have been conducted on a wheeled-mobile robot, and the results have been compared between the EKF and the UKF. The obtained results have shown that the UKF algorithm has provided improved performance in comparison with EKF.

Li, W. and H. Leung (2003) had investigated in the vehicle localization studies and the constrained unscented Kalman tiller (CUKF) algorithm is proposed to fuse differential global position system (DGPS), inertial navigation system (INS) and digital map to estimate the vehicle states. They are using the road geometry information obtained from a digital map data base. The measurements of DGPS and INS are used to set up the dynamic and measurement equations of the nonlinear filtering. The vehicle states are first estimated by the loosely coupled DGPS/INS system and the unconstrained Unscented Kalman Filter (UUKF), and after that the UUKF estimates are projected into the state constraints to obtain the final CUKF estimates. Synthetic and real data are used to evaluate the performance of the CUKF algorithm for fusing DGPS, INS and digital map [20]. The results obtained from the computer simulations demonstrated that the CUKF can improve the estimation accuracy of the vehicle states effectively.

Ghahremani, E. and I. Kamwa (2011) had investigated on the online state estimation of synchronous generator by using the Unscented Kalman Filter. They proposed online state estimator in the model based category according to above classification, uses the UKF algorithm to generate the estimated states from the available signals obtained from a Phasor Measurements Units (PMU), which is assumed to be installed in the substation of a power plant [21]. The UKF algorithm allows to overcome the limitations of the linearization process required by the traditional EKF method, and also to increase the operational range of the system variables around the operating point by not using the linearization in the state estimation algorithm. The implemented UKF based scheme produced high quality results and also showed greater accuracy of the state estimates in the presence of noise, compared to the traditional EKF method.

St-Pierre, M. and D. Gingras (2004) had published a paper to compare the UKF and the EKF. The paper describes an empirical analysis evaluating the performances of the UKF and comparing them with the EKF performances. They states that the EKF can be replaced by better algorithms like the UKF. The two performance metrics are the precision of the fusion and the computational time to perform the fusion. The accuracy is evaluated by taking the Euclidian distance between the estimated position and the true position. The UKF method has a slightly better performance than the EKF when used as a fusion method in a positioning module of an integrated navigation information system [22].

There are several of different types of unscented Kalman filter, for example the constrained and unconstrained UKF, the sequence UKF and other types of UKF. All types of UKF have their similarity in the UKF algorithm and only difference in its applications. As a conclusion from the above studies, the UKF addressed the approximation issues of the EKF. The state distribution is again represented by Gaussian random variable (GRV), but is specified using a minimal set of carefully chosen sample points. These points completely capture the true mean and covariance of the GRV. The UKF consistently achieves a better level of better accuracy than the EKF at a comparable level of complexity. In EKF the state distribution is propagated analytically through the first-order linearization of the nonlinear system due to which, the posterior mean and covariance could be corrupted. The UKF which is a derivative-free alternative to EKF is able to overcome this problem by using a deterministic sampling approach. The state distribution is represented using a minimal set of carefully chosen sample points, called sigma points. Same as in the EKF, UKF consists of the same two steps which are the model forecast and data assimilation, except they are preceded now by another step for the selection of sigma points.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Definition

This important chapter explains in detail the samples, instruments, materials, procedures and data gathering methods used in this project research. The proposed methods of early warning for voltage instability is based on analyzing the collected data from PMUs at the selected load area which under investigation by TNB-R.

3.2 Voltage instability predictor (VIP)

The VIP method is based on the assumption that voltage instability is closely related to maximum loadability of a transmission network [9], thus the Thevenin impedance is equal to the apparent load impedance at the Point of collapse (PoC). Figure 3.1 shows a load bus and the rest of the system treated as a Thevenin equivalent.

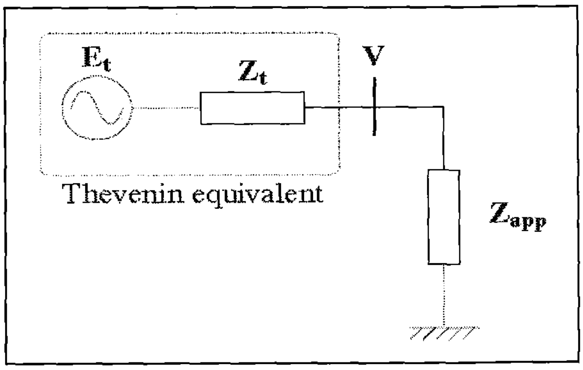

Figure 3. 1 Local bus and the rest of the system treated as a Thevenin equivalent [8]

It is noted that no assumption has been made about the characteristic of the load. The apparent impedance Z_{app} is merely the ratio between the voltage and current phasors measured at the bus. Tracking the Thevenin equivalent is essential for the detection of voltage collapse.

There are many methods to track the Thevenin parameters. The tracking is based on Equation (3.1).

$$\boldsymbol{E_{th}} = \boldsymbol{V} + \boldsymbol{Z_{th}}.\boldsymbol{I} \qquad (3.1)$$

Denoted that:

$$E_{th} = E_r + jE_i$$
$$V = V_r + jV_i$$
$$I = I_r + jI_i$$

Rewritten the above equations into a matrix form:

$$\begin{bmatrix} \mathbf{1} & \mathbf{0} & -\boldsymbol{I_r} & \boldsymbol{I_i} \\ \mathbf{0} & \mathbf{1} & -\boldsymbol{I_i} & -\boldsymbol{I_r} \end{bmatrix} \times \begin{bmatrix} \boldsymbol{E_r} \\ \boldsymbol{E_i} \\ \boldsymbol{R_{th}} \\ \boldsymbol{X_{th}} \end{bmatrix} = \begin{bmatrix} \boldsymbol{V_r} \\ \boldsymbol{V_i} \end{bmatrix} \qquad (3.2)$$

The subscripts r and i indicated the real and the imaginary part of phasors. Note that V and I are directly available from the measurements at the local bus. The unknowns are R_{th}, X_{th}, E_r and E_i. In Equation (3.2) there are two equations, and four unknowns, so clearly, measurements taken at two or more different times are required to solve for the unknowns. In the real environment, measurements are not precise and the Thevenin parameters drift due to the system's changing conditions. To suppress oscillations, a larger data window needs to be used. The estimation therefore attempts to minimize the error in a least-square sense.

3.3 Use of radial equivalent independent (REI) network

The complexity of the interconnectivity of power system network today has created a big challenge to and has received attention by power system engineers to simplify the network for efficient system analysis. In 1970s, P. Dimo introduced an equivalent network for power system called Radial Equivalent Independent (REI) network. By the use of REI network, the analysis can be simplified by decreasing the size of the system to few nodes. Wide Area Power System (WAPS) aré divided into three subsystems, which are internal power system, external power system, and boundary power system as shown in Figure 3.2 [2].

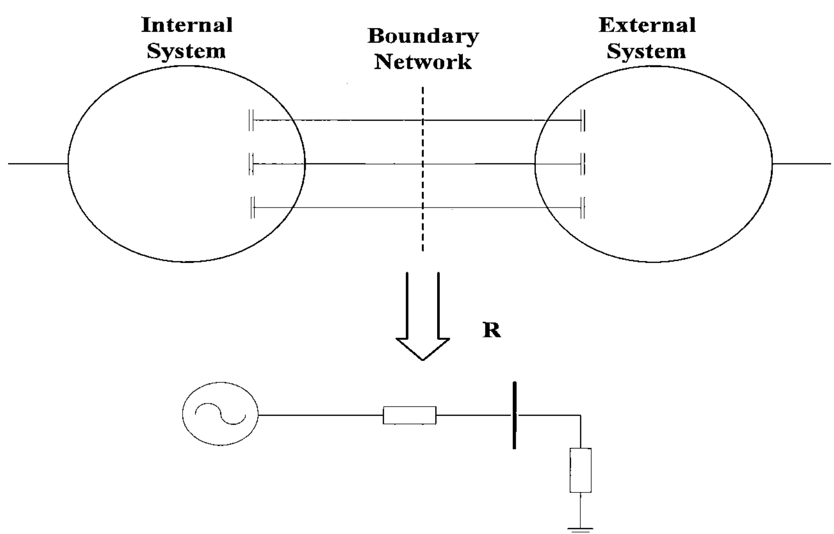

Figure 3. 2 WAPS and the simplified network [2]

Figure 3.2 illustrates the WAPS and the simplified network. Further investigation will be focusing on the implementation of the REI network to simplify the system.

REFERENCES

[1] TNB *Announcement on the Increase in Electricity Tariff in Peninsular Malaysia Due to the Revision of Natural Gas Price, Revision of Base Tariff & Implementation of Feed-In-Tariff (FiT) for Renewable Energy (RE).* 2011.

[2] Sarmin, M.K.N.M., W. Nakawiro, et al., *Real-Time Voltage Stability Monitoring For TNB Network.* Proceedings of the IASTED Asian Conference Modelling, Identification, and Control, 2012. **(AsiaMIC 2012)**: p. 7.

[3] Karlsson, D., M. Hemmingsson, and S. Lindahl, *Wide area system monitoring and control - terminology, phenomena, and solution implementation strategies.* Power and Energy Magazine, IEEE, 2004. **2**(5): p. 68-76.

[4] Momoh, J.A., X. Yan, and G. Boswell. *Voltage stability enhancement using Phasor Measurement Unit (PMU) technology.* in *Power Symposium, 2008. NAPS '08. 40th North American.* 2008.

[5] Sheikh Abdullah, S.K. and N.S. Nik Yusuf. *Tenaga nasional berhad Wide Area Measurement System based applications.* in *Power and Energy Conference, 2008. PECon 2008. IEEE 2nd International.* 2008.

[6] Kun, Z., L. Nordstrom, and L. Ekstam. *Application and analysis of optimum PMU placement methods with application to state estimation accuracy.* in *Power & Energy Society General Meeting, 2009. PES '09. IEEE.* 2009.

[7] Hongxian, W. and J. Giri. *PMU Impact on State Estimation Reliability for Improved Grid Security.* in *Transmission and Distribution Conference and Exhibition, 2005/2006 IEEE PES.* 2006.

[8] Warland, L. and A.T. Holen. *A voltage instability predictor using local area measurements (VIP++).* in *Power Tech Proceedings, 2001 IEEE Porto.* 2001.

[9] Taylor, C.W., *Power System Voltage Stability*. . Vol. The EPRI Power System Engineering Series. 1994: McGraw-Hill, Inc.

[10] Canizares, C.A. and F.L. Alvarado, *Point of collapse and continuation methods for large AC/DC systems*. Power Systems, IEEE Transactions on, 1993. **8**(1): p. 1-8.

[11] Kundur, P., *Power System Stability and Control*. 1994: McGraw-Hill, Inc.

[12] Zarraga, F.L., et al. *A Hilbert-Huang based approach for on-line extraction of modal behavior from PMU data*. in *North American Power Symposium (NAPS), 2009*. 2009.

[13] Norden E Huang, S.S.P.S., *Hilbert-Huang Transform and Its Applications*. Vol. 5. 2005: World Scientific Publishing Co. Pte. Ltd.

[14] Alammari, R.A., *Voltage Stability Margin Identification Using Local Measurements And Linear Kalman Filter*. Engineering Journal of the University of Qatar, 2002. **15**: p. 153-164.

[15] Hongwen, H., et al., *State-of-Charge Estimation of the Lithium-Ion Battery Using an Adaptive Extended Kalman Filter Based on an Improved Thevenin Model*. Vehicular Technology, IEEE Transactions on, 2011. **60**(4): p. 1461-1469.

[16] Sayadi, O. and M.B. Shamsollahi, *ECG Denoising and Compression Using a Modified Extended Kalman Filter Structure*. Biomedical Engineering, IEEE Transactions on, 2008. **55**(9): p. 2240-2248.

[17] Pera, et al. *Robust Extended Kalman Filtering in Hybrid Positioning Applications*. in *Positioning, Navigation and Communication, 2007. WPNC '07. 4th Workshop on*. 2007.

[18] Wan, E.A. and R. Van der Merwe. *The unscented Kalman filter for nonlinear estimation*. in *Adaptive Systems for Signal Processing, Communications, and Control Symposium 2000. AS-SPCC. The IEEE 2000*. 2000.

[19] Partovibakhsh, M. and L. Guangjun. *Online estimation of model parameters and state-of-charge of Lithium-Ion battery using Unscented Kalman Filter*. in *American Control Conference (ACC), 2012*. 2012.

[20] Li, W. and H. Leung. *Constrained unscented Kalman filter based fusion of GPS/INS/digital map for vehicle localization*. in *Intelligent Transportation Systems, 2003. Proceedings. 2003 IEEE*. 2003.