Optimal Node Voltage State Estimation in Power Systems: A Comprehensive Analysis and Simulation Model Validation

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Abstract

Node voltage state estimation is a critical aspect of power system analysis, aiming to determine accurate voltage magnitudes and angles at various nodes within an electrical grid. This research focuses on developing an algorithm for node voltage state estimation, treating these parameters as state variables. The algorithm enables the calculation of additional vital parameters such as currents, power flows, and injections, essential for power system optimization and management. The study employs the maximum likelihood estimation (MLE) method, assuming Gaussian-distributed measurement errors, to infer optimal parameter values for a network's state parameters. The approach is applied to power networks using a polar coordinate system, facilitating the analysis of voltage magnitude, real and reactive power flow, and power injection.

Keywords: Node Voltage State Estimation, Power Systems, Simulation Model, Grid Stability, Power System Operation

1. Introduction

In the early stages of power system monitoring, supervisory control systems played a pivotal role by overseeing essential components like circuit breakers, generator outputs, and system frequency. However, these systems had limitations as they solely focused on monitoring and basic control functions. The need for more comprehensive capabilities led to the enhancement of these systems through the integration of real-time wide-data acquisition.

The incorporation of real-time wide-data acquisition marked a significant advancement, enabling control centres to gather extensive measurements from the entire power system. This technological leap paved the way for the development of the first Supervisory Control and Data Acquisition (SCADA) system. The primary objective was to conduct security analyses, ensuring the reliability and stability of the power grid.

Despite these advancements, challenges persisted. Factors such as errors in measurements and communication noises could introduce inaccuracies into the SCADA system, compromising the reliability of the information it provides. Moreover, certain critical parameters, such as voltage angles, were not conventionally measured, and knowledge of transmission line flows was limited to specific lines. Attempting to measure all possible parameters proved economically impractical.

Professor Schweppe recognised these limitations and introduced the concept of the state estimation function. This innovative approach addressed the gaps in the SCADA system by estimating the system's state based on available measurements. The state estimation function expanded the capabilities of the SCADA system, ultimately giving rise to the Energy Management System (EMS).

The EMS, equipped with various specific applications, including the state estimator, revolutionised power system monitoring. The state estimator played a crucial role in estimating the complete state of the power system, even when certain parameters were not directly measurable. The monitoring systems' information was much more accurate and trustworthy thanks to this all-encompassing strategy, giving control centers a deeper understanding of the dynamics of the power grid.

A state estimator is a crucial component in power systems that plays a key role in monitoring and assessing the current operating state. It operates by analysing various efficiency-related quantities, such as voltage magnitudes and line loadings. The primary objective is to provide an accurate representation of the system's condition, allowing for the identification of potential issues and vulnerabilities.

The security assessment function then makes use of the data gathered by the state estimator. This function is responsible for evaluating contingencies, which are unforeseen events or disturbances in the power system. By leveraging the data obtained from the state estimator, the security assessment function can effectively analyse the impact of these contingencies on the system's stability and reliability.

2. Key functions typically included in a state estimator encompass:

Voltage Magnitude Monitoring: One of the fundamental aspects of a state estimator is tracking the magnitudes of voltages at different points in the power system. Deviations from normal voltage levels can indicate potential issues, such as equipment malfunctions or overloads.

Line Loading Analysis: The state estimator assesses the loading conditions on transmission lines. Monitoring the line loadings is critical for identifying potential congestion or excessive stress on the power grid, which could lead to operational challenges.

Contingency Analysis: State estimators excel in contingency analysis, wherein they evaluate the system's response to unexpected events like equipment failures or sudden changes in demand. This capability allows power system operators to anticipate and mitigate potential issues promptly.

Remedial Action Determination: Based on the analysis of the current operating state and potential contingencies, the state estimator assists in determining remedial actions. These actions could involve adjusting control settings, activating protective devices, or implementing other measures to restore or maintain system stability.

3. Methodology

Node voltage state estimate is a critical component of power system analysis that aims to ascertain the magnitude and angle of voltage at different buses in a power network. Within this framework, buses symbolise distinct junctures or terminals in the electrical network where diverse power elements are linked.

The primary goal of the node voltage state estimation technique is to provide precise estimates for the magnitude and angle of the voltage, using them as state variables. These state variables accurately describe the electrical condition of the power system at various points.

Upon successful determination of the values of these state parameters, the algorithm gains the capacity to compute additional significant such as currents and power flows along the branches of the network, electrical parameters. Moreover, it enables the calculation of power injections at specific nodes within the system.

The node voltage state estimate is an essential tool for power system operators and planners. Engineers may evaluate the overall condition and efficiency of the power grid by acquiring accurate measurements of voltage magnitudes and angles. Furthermore, the capacity to calculate power flows, currents, and injections assists in the optimisation and administration of the network, leading to improved dependability and efficiency.

4. Optimal Parameter Inference

It is the goal of state estimation to use measured values to find the most likely values of the network's state parameters using the commonly used maximum likelihood estimation statistical approach. This method is based on the premise that the input measurements are distributed according to a known probability distribution with unknown parameters. By using these parameters to define the joint probability density function, a likelihood function is generated, which reaches its maximum when the unknown parameters are very close to their actual values. Maximum likelihood estimates for the network's state parameters are obtained by solving the ensuing optimisation problem, providing a reliable and organised approach to deriving likely values from observed data.

For the sake of this study, we will assume that the measurement errors are normally distributed over a Gaussian curve. Two parameters, the mean (μ) and the standard deviation (σ), completely define the Gaussian distribution. The distribution's central tendency and its spread are defined by these parameters, respectively.

Finding the most likely values for the normal distribution's mean and standard deviation that best explain the measurement errors is the purpose of using the maximum likelihood estimation (MLE) approach.

Finding the parameter values that maximise the likelihood function—which represents the probability of witnessing the provided data under a certain set of parameters—is the goal of maximum likelihood estimation, a statistical method. The normal probability density function establishes the likelihood function for a normal distribution.

The Normal probability density function for a random variable X with a mean value μ and standard deviation σ is mathematically defined as follows:

$$f(x;\mu,\sigma)=\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

Here, $f(x;\mu,\sigma)$ represents the probability density function, and the parameters are μ (mean) and σ (standard deviation). The goal of maximum likelihood estimation is to find the values of μ and σ that maximize the likelihood of observing the given data.

Critical parameters for the study of power networks include power injection, actual and reactive power flow, and voltage magnitude. In order to comprehend and control the behaviour of power systems, certain factors are crucial. The method relies on state parameters, namely the magnitude and angle of the voltage in polar coordinates, to determine the aforementioned parameters.

A state vector of 2N−1 items is produced when a polar coordinate system is used in a power network with N buses. The vector includes the magnitudes of N bus voltages and the angles of N−1 bus voltages. The state vector is constructed with the assumption that the slack bus (bus number 1) is the reference bus for voltage angles, and the reported voltage angles are normally provided relative to a reference value of zero.

The calculation of measured parameters is based on the general two-port π model for network branches (figure 1). The formulation involves the following key expressions:

Real and reactive power injection at bus :

$$P_i=V_i\sum_{j=1}^{N}V_j\left(G_{ij}\cos\left(\theta_i-\theta_j\right)+B_{ij}\sin\left(\theta_i-\theta_j\right)\right)$$

$$Q_i=V_i\sum_{j=1}^{N}V_j\left(G_{ij}\sin\left(\theta_i-\theta_j\right)-B_{ij}\cos\left(\theta_i-\theta_j\right)\right)$$

where G_{ij} and B_{ij} are the conductance and susceptance of the line connecting buses i and j, V_i is the voltage magnitude at bus i, and θ_i is the voltage angle at bus i.

Real and reactive power flow from bus i to bus :

$$P_{ij} = V_i^2\left(G_{ij}\cos\left(\theta_i - \theta_j\right) + B_{ij}\sin\left(\theta_i - \theta_j\right)\right) - V_iV_j\big(G_{ij}\cos\left(\theta_i - \theta_j\right) + B_{ij}\sin\left(\theta_i - \theta_j\right)\big)$$

$$Q_{ij} = V_i^2\left(G_{ij}\sin\left(\theta_i - \theta_j\right) - B_{ij}\cos\left(\theta_i - \theta_j\right)\right) - V_iV_j\big(G_{ij}\sin\left(\theta_i - \theta_j\right) - B_{ij}\cos\left(\theta_i - \theta_j\right)\big)$$

These formulations enable the calculation of power-related parameters based on the state variables of a power network, providing a foundation for state estimation using the weighted least squares method.

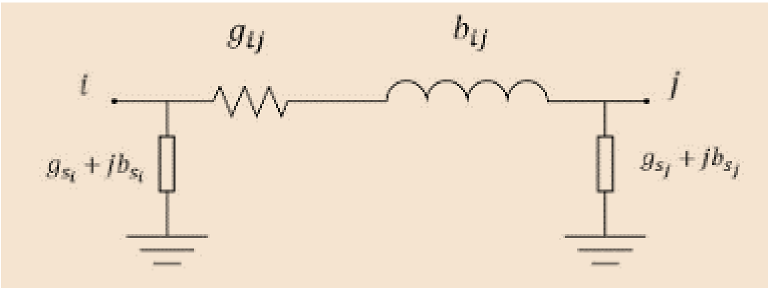

Figure 1. Analysis of a Network Branch: The Dual-Port Configuration"

5. Result

A power system state estimate is made possible by integrating Matpower parameters into the MATLAB-based simulation model. These factors cover network structure, needs, and generators. The model incorporates uncertainties that mirror real-world settings by making use of MATLAB's norm function for measurements. Measurement precision and confidence level, as well as a tolerable margin of error for approximation, are critical parameters. The weighted least squares (WLS) state estimation technique takes the produced random measurements, confidence level, and tolerance as inputs, after which operational parameters are given real values by Matpower power flow analysis. This comprehensive method ensures an accurate and computationally efficient simulation, assisting in the reliable monitoring and management of power systems.

This research uses the UKGDS 95-bus test distribution network to evaluate a MATLAB-based simulation model. The simulation was run under peak load conditions with a base power of 100 MVA, and this network is used as a realistic 11 kV system. Figure 2 shows the network diagram that was obtained in 2015 from the Control & Power Research Group.

We used measurements from the real network to make sure the simulation was accurate. In Table 1, you can see all of these metrics and the accuracy of each one. Notably, the evaluation gained a statistical component with the standard deviation values calculated using a 95% confidence level.

The fact that the UKGDS 95-bus test distribution network was selected for the evaluation shows that the model can manage a complicated electrical system like the one in the real world. Because the 11 kV network provides a representation of real-world power distribution scenarios, the results are applicable to actual operational settings.

The study gains legitimacy from its reliance on data from the Control & Power Research Group, a reputable source. Using data from well-known sources strengthens the assessment by comparing the simulation model to a solid reference point.

If you want to know how reliable the simulation results are, you need to look at Table 1, which includes accuracy numbers for the measurements. The statistical rigour of the evaluation is further strengthened by including standard deviations at a 95% confidence level, which sheds light on the data's variability and confidence level.

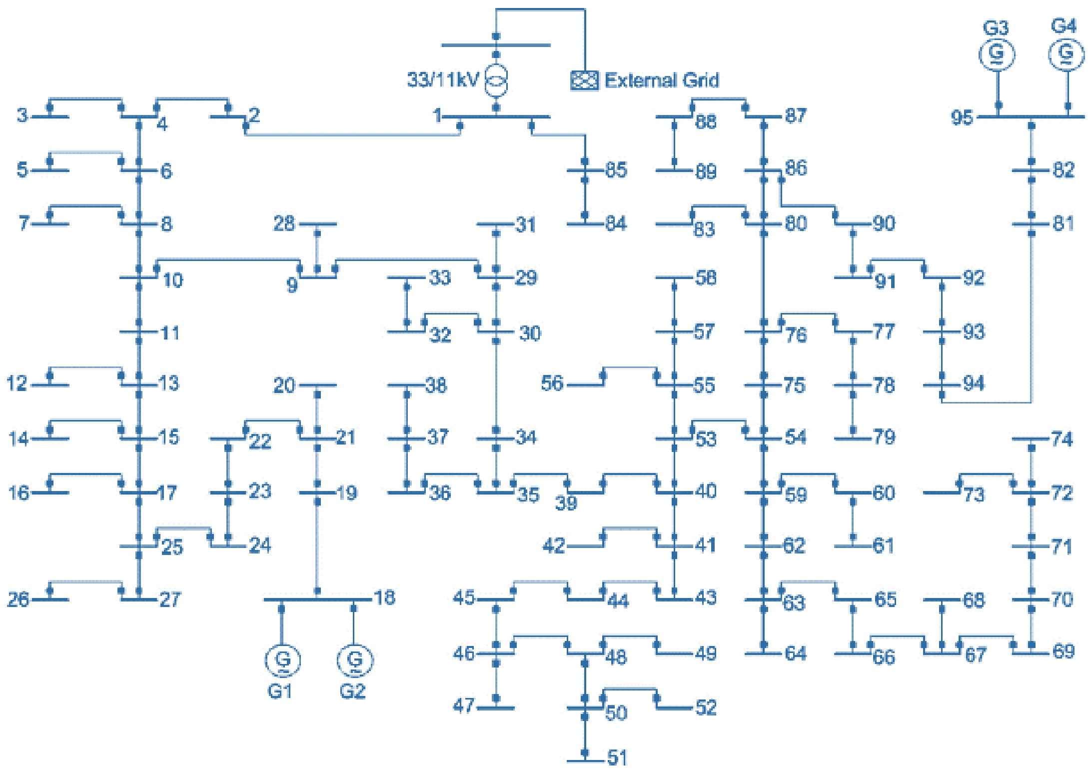

Figure 2. Structure of the UKGDS 95-Bus Test Distribution Grid

Table 1. Precision Assessment of Recorded Measurements in the Network

Measured Parameter	Measurement Location	Measurement Type	Accuracy
Voltage Magnitude	Bus #1 (Slack)	Real Time	3%
	Buses #18 & 95 (Generators)	Real Time	3%
Power Flow	Branches 1-2, 1-85, 18-19, 95-82	Real Time	3%
Power Injection	All Load Buses	Pseudo Measurement	50%
	All Zero Injection Buses	Virtual Measurement*	-

The evaluation of the simulation model commenced with an assessment using ideal or perfect measurements—essentially, measurements devoid of noise or errors. This implies that the values attributed to the available measurements in Table 1 were presumed to be identical to the values derived from power flow analysis. In this context, the focus was on comparing the estimated values of voltage magnitude and voltage angle at various buses with their corresponding true values.

Figures 3 and 4 depict this comparative analysis for voltage magnitude and voltage angle, respectively. The expectation was that, given the perfect measurements, the estimated values would align precisely with the true values obtained during power flow analysis. As anticipated, the results substantiate this assumption, revealing that all estimated values of voltage magnitudes and voltage angles coincide with their true counterparts.

The figures serve as visual representations of the accuracy and reliability of the simulation model under the ideal scenario of noise-free measurements. The perfect alignment between estimated and true values underscores the model's capability to faithfully reproduce the power flow analysis results. This initial evaluation sets the stage for further examination under more realistic conditions, where the impact of measurement inaccuracies and uncertainties would be considered.

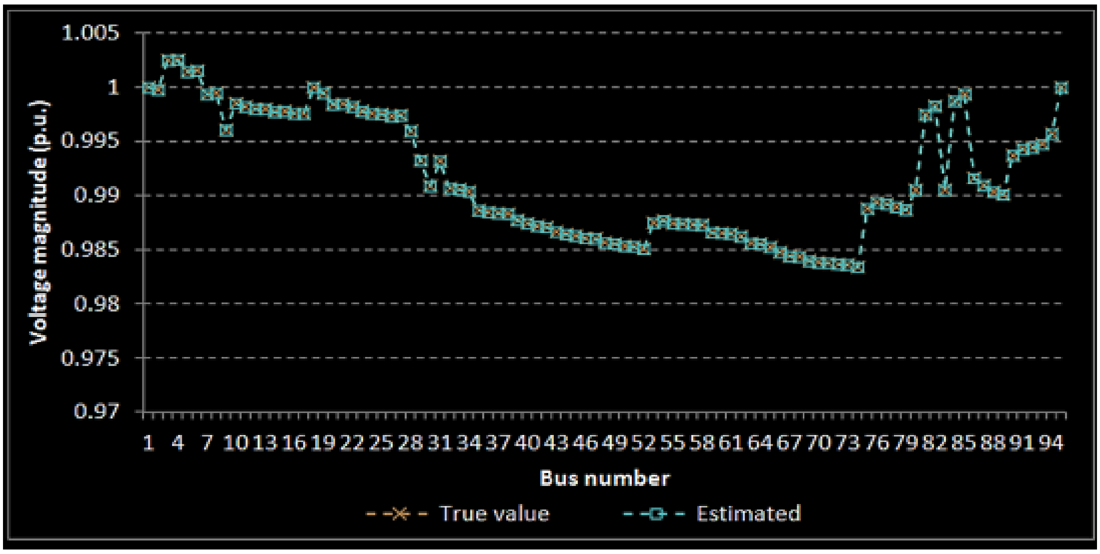

Figure 3. Voltage Magnitude Estimation Accuracy

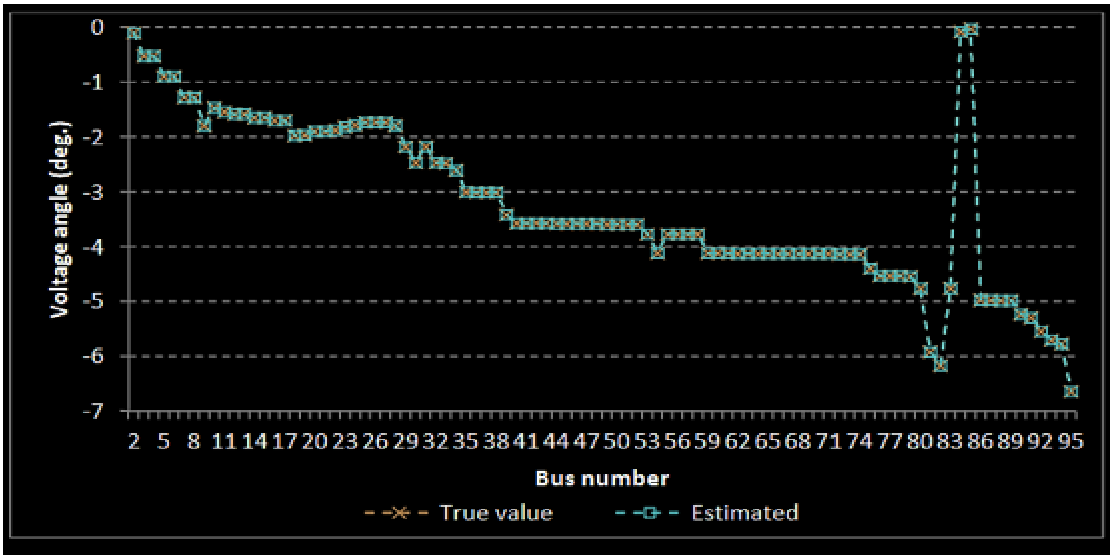

Figure 4. Voltage Angle Estimation Precision

6. Conclusion

The research presents a comprehensive analysis of power networks, emphasizing the significance of voltage magnitude and angle in understanding and managing power systems. The formulation of measured parameters, utilizing a two-port π model for network branches, establishes a foundation for state estimation using the weighted least squares method. A MATLAB-based simulation model, integrating Matpower parameters, is employed to assess the efficacy of the proposed algorithm. The model is tested on the UKGDS 95-bus test distribution network, representing real-world conditions, and validated using measurements from the Control & Power Research Group. The simulation results under ideal conditions demonstrate the model's accuracy in reproducing power flow analysis. Future work involves evaluating the algorithm under realistic conditions, considering measurement inaccuracies and uncertainties, to further enhance the model's reliability in power system monitoring and control.

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