Improving Distribution Network Model Accuracy using Impedance Estimation from Micro-Synchrophasor Data

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***Abstract*--An accurate network model is essential for performing detailed analysis of a power system. The quality of many distribution network models is very diverse, especially for low voltage (LV) networks. To help identify areas where the model is incomplete or incorrect, Micro Phasor Measurement Units (µPMUs) can be integrated into a network. These µPMUs would work together, with a trusted cloud back-end system.**

The basis for this paper is to determine how the data collected by µPMUs can be used, and what can be calculated from this data to help recognize areas where the network model is inaccurate and may need resurveyed. As a preliminary investigation to determine the feasibility of the approach, this paper discusses the calculation of the impedance of both a transformer and line, and compares the values obtained from µPMU data to the level of value expected on the network.

***Index Terms*—Micro-Synchrophasor, Phasor Measurement Unit, Underground cable modeling, Parameter estimation.**

I. Introduction

The technologies available to utilities for monitoring the power system are changing as the use of advanced electronics and sensors in consumer electronics have made components, and the software to utilize them, cheaper and widely available. These advanced sensors facilitate an understanding of the network that was previously unattainable.

At the same time, there is increased penetration of distributed generation on the distribution network. Where as in the past this network could be assumed to have a predictable load profile, these changes are impacting online and offline analysis of the network, with the quality of the network models at distribution being more variable than at transmission. This creates challenges in collecting, integrating and aligning data from multiple disparate sources then analysing the impact on the network. There is growing interest in shifting the world of planning and operations, from reactive methodologies, where events are detected in real time, to predictive, with risk based analytics and preventative approaches.

This project builds upon on an existing project at Lawrence Berkeley National Laboratory (LBNL) and California Institute for Energy and the Environment (CIEE), funded by ARPA-E [1][2]. This project focused on developing and using micro phasor measurement units (µPMUs) to analyse distribution networks to help identify issues with network model quality. One of the key outcomes of this project has been in understanding the data quality requirements for utilizing these sensors for model validation, in unbalanced distribution networks. The µPMU is connected to the distribution system normally through an imperfect voltage and current transducer. A fundamental early application for impedance detection, immune to such accuracy issues, is the change in impedance over time. A combination of cloud based analytics, and simple commonly used impedance detection methodologies, can be utilized to determine a change in component impedance. If this estimated impedance moves out of a reasonable range, it is indicative of a need to either update and calibrate the network model, or consider checking and testing that particular line segment or transformer. Rapid changes in impedance could indicate a reconfiguration, or fault condition.

The data that is collected by LBNL and utility partners is used to complete impedance calculations to determine the characteristics of the line and compare this with the network model. As µPMUs contain a Global Positioning System (GPS) chip for timing purposes, it is possible to use this data along with a detailed integrated connectivity/geographical model to automatically establish the position of a µPMU both geographically and in terms of its position in the electrical network.

A cloud-based system will allow multiple µPMUs to automatically connect, authenticate, integrate and send their data to the back-end system. A Trusted Cloud [3] platform can help to ensure the connection and data is secure. The collected data and network model will be used for both real time and offline analysis. This will include on-going calculations using data from multiple µPMUs, with automatic updates based on device locations and network connectivity analysis. Results of this will enable the identification of any calculations that indicate the parameters differ from that of the model, and from that of the previous calibrated impedance value for that

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component. Similar work has been carried out for the case of balanced loads at the transmission level whereby the impedance of a transformer and overhead line was investigated [4].

Previous work has focussed on the application of μPMUs for distribution and the importance of measurement accuracy [1][2]; the application of trusted cloud platforms to the power industry [3]; the use of integrated data standards [4] for transmission and distribution networks; and the application of μPMUs for network monitoring [5]. The concept of using μPMU for power system state estimation is not new. It has been suggested since the GPS technologies have been available that wide area measurement and state estimation could be achieved using these devices [8]. Methods already being tested include using a linear three phase state estimator for distribution networks [9]. In this instance it is solved using the weighted least squares method and provides good accuracy. The test network for this work was a simulated IEEE 13-bus feeder. The implementation, testing and performance of PMUs in state estimation of a transmission network is explored in [10], and demonstrates that success of the method depends greatly on the accuracy of the PMU measurements. A three phase linear state estimation using only phasor measurements has also been explored [11]. This was a real-time implementation on a 500 kV transmission network, running 30 times a second. A state distribution level estimator was deployed at a BC Hydro control centre [12]. Although the work is sound, the inputs to the state estimation were not from PMUs but from load profile pseudo measurements. A real-time three-phase state estimator for distribution networks has been deployed on the EPFL (École Polytechnique Fédérale de Lausanne) campus in Switzerland [13]. The network is comprised mainly of short lines, and has a variable load with active power injections. The inputs to the state estimation are PMU measurements sent via a PDC, and the results have an accuracy range of a few percent.

This paper will look at how the data collected can be used to estimate the line and transformer parameters. The intended purpose is to identify any inconsistencies between the expected values and those calculated. Section II will discuss in more detail the data that was collected from the μPMUs and the network they were on. Section III covers the methods and equations used to calculate the impedances, and Section IV will examine what the results mean and the challenges in the approach. Finally, Section V will look at what can be done in the future to improve the approach, such as using more complex analysis.

II. PMU Data Collection

A. *Type of μPMU*

The μPMUs used in the LBNL and utility test network were developed by Power Standards Laboratory [6] with costs that are a fraction of those used at transmission level, allowing for a wider deployment and use beyond real time monitoring. μPMUs can capture portions of the operating state of the system to provide actionable intelligence in real-time. Our research focuses on building a bottom-up view of the electric power distribution system using μPMU measurements in the context of limited availability of accurate system models and supplemental measurements (such as SCADA and AMI). To do so, we utilize μPMU measurements to parameterize approximations to system power flows.

B. *Data from μPMUs*

The μPMU's installed on the LBNL network had a sampling frequency of 120 Hz. For a given sample the dataset contains the magnitude and angle of the voltage for all three phases, the magnitude and angle of the current for all three phases and the time stamp [6]. This data is available for a number of μPMUs across two test networks. As part of this work one line of

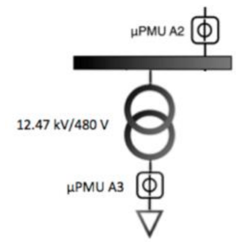

Figure 1: Device configuration for transformer estimation

12.47KV (line-to-line) with a μPMU at either end was examined. This data was problematic to analyse due to the lack of an appreciable voltage drop across the line as a result of low loading levels. In order to carry out a more meaningful analysis a line from a partner utility was used along with a transformer from the LBNL network.

C. *Measurement Accuracy*

Measurement accuracy of the μPMU and dependencies, which are added from the instrument transformers required, were discussed in [1]. In this work it was found that there is an inherent accuracy barrier in both the existing network models, and utilization of advanced sensor data. These modelling accuracy barriers can limit distribution grid development in areas such as distributed generation interconnection, and advanced controls/automation. The sensor accuracy data is not a key limit for the existing state of distribution planning. Data needs for real time operational control objectives are very different from initial assessment in the planning context. The applications of the data must be appropriate based on the bandwidth for error, which accounts for the entire measurement chain from the wire to the point where data is utilized. An integrated approach for control algorithms and validation is required.

D. *Network Model*

Fig. 1 shows the configuration on the μPMU's for the purpose of estimating the transformer parameters. An estimation of the impedance of a transformer is carried out using μPMU A2 and A3. There was a short cable connecting μPMU A2 to the transformer, however, the impedance of this was assumed negligible with respect to the transformer.

In the second data case, from a partner utility, we have two μPMUs at either end of an overhead line, which is approximately 2 miles long, and has significant daytime loading. This line was examined as it was determined that the loading of the cables at LBNL was insufficient to result is appreciable voltage drops along the cable.

III. Equations

The intention of this work is to help operators and planners identify any obvious, large discrepancies between the measured parameters of the network and those present in the network model, in an online or offline setting. The assumption is that should large, unexplained discrepancies be discovered, or a gradual change in time, a more detailed survey of the equipment would be undertaken so as to allow the operator to update their network model, or send field crews to perform remedial action. As a proof of concept, a simple analysis of the output data using two different methods for single line power flow was used to determine the impedance magnitude across the line, treating the lines as single phase cables and thus ignoring mutual impedances.

Following this the impedance of an unbalanced three-phase line located in Southern California was estimated using an Ordinary Least-Squares (OLS) method. Finally the impedance of a delta-grounded wye transformer located at LBNL was estimated.

A. Simple Methods for Impedance Magnitude Estimation

a) Ohm's Law

The first equation applied to the data is to use the measured voltage and current phasors in combination with Ohm's Law to determine the impedance magnitude across the line:

$$\Delta V = I \cdot Z$$
$$|Z| = \frac{|\Delta V|}{|I|} \tag{1}$$

This allows for a quick, high-level comparison of the calculated impedance with the model impedance. Should a significant error exist between this estimated and model impedance a more in-depth analysis is necessary considering a more complex model accounting for any loading unbalance in the system.

B. Impedance Estimation in Unbalanced, Three-Phase Lines

We explore the three-phase, unbalanced case using a simple setup for which we have measurement data: a single line connecting a substation to the point of common coupling for a large solar installation. The solar installation and the substation are both monitored by μPMUs, and a few seconds' worth of voltage and current measurements from those μPMUs is sufficient to make a rough approximation of the impedance of the connecting cable.

The problem can be written as an Ohm's Law equation in matrix form, taking into account both the long distribution line connecting the substation (which will be our focus in this estimation) and the shorter line connecting the PV. This short line was assumed to have a negligible voltage drop with respect to the primary line of interest.

$$\vec{V}_{sub} - \vec{V}_{PV} = \hat{Z}_{sub}\vec{I}_{sub} \tag{4}$$

Where the Z terms above are matrices of the form:

$$\hat{Z} = \begin{bmatrix} Z_{AA} & Z_{AB} & Z_{AC} \\ Z_{AB} & Z_{BB} & Z_{BC} \\ Z_{AC} & Z_{BC} & Z_{CC} \end{bmatrix} \tag{5}$$

Re-arranging allows the elements of the substation impedance matrix to be collected in a vector and solved with an ordinary least squares (OLS) method.

C. Transformer Impedance Estimation

The transformer under investigation was a delta-grounded wye transformer on the LBNL network. In order to perform impedance estimation the primary side voltage was referred across the transformer to the secondary side, as shown in equation (6), whereby uppercase subscripts refer to the primary side

$$[A_t][VLN_{ABC}] - [VLG_{abc}] = [Z_{abc}][I_{abc}] \tag{6}$$

with the following matrices having the form

$$[A_t] = \frac{1}{n_t}\begin{bmatrix} 1 & 0 & -1 \\ -1 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix} \qquad [Z_{abc}] = \begin{bmatrix} Z_a & 0 & 0 \\ 0 & Z_b & 0 \\ 0 & 0 & Z_c \end{bmatrix} \tag{7}$$

$$n_t = \frac{VLL_{\text{Rated High Side}}}{VLN_{\text{Rated Low Side}}}$$

whereby LL denotes the line-to-line voltage and LN denotes the line-to-neutral voltage.

IV. Results

A. Simple methods for calculating impedance change

TABLE 1: Impedance Magnitude Estimates

	Model Data	Ohms Law
|Z aa|	1.2497	0.984
|Z bb|	1.2497	0.906
|Z cc|	1.2497	0.969

There are number of potential reasons to explain these discrepancies:

- The potential transformers being used were not calibrated correctly resulting in inaccurate readings.
- The network model does not reflect the as-built network.
- There is an issue with the network and the readings reflect degradation to the cable or attached equipment.

The reasons for these discrepancies are being investigated by looking at the data over a longer period to see longer trends for the two lines, checking the calibration of the equipment, and verifying the configuration of the installed equipment. While it has yet to be determined whether this analysis of the data has indeed identified an issue with the network, it highlights how the measured values can differ from what is expected from the network model.

The purpose of this work is not to necessarily directly update network models with measured values, but instead to help identify where there could be issues with the network model. It could be that in many cases the discrepancies are not significant enough to impact on the operation of the network, but planners may need to be aware of that when analysing how the network would be impacted by other changes to the grid. To determine the more exact unbalanced network impedance we must apply more complex analytics to the data. The simplistic method could indicate a problem in the data whereas the complex methods seek to correct the impedance value.

B. Unbalanced, Three-Phase Results

Following this simple analysis a more robust methodology unbalanced three phase model was employed. When this method was tested on our field data, our estimated impedance matrix was:

$$\hat{Z}_{estimated} = \begin{bmatrix} 0.5+1.29j & 0.12+0.37j & 0.21+0.18j \\ 0.12+.37j & 0.59+1.24j & 0.10+0.29j \\ 0.21+.18j & 0.10+0.29j & 0.45+1.08j \end{bmatrix}$$

This can then be compared against the values given by the utility feeder model:

$$Z_{real} = \begin{bmatrix} 0.523+1.135j & 0.146+0.387j & 0.146+0.387j \\ 0.146+0.387j & 0.523+1.135j & 0.146+0.387j \\ 0.146+0.387j & 0.146+0.387j & 0.523+1.135j \end{bmatrix}$$

Our estimation is reasonable for the basic least-squares method that was used. The variation between our three calculated mutual impedance values is likely due to the measurement error introduced by instrumentation transformers in the circuit. With more advanced methods that treat that error explicitly, we expect to see significant reductions in that variation.

C. Transformer Impedance Estimations

The initial estimate of the transformer impedance, referred to the primary side, is shown below

$$\hat{Z}_{estimated} = \begin{bmatrix} 1.38+6.47j & 0 & 0 \\ 0 & 0.86+6.18j & 0 \\ 0 & 0 & 0.71+7.13j \end{bmatrix}$$

This can be compared against that of the nameplate data.

$$Z_{real} = \begin{bmatrix} 0.899+5.886j & 0 & 0 \\ 0 & 0.899+5.886j & 0 \\ 0 & 0 & 0.899+5.886j \end{bmatrix}$$

As can be seen from the above matrices, the estimated impedances lie within a reasonable range of the actual values. The discrepancies may exist due to the low loading of the transformer, ~15-20%, and thus the no-load losses may be attributed disproportionally to each individual amp relative to lab testing. Another reason for the discrepancy may be the effect of non-linear loads on the transformer. These effects may compound the effects of the instrumental transformers utilized in measuring the values.

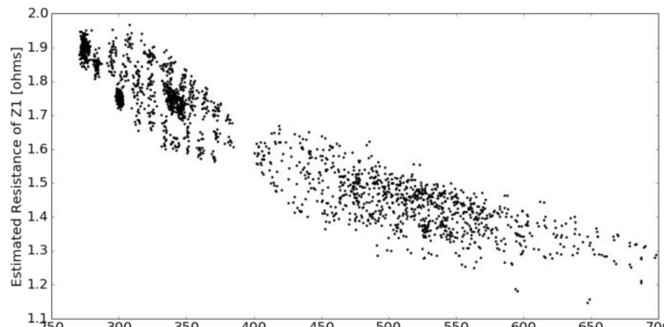

Figure 2: Estimates of transformer resistance as function of current

Fig. 2 shows the estimated resistance of Z_1 corresponding to each loading level. It is seen that the estimates at higher loading levels are significantly above the nameplate rating. This is postulated to be due to the assumption of the magnetizing current being negligible with respect to the load current in the deployed transformer model. As the load current increases this assumption becomes more valid and the estimated tend towards the nameplate rating. Further analysis across a higher proportion of the transformer loading range is necessary to draw conclusive results regard=ding the behaviour of transformers at lower loading levels.

V. Future Work

As stated previously, this is intended as a method of identifying where the network construction and network model may differ to help prioritise areas that need to be resurveyed. The method and equations used are rudimentary and are deliberately using the voltage and current measurements from each μPMU independently of any construction information within the network model. This is preliminary testing to check the feasibility of the proposed method. The aim was to check if there are any impedance discrepancies between network models. The accuracy of readings is also important when dealing with LV distribution networks, as the change in voltage and current is small compared to those changes in transmission networks.

The mutual impedances and line susceptance have deliberately been disregarded to begin with as a first pass to identify potential issues with the network. Future work will focus on validating the readings and applying the data to more complex methods, including complex mesh analysis. The calculation of impedance in a meshed network will allow identification of any change in the condition of network topology by determining where the change has occurred. This work has already begun, and will take into account more complex analysis using cloud-computing resources.

The initial results, considering mutual impedances, from the three-phase line impedance calculations are encouraging. There is however, further room for improvement. Future work will begin with supplementing OLS with more sophisticated algorithms that account for instrumentation transformer error, and potentially environmental factors as well. Once that has been accomplished and μPMU–based impedance estimation methods fully developed, further research will involve integrating impedance monitoring into control strategies that make use of μPMU-measured voltage and current angles as operating variables.

The transformer parameter estimation provided reasonable results for a rudimentary algorithm that ignored potential stable errors introduced by the instrumental transformers. An analysis of the impedance estimations at various loading levels, as well as various temperatures may shed light on the operational behaviour of distribution transformers and in turn improve modelling practices.

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VII. Biographies

Ciaran Roberts (M ’15) received his BSc degree from University College Dublin in 2013 and an MSc in Energy Systems Engineering in 2015. He currently works at Lawrence Berkeley National Laboratories and is primarily focused on power distribution engineering and distributed energy resources.

Corinne Shand (S ’11) received the M.Eng in Electrical Energy Systems from the University of Strathclyde in 2013. She is currently a Research Engineer at Open Grid Systems Ltd and is undertaking an Industrial Ph.D at Brunel University in London. Her research work is focused on ‘big data’ challenges for the smart grid including data integration, visualization and analysis.

Kyle Brady received a BA in Physics from the University of California, Berkeley in 2010. He then worked for three years as a Research Assistant at the RAND Corporation in Washington, DC. He is currently enrolled in a combined MS/PhD program in Electrical Engineering, also at U.C. Berkeley. His research interests include distribution network operations, microgrids, and distributed energy resources.

Emma Stewart (SM ’14) completed her undergraduate degree in Electrical and Mechanical Engineering from the University of Strathclyde in 2004 and a PhD in Electrical Engineering in 2009. Her field of research included the electrical integration of hydrogen and renewable technologies to power systems. Dr. Stewart joined Lawrence Berkeley National Laboratories in 2013, and is currently engaged in distribution measurement and analysis techniques for smart grid applications.

Alan McMorran (M ’02) received the B.Eng. in Computer & Electronic System and a Ph.D. in Electronic & Electrical Engineering from the University of Strathclyde in 2002 and 2006 respectively. His research and development work has focused on model-driven architectures for data management, visualization and transformation and related technologies. Alan is currently Managing Director at Open Grid Systems Ltd.

Gareth Taylor (SM ‘12) received his BSc degree from the University of London, UK in 1987 and MSc and PhD from the University of Greenwich, UK in 1992 and 1997, respectively. He was the National Grid UK post-doctoral scholar at Brunel University, UK from 2000-2003. He is currently a professor of power systems and director of the Brunel Institute of Power Systems, Brunel University, UK. His research interests include smart grids, active network management, power system operation and network optimization.