Secondary Circuit Model Generation Using Limited PV Measurements and Parameter Estimation

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***Abstract*— This paper presents an approach for generating simplified secondary circuit models with limited SCADA and PV micro-inverter measurement data. The proposed method is computationally efficient and can be utilized with typically available measurement data. The method is applied to models of three real U.S. utility feeders with PV micro-inverter measurements. The proposed simplified secondary circuit modeling approach decreases the PV voltage simulation errors in all the three feeders compared to using generic secondary circuit models. This paper also presents approaches for improving the feeder voltage regulating device model set points by utilizing the PV voltage measurements.**

***Index Terms*—Load Modeling, Power Distribution, Power System Measurements, Smart Grids**

I. Introduction

To analyze and operate distribution systems with growing amounts of PV and other distributed energy resources (DER), more accurate distribution system models are required. Since many DERs are located in secondary (low-voltage) circuits, it is becoming important to include the secondary circuits into the distribution models. This is particularly important since the low-voltage secondary circuits have higher per unit impedances, which result in a large share of the feeder per unit voltage drop as well as some losses [1]. Well-modelled secondary systems will allow for high penetrations of DERs through such things as improved hosting capacity analysis and more accurate optimization and control. However, the vast majority of existing utility feeder models do not include the secondary circuits at all. When modeled, they are represented with limited detail.

Simultaneously, the on-going extensive roll-out of smart meters and growing number of PV micro-inverters [2] and other modern distribution system sensors rapidly increase the available measurement data along the distribution feeders. This new data can be leveraged to calibrate existing utility feeder models. However, automated methods are needed in order to achieve this in a cost-effective way.

The Big Data from AMI and other emerging sensors has raised the interest in new methods for distribution system parameter estimation (DSPE) [3]–[5]. In our past work, we have presented methods to estimate secondary circuit topology and parameters when a dense grid of smart meter measurements is available [6]–[8]. In this paper, we extend the parameter estimation methodology to the case when only a limited number of PV micro-inverter or similar measurements are available. In particular, this paper further develops the approach that we have shown in [7] for generating simplified distribution system secondary models with limited PV measurement data. This paper also presents parameter estimation results for three real U.S. utility feeders with micro-inverter measurements. The significance of the results is discussed and challenges related to secondary circuit parameter estimation on real utility feeder models are highlighted.

This paper has the following structure. Section II briefly presents the simplified secondary circuit parameter estimation method. Section III presents the utility feeder models and discusses some of the challenges related to modeling the voltage regulating devices with limited data. Section IV presents the parameter estimation results by first validating the methodology with test data set and then by applying the method to PV inverter measurements. Section IV also shows parameter estimation impact on PV location feeder hosting capacity. Section V discusses the results and the challenges related to parameter estimation with limited data. Finally, Section VI concludes the paper.

II. Secondary Circuit Parameter Estimation

The objective of distribution system secondary circuit parameter estimation (DSPE) is to find the most likely values of resistance (R) and reactance (X) parameters of a secondary circuit. DSPE with a dense network of smart meters has been discussed in [6], [7]. If some smart meters do not report voltages, the secondary circuit parameters can be estimated with a modified DSPE algorithm shown in [6]. This paper addresses the common case when a utility does not have a dense network of smart meters (or other sensors) in the secondary circuits. This paper assumes that no (or very limited) AMI measurements are available but historical PV system measurements are available. Given this data, this paper utilizes the simplified secondary circuit parameter estimation algorithm (SDSPE) proposed in [7] to create simplified secondary circuit models shown in Figure 1 and to estimate their parameters. The objective is to improve the PV (or other sensor) voltage simulation accuracy.

The simplified secondary circuit has one or more customers with a PV system. The discussion here focuses on one customer with a PV system in each secondary circuit, but generalization to multiple PV systems is trivial. The customer with the PV system is assumed to be connected to the service transformer secondary over a service line with a known line type (i.e. known per-unit-length resistance and reactance) but unknown line length. The secondary system also has other customers with loads connected to the service transformer with potentially several service lines. Although Figure 1 does not represent all possible circuit topologies, it is the best assumption given the limited available measurements and that the topology is unknown.

The PV system is assumed to measure its active power output P_{PV} and voltage V_{PV} shown in blue in Figure 1. The secondary circuit loads P_1, P_0 shown in green in Figure 1 are estimated from feeder SCADA active power measurements with load allocation. The reactive power loads Q_1, Q_0 shown in green in Figure 1 are estimated from the active power loads P_1, P_0 with a constant power factor. The active (and reactive) power measurements can be utilized for customers that have smart meters (if any). Moreover, if feeder SCADA reactive power measurements and feeder capacitor states are available, the reactive power loads Q_1, Q_0 can be estimated from the sum of feeder reactive power load and the capacitor reactive power generation.

The feeder primary (medium-voltage) system, including the voltage regulation device operation and the service transformer connection, is assumed to be well-modeled. Thus, transformer primary side voltage referred to the low-voltage side, V_0, can be estimated with time-series power flow simulation. However, in practice, due to primary circuit modeling inconsistencies and the simplifications of load allocation, the simulated voltages may not be very accurate.

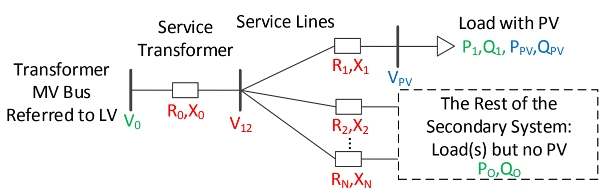

Figure 1. Simplified secondary circuit model with a PV system: available measurements are in blue, values that can be roughly estimated are in green, and unknown values and parameters are in red

For the portion of the secondary circuit without voltage measurements, it is not possible to estimate the impedances $R_2, X_2, \dots, R_N, X_N$ or topology. Moreover, since the substation reactive power measurements are estimated from the substation active power measurements ($Q_1 = \alpha P_1$, $Q_O = \alpha P_O$ where $\alpha = \sqrt{1/(PF)^2 - 1}$), and PV systems typically operate at unity power factor ($Q_{PV} = 0$), only one of the each parameters in parameter pairs R_0, X_0 and R_1, X_1 can be estimated [7]. Therefore, the load P_O, Q_O can be lumped to the service transformer secondary. If the line per-unit-length resistance r_1 and reactance x_1 and the transformer X/R-ratio $(X/R)_0$ are assumed to be known, the transformer resistance, R_0 and the line length, L_1, can be estimated utilizing M measurements with the linear model (bold indicate vectors or matrices)

$$\boldsymbol{V}_0 - \boldsymbol{V}_{PV} = R_0 \boldsymbol{\mathcal{X}}_0 + L_1 \boldsymbol{\mathcal{X}}_1 + \boldsymbol{\epsilon}, \tag{1}$$

where $\boldsymbol{\epsilon}$ represents the model and measurement error, the predictors are given by

$$\boldsymbol{\mathcal{X}}_0 = \boldsymbol{I}_{R0} + (X/R)_0 \boldsymbol{I}_{X0}, \tag{2}$$

$$\boldsymbol{\mathcal{X}}_1 = r_1 \boldsymbol{I}_{R1} + x_1 \boldsymbol{I}_{X1}, \tag{3}$$

and $\boldsymbol{I}_{R0}, \boldsymbol{I}_{X0}, \boldsymbol{I}_{R1}, \boldsymbol{I}_{X1}$ are given by

$$\boldsymbol{I}_R = \boldsymbol{P}/\boldsymbol{V} = \boldsymbol{I} * PF \text{ and } \boldsymbol{I}_X = \boldsymbol{Q}/\boldsymbol{V} = \boldsymbol{I}\sqrt{1 - (PF)^2}. \tag{4}$$

The predictors $\boldsymbol{\mathcal{X}}_0, \boldsymbol{\mathcal{X}}_1$ are linearly independent provided that $\boldsymbol{P}_{PV} \not\equiv 0$. Once R_0 and L_1 have been estimated, the transformer reactance can be calculated with $X_0 = R_0 (X/R)_0$ and the line impedances with $R_1 + jX_1 = L_1(r_1 + jx_1)$. As a result, the circuit in Figure 1 can be simplified to the circuit shown in Figure 2.

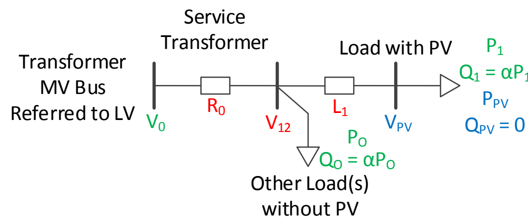

Figure 2. SDSPE simplified secondary circuit with a PV system: available measurements are in blue, values that can be roughly estimated are in green, and unknown values and parameters are in red

If the secondary circuit has $N > 1$ PV systems (model (1) is used for secondary circuits with only one PV system), the line parameters are first estimated with linear model

$$\boldsymbol{y} = \boldsymbol{\mathcal{X}}\boldsymbol{\beta} + \boldsymbol{\epsilon}, \tag{5}$$

where $\boldsymbol{\epsilon}$ represents the model and measurement error, the response variable $\boldsymbol{y}$ is given by

$$\boldsymbol{y} = \left[V_{PV1,1}, \dots, V_{PV1,M}, \dots, V_{PVN,1}, \dots, V_{PVN,M}\right]^{\mathrm{T}}, \tag{6}$$

the unknown parameter vector is given by

$$\boldsymbol{\beta} = \left[V_{12,1}, \dots, V_{12,M}, R_1, X_1, \dots, R_N, X_N\right]^{\mathrm{T}}, \tag{7}$$

and the design matrix $\boldsymbol{\mathcal{X}} \in \mathbb{R}^{(MN)\times(M+2N)}$ is given by

$$\boldsymbol{\mathcal{X}} = \begin{bmatrix} \mathrm{I} & [-\boldsymbol{I}_{R,1} & -\boldsymbol{I}_{X,1}] & \cdots & \mathbf{0} \\ \vdots & \vdots & & \ddots & \vdots \\ \mathrm{I} & \mathbf{0} & & \cdots & [-\boldsymbol{I}_{R,N} \quad -\boldsymbol{I}_{X,N}] \end{bmatrix}, \tag{8}$$

where $\mathrm{I} \in \mathbb{R}^{M\times M}$ are identity matrices, $\boldsymbol{I}_{R,i}, \boldsymbol{I}_{X,i} \in \mathbb{R}^{M\times 1}, i \in \{1, \dots, N\}$ are the branch current measurements, and the zero submatrices have suitable sizes. It should be noted that as long as $\boldsymbol{I}_{R,i} \neq \boldsymbol{I}_{X,i} \forall i \in \{1, \dots, N\}$, the columns of $\boldsymbol{\mathcal{X}}$ are linearly independent. After the line parameters have been estimated, the service transformer parameters are estimated with

$$\boldsymbol{V}_0 - \boldsymbol{V}_{12} = R\boldsymbol{I}_R + X\boldsymbol{I}_X + \boldsymbol{\epsilon}. \tag{9}$$

There are various ways to estimate the parameters from the linear models (1), (5) and (9). In this paper, the parameters were estimated with (ordinary least squares) linear regression. If linear regression resulted in negative (or too small) parameters, linearly constrained least squares algorithm was used, instead [6].

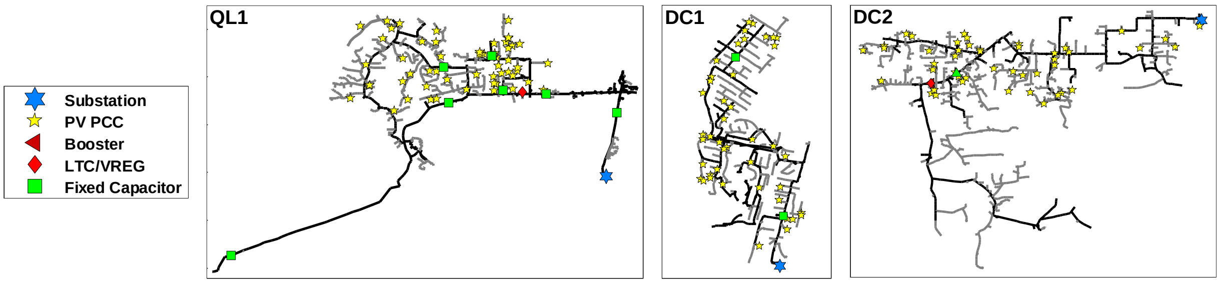

Figure 3. Topologies of the full circuit models of feeder QL1 (left), DC1 (middle), and DC2 (right)

III. Utility Feeder Modeling

The SDSPE algorithm was applied to models of three real California utility feeders shown in Figure 3. This section introduces the feeder models and discusses some of the challenges related to the modeling of the feeder voltage regulating device operation. The feeder models, each of which consists of thousands of buses, lines, and loads, as well as hundreds of transformers, were reduced using the approach shown in [9]. Specifically, the secondary circuits without PV systems were reduced to fixed-current loads at the service transformer primary. The secondary circuits with PV system(s) were converted to the simplified secondary circuit format illustrated in Figure 2 for one PV system. It should be noted that the original feeder models included only generic secondary circuit models consisting of a service transformer with typical parameters and a triplex cable feeding each load. Service line types were selected so that the lines had sufficient capacity to serve the loads. This is a common utility practice to model the secondary circuits. TABLE I lists the key feeder model characteristics.

TABLE I. Full and Reduced Utility Feeder Model Details

Feeder	QL1	DC1	DC2
Feeder Type	suburban	urban	rural
Voltage Level [kV]	20.78	12	12
# Customers	3500	3700	1200
Feeder Peak Load [MW]	18.63	8.08	3.6
Farthest 3-Phase Bus [km]	12.6	6.7	17.9
# PV Systems	44	36	31
LTC Set Point	120	123	121
# Capacitors – Control Mode	1-fixed 6-temperature	2-fixed	1-voltage
# Voltage Regulators	1	0	1
Available Reliable SCADA measurements	MW, MVAr, phase currents	MW	MW

Since the historical LTC primary voltages, secondary voltages, and taps were not available for the feeders, sub transmission was simply modeled as a constant Thevenin equivalent in all the three models. Moreover, the LTC voltage control set point were not known with a high confidence for any of the feeders. The LTC set points were selected to provide consistent results regarding positive average secondary circuit voltage drops with the smallest average differences between simulated PV voltages and measured PV voltages. Without substation voltage measurements, it was not possible to verify the accuracy of the simulated LTC medium-voltages.

Feeders QL1 and DC2 have controlled capacitors that have a significant impact on the feeder voltage profile. Since the historical capacitor states were not available, it was necessary to estimate the capacitor states. Feeder QL1 capacitor states were estimated with the available SCADA feeder reactive power measurements. First, the total feeder reactive power load $Q_{load,tot}$ was estimated with load allocation from the feeder active power measurements using a constant power factor. Then, the total capacitor generated reactive power $Q_{cap,tot}$ was estimated by subtracting $Q_{load,tot}$ from the measured feeder reactive power consumption $Q_{feeder,meas}$. Reactive power losses were neglected. When simulating the feeder voltages, the capacitors were turned on until simulated capacitor reactive power generation was close to the estimated capacitor reactive power generation. The capacitors were switched in a priority switching order, which was determined based on the capacitor temperature control set points.

Since the feeder reactive power measurements were not reliable for feeder DC2, the feeder capacitor state was estimated utilizing the PV voltage measurements. The capacitor has a significant impact on the PV voltages as shown in Figure 4 on the left. The average absolute change in the simulated PV voltages was 7.45 volts when the capacitor switched on. Similar (but opposite) changes were observed in the simulated PV voltages when the capacitor was turned off. Figure 4 on the right shows a histogram of the average absolute change (from one sample to the next) in the measured PV voltages in feeder DC2. Since there were no changes even close to the level of 7.45 volts, it was assumed that the capacitor state did not change during the entire month. It should be noted that no PV measurements were available during the night time and it is possible that the capacitor state changed during the nigh-time. However, without feeder reactive power measurements (or PV night-time voltage measurements), it was impossible to determine if there were capacitor state changes or not.

IV. Parameter Estimation Results

This section presents the parameter estimation results for the three feeder models. First, the parameter estimation algorithm and implementation is validated by estimating the parameters with simulated PV voltages and service transformer medium-voltage. Then, the results for parameter estimation with PV voltage measurements are shown.

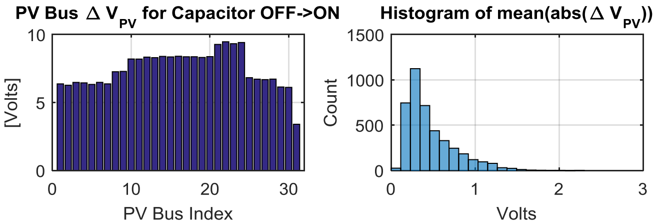

Figure 4. Feeder DC2 capacitor state impact on the PV voltages

A. Parameter Estimation Validation with Simulated Voltages

First, the simplified secondary circuit parameters of the three feeder models were estimated with 8928 samples (one month of 5-min samples) of simulated PV and service transformer voltages. The PV voltages and service transformer medium-voltages were simulated with time-series power flow with measured PV powers and load powers modeled with load allocation. The parameter estimation results with simulated voltages are summarized in TABLE II. All parameters were estimated with linear regression very close to the original parameters. The linearly constrained least squares algorithm was not needed to force the parameters to be positive. The minimum R-squared value of the parameter estimation linear regression problems was above 0.9999 indicating that all the linear regression models provided an excellent fit to the data.

TABLE II. Parameter Estimation Accuracy with the Simulated PV Voltages and Service Transformer Medium-Voltages

Feeder	Average Absolute of		Max. Absolute of	
	$\frac{(R_{est}-R_{orig})}{R_{orig}}$	$\frac{(X_{est}-X_{orig})}{X_{orig}}$	$\frac{(R_{est}-R_{orig})}{R_{orig}}$	$\frac{(X_{est}-X_{orig})}{X_{orig}}$
QL1	0.26	0.25	0.96	0.96
DC1	0.30	0.33	3.57	3.57
DC2	0.33	0.34	1.25	1.25

B. Parameter Estimation With PV Voltage Measurements

Next, the simplified secondary circuit parameters of the three feeders were estimated with 8928 samples (one month of 5-min samples) of actual PV voltage measurements. The transformer medium-voltages were simulated with time series power flow utilizing the measured PV generation and load-allocated loads. Figure 5 shows absolute average differences between the measured and the simulated PV voltages. Simulating the PV voltages with the estimated parameters (as opposed to the original generic feeder parameters) effectively reduces the average absolute voltage simulation errors on average by 0.57 Volts (19.3% reduction), 1.64 Volts (71.5% reduction), and 0.40 Volts (22.5% reduction), for feeders QL1, DC1, and DC2, respectively.

C. Application of Parameter Estimation in Hosting Capacity

Correctly modelling the unknown secondary system impedance parameters can improve integration of DER through such things as improved hosting capacity analysis and more accurate optimization and control. For example, the amount of PV that can be interconnected at a customer location is highly dependent on the impedance to the location that causes voltage rise. In order to demonstrate the differences, the PV locational hosting capacity analysis method from [10] has been applied to each of the secondary systems estimated in the previous section. As seen in Figure 6, the hosting capacity changes significantly (±90%) by using estimated parameters instead of generic standard impedances.

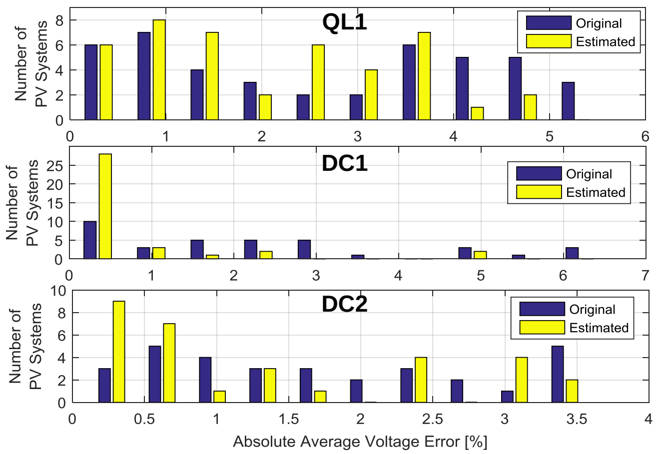

Figure 5. Feeder QL1 (top), DC1 (middle), and DC2 (bottom) absolute average voltage error for each PV system simulated with the original (in blue) and estimated (in yellow) parameters

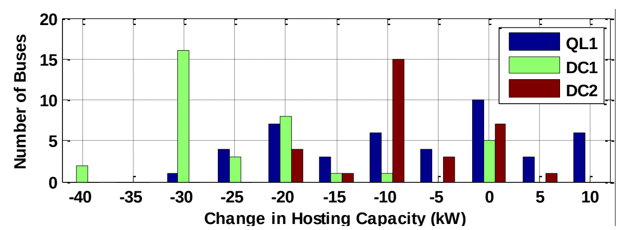

Figure 6. Change in PV hosting capacity with secondary system models improved with parameter estimation.

V. Discussion

PV measurement data can be effectively utilized to improve feeder voltage simulation accuracy by validating feeder voltage regulating device modeling and by performing secondary circuit parameter estimation. Next, some of the key findings from parameter estimation on the three feeder models are highlighted.

Figure 7 shows the boxplots of the PV voltage simulation errors for the feeder DC2. Parameter estimation is unable to reduce the variance in the voltage simulation errors, which results from the modeling inaccuracies and simplifications. In some cases, these inaccuracies and simplifications resulted in unrealistic parameters such as extremely long service line lengths as shown in Figure 8 for feeder QL1. The two main sources of error for the analyzed feeders seemed to be inaccuracies in the medium-voltage level modeling and modeling loads through load allocation.

Parameter estimation is much more sensitive to voltage measurement error than power/current measurement error [6]. Therefore, when utilizing simulated voltages to estimate, e.g., service transformer impedances, the voltages must be accurately simulated. For the analyzed feeders, it turned out to be very challenging to identify the capacitor and LTC states with limited data. In order to reach good accuracy in parameter estimation regression models that utilize simulated voltages, it is necessary to correctly model the voltage-regulating device operation. Otherwise, one can observe negative or unrealistically high simulated voltage drops over the secondary circuits that the parameter estimation is trying to model by adjusting the impedance parameters.

Load allocation simplifies true load behavior and can lead to significant modeling errors especially at the secondary circuit level close to the loads [1]. A load modeled with load allocation has much smoother profile than the load has in reality resulting in underestimated voltage drops, losses, etc. In parameter estimation, load allocation was observed to result in very poor fits for regression problems of form (9), whose response value is calculated as a difference of very smooth voltages simulated with smooth allocated load profiles and highly variable PV voltage measurements. For some such regression problems, the predictors (calculated based on allocated loads) are unable to explain almost any of the variation in the response variable (calculated as a difference of simulated and PV measured voltage).

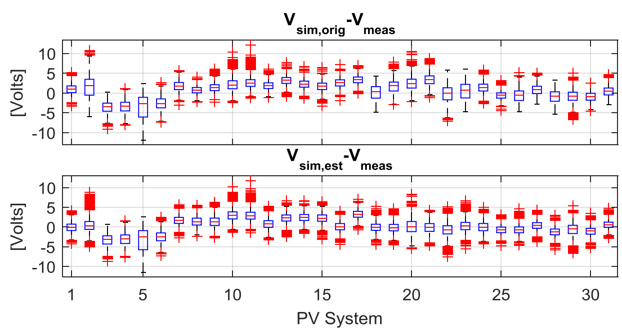

Figure 7. Feeder DC2 error of PV bus voltages simulated with the original (top) and estimated (bottom) parameters

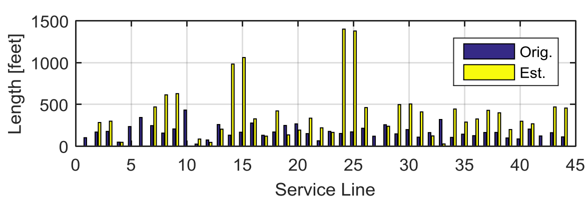

Figure 8. Original (in blue) and estimated (in yellow) service line lengths for the feeder QL1

VI. Conclusions

This paper presents an approach for generating simplified secondary circuit models with limited substation SCADA and PV micro-inverter measurements. The method is applied to models of three real U.S. utility feeders with PV micro-inverter measurements. Compared to the base case of utilizing generic secondary circuit models, using the proposed simplified secondary circuit models with estimated parameters reduced the absolute average PV voltage simulation errors in the three feeder models on average by 0.57 Volts (19.3% reduction), 1.64 Volts (71.5% reduction), and 0.40 Volts (22.5% reduction). The errors were reduced for most of the PVs but for some PVs the error reduction was minor. For limited number of PVs, the errors either remained constant or were slightly increased. This is likely explained by the inconsistencies in feeder modeling that resulted in highly uncorrelated parameter estimation regression model response and predictor variables.

The simplified secondary circuit parameter estimation with limited data had two major challenges. First, it turned out to be challenging to accurately model the medium-voltage circuit. In particular, it was very challenging to accurately identify historical feeder voltage regulating device operation. Second and the leading problem was modeling loads with substation load allocation. Load allocation results in smooth load profiles that may be highly uncorrelated with true individual loads at the secondary circuit level. This was particularly problematic in parameter estimation regression problems whose response variable is calculated as a difference of measured voltages (typically high variability) and voltages simulated with loads modeled with load allocation (typically low variability). AMI data seems to be mandatory to perform accurate distribution system secondary circuit parameter estimation. Future work should study parameter estimation accuracy in the common case when smart meter active power measurements are available for many loads but only a limited number of voltage measurements are available from PV micro-inverters.

References

[1] J. A. Taylor, T. A. Short, and B. Bushey, “Efficiency impacts of distribution secondaries,” in *IEEE Transmission and Distribution Conference and Exposition*, Orlando, FL, USA, 2012, pp. 1–6.

[2] J. S. John, “Can Microinverters Stabilize Hawaii’s Shaky Grid? : Greentech Media,” 02-Feb-2015. [Online]. Available: http://www.greentechmedia.com/articles/read/enphase-to-help-hawaii-ride-its-solar-energy-wave.

[3] A. J. Berrisford, “A tale of two transformers: An algorithm for estimating distribution secondary electric parameters using smart meter data,” in *Annual IEEE Canadian Conference on Electrical and Computer Engineering*, Regina, SK, Canada, 2013.

[4] B. Wang and W. Luan, “Generate distribution circuit model using AMI data,” in *China International Conference on Electricity Distribution*, 2014, pp. 1251–1255.

[5] T. A. Short, “Advanced metering for phase identification, transformer identification, and secondary modeling,” *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp. 651–658, 2013.

[6] J. Peppanen, M. J. Reno, R. Broderick, and S. Grijalva, “Distribution System Secondary Circuit Parameter Estimation for Model Calibration,” Sandia National Laboratories, SAND2015-7477, Sep. 2015.

[7] J. Peppanen, M. J. Reno, R. Broderick, and S. Grijalva, “Distribution System Model Calibration with Big Data from AMI and PV Inverters,” *IEEE Trans. Smart Grid*, pp. 1–8., 2016.

[8] J. Peppanen, M. J. Reno, R. Broderick, and S. Grijalva, “Distribution System Low-Voltage Circuit Topology Estimation using Smart Metering Data,” in *IEEE PES T&D Conference & Exposition*, Dallas, Texas, 2016, pp. 1–5. [In Review].

[9] M. J. Reno, K. Coogan, R. Broderick, and S. Grijalva, “Reduction of distribution feeders for simplified PV impact studies,” in *Photovoltaic Specialists Conference*, Tampa Bay, FL, USA, 2013, pp. 2337–2342.

[10] M. J. Reno, K. Coogan, S. Grijalva, R. J. Broderick, and J. E. Quiroz, “PV interconnection risk analysis through distribution system impact signatures and feeder zones,” in *2014 IEEE PES General Meeting | Conference Exposition*, 2014, pp. 1–5.

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