SAND2019-6602C

Identifying Common Errors in Distribution System Models

Logan Blakely[1], Matthew J. Reno[1], Jouni Peppanen[2]

[1]Sandia National Laboratories, Albuquerque, New Mexico, 87185, USA
[2]Electric Power Research Institute, Palo Alto, CA, 94304, USA

Abstract — **This paper discusses common types of errors that are frequently present in utility distribution system models and which can significantly influence distribution planning and operational assessments that rely on the model accuracy. Based on Google Earth imagery and analysis of correlation coefficients, this paper also illustrates some common error types and demonstrates methods to correct the errors. Error types include mislabeled interconnections between customers and service transformers, three-phase customers labeled as single-phase, unmarked transformers, and customers lacking coordinates. Identifying and correcting for these errors is critical for accurate distribution planning and operational assessments, such as load flow and hosting capacity analysis.**

I. Introduction

New DER installations are being connected to distribution system in ever-increasing quantities. This poses challenges if the utility modeling of the distribution system has inaccuracies, and it has been shown that there are a number of different errors that are often present [1]. Common errors include mislabeled phases, incorrectly labeled connections between homes and service transformers, location errors for service transformers, and unlabeled photovoltaic (PV) installations; current research is working on identifying and correcting each of these as well as others [2]–[4]. Inaccurate models can affect the operation of the grid, for example if the behavior of PV installations is modeled poorly due to errors in the model of the distribution system. New PV installations can also be delayed due to uncertainty in hosting capacity results because of errors in the models [5]; furthermore accurate simulations are critical to prevent unwanted consequences of DER affecting the grid [6]–[8]

This paper addresses the issue of quantifying the types of errors that are potentially present in models of the distribution system. The contributions of this paper include summarizing the distribution system error types found in the literature, showing specific examples of a subset of those errors in real distribution systems, and discussing a correlation coefficient methodology for analyzing a subset of the errors.

The remainder of the paper is structured as follows, Section II presents a broad overview of some of the techniques used in some of the more well-researched error types, Section III details a selection of examples of some of these error types, as well as correlation coefficient analysis using advanced metering infrastructure (AMI) data from the northeastern United States, and conclusions in Section IV.

II. Literature Review

Table 1 shows a list of selected types of errors or inaccuracies that may be present in the distribution system models, along with a selection of references as applicable; neither the list of error types nor the references list is intended to be exhaustive. Entries shown in bold have examples shown in Section III. There are a wide variety of errors listed with causes ranging from unlogged, or erroneously entered, maintenance information to the information not ever being present in the model to begin with. The increasing penetrations of DER have dramatically increased the importance of simulations to determine issues like hosting capacity for new PV installations [7], [9]–[11]. This has made the task of validating and correcting the distribution system models crucial for the continuing integration of DER.

As listed in Table 1, a significant amount of research is going into identifying and correcting some of these error categories, while others have little research associated with them. Although there are many different types of errors and consequences of those errors, one thing that they all have in common is that manually correcting the errors is prohibitively expensive and time-consuming. Manual verification of these types of errors would require crews in the field inspecting each section of the distribution system. In some cases, it may not even be possible to plausibly verify some of these errors. Consider the issues of underground cabling in urban areas or the behind-the-meter nature of PV installation parameters. The majority of research listed in Table 1 is leveraging newly available data, often from AMI to detect these errors, validate the models, and correct as necessary.

Phase identification is an error type that has been heavily researched. Phase identification approaches proposed in the literature include correlation coefficient analysis [1], [3], [12], [13], clustering [4], [14]–[16], supervised machine learning [17], and video analysis [18].

Common techniques for correcting meter to transformer pairing errors include correlation coefficient analysis [1], [4] and linear regression [12], [19]. Linear regression is also commonly used in parameter estimation tasks to determine line lengths and wire types [19], [20].

Reconfigured topology detection approaches include using mutual information to construct a tree representation of the topology [21], using the KullBack-Leibler divergence metric

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

with graphical models [22], [23], and topology 'signature' matching using phasor measurement unit (PMU) data [24].

TABLE 1 - LIST OF COMMON ERROR TYPES

Error Categories	Error Types
System State and Setting Errors	[21], [22], [24]–[27]
	State of switches (normal open or closed)
	Capacitor states
	Voltage regulator settings
	Switching capacitor settings
Phase Label Errors	[1], [4], [12]–[18]
	Individual transformer phase label error
	Lateral phase label error
	Three-phase customer labeled as single-phase
	Single-phase customer labeled as three-phase
Data Missing from the Model	[3], [23], [25], [28]–[30]
	Missing/Incorrect GIS coordinates
	Unmarked transformers
	Unmarked PV installations
	Unmetered load (unmarked customers or other sources)
	Connection (LN or LL) and grounding
PV Installations	[3], [31]–[33]
	PV kW rating
	Tilt
	Azimuth
	Volt/VAr settings
	Connection (LN or LL)
	Inverter size
	Connect/disconnect dates
Meter Configuration	[27], [34]
	PT or CT ratios
	Units (kW vs mW)
	Time zone
	Measurement location
	Unknown collection type (time-avg or instantaneous)
	Unknown meter accuracy
Model Parameters	[1], [4], [12], [19], [20], [23], [26]
	Wire Types, overhead line configuration, underground cable insulation, lengths, and number of phases
	Transformer rating, connection (LN or LL), or turns ratio error
	Substation short circuit impedance
	Meter to transformer connection errors
New or Replacement Equipment	New home construction
	Reconductoring of lines
	New voltage regulation equipment
	Service transformer replacement

PV system detection approaches include statistical inference based on Spearman's rank coefficient [3], support vector machines [31], and location-specific weather analysis combined with AMI load time series data [32]. Further analysis of PV system configurations have been demonstrated with non-linear least squares curve fitting, combined with a deep neural network approach [33].

Much of the research into the issue of unmetered load is focused on theft detection. The main approaches used include linear programming [25], aggregating data from multiple sources, including extra sensors [29], the classification approach, such as using support vector machines (SVM) [28], and game theory [30].

III. DISTRIBUTION SYSTEM MODEL ERROR EXAMPLES

A. *Data and Analysis Methodology*

The AMI data used in the following examples spans a 486-day period for 1 feeder serving ~1000 customers in the north-eastern United States. The data was collected using the averaging method at 15-minute intervals to an accuracy of 0.0001V. The dataset contains time series of voltage, real power, and reactive power. In addition, the dataset contains GIS coordinates for the customers, the electrical model, equipment information, and customer-transformer connection labels. While manual verification of the errors is difficult, publicly available imagery taken from Google Earth has proven to be useful in validating a subset of the results. All Google Earth and Google Street View images for the novel examples shown here were taken from the set of images available in 2018; the overhead satellite views are from 2018 and the Google Street view images vary somewhat in timestamp.

The examples labeled in bold from Table 1 are explored in more detail below, and (unless otherwise specified) were proposed by a phase identification algorithm, being tested as part of previous research [14], as possible candidates for further analysis. That algorithm used a spectral clustering approach with a sliding window ensemble to identify the phase of customers based on the voltage time series. That method also produced a list of customers where the results indicated that there was some issue that was unexplainable by a simple mislabeled phase for a given transformer. This small subset of customers was then analyzed using correlation coefficients and other information present in the utility model. The following section presents a selection of those customers to demonstrate, using actual feeder data, the types of errors that can be found in utility models and one possible method for analyzing/correcting some of these errors.

It has been shown that voltage profiles on the same phase and/or closer in distance will be more correlated with each other than voltage profiles that are on different phases and/or farther apart,[1], [4], [12], [35]. We are using Pearson correlation coefficients to analyze the relationship between the customers shown in these examples (unless otherwise specified).

B. *Mislabeled Phases*

Figure 1 and Figure 2 show an example of a phase labeling error where the transformer labeled 80 in Figure 1 is labeled in the utility model as being on Phase C (blue coloring). However, the Google Street View image in Figure 2 clearly shows the transformer connected to the wire in the center. The middle wire in this location was verified to be phase B using other Google Street View imagery. This example was first shown in [14] and demonstrates a straightforward example of a transformer labeled as being connected to an incorrect phase.

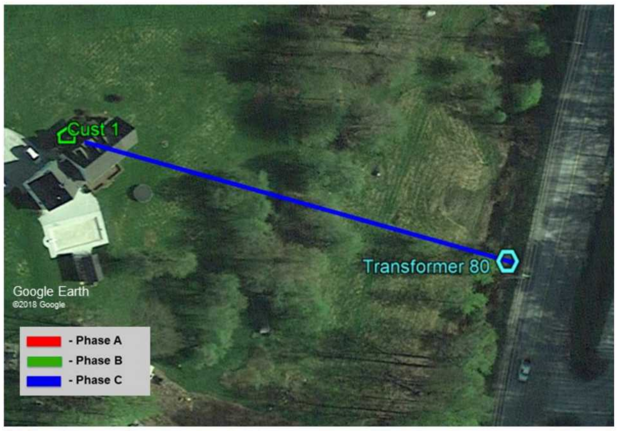

Figure 1 - Example of a phase labeling error with the utility model incorrectly placing the transformer and customer on Phase C (blue) [14]

Figure 2 - Example of a phase labeling error with the correct phase being Phase B [14]

C. Meter to Transformer Label Error

Figure 3 shows an example of a predicted meter to transformer labeling error. The customer plotted in green was flagged as a potential error; that customer is labeled as being on the Phase B transformer shown with the red pushpin, however all of the top ten most correlated customers to the customer in green are connected to the Phase A transformer shown with the blue pushpin in Figure 3. Figure 4 shows plots of normalized voltage over time; the dashed green line represents the customer in question. Blue lines show the two most correlated customers, from the transformer plotted in blue in Figure 3, and the red lines represent two customers from the transformer plotted in red in Figure 3 where the customer was labeled in the utility model. Visually, Figure 4 clearly illustrates that the customer plotted in the dashed green line is much more correlated to the customers in blue than the customers in red. While the street view images are unclear in this case, not allowing complete validation of the error, the correlation coefficients strongly indicate that this customer represents a transformer labeling error.

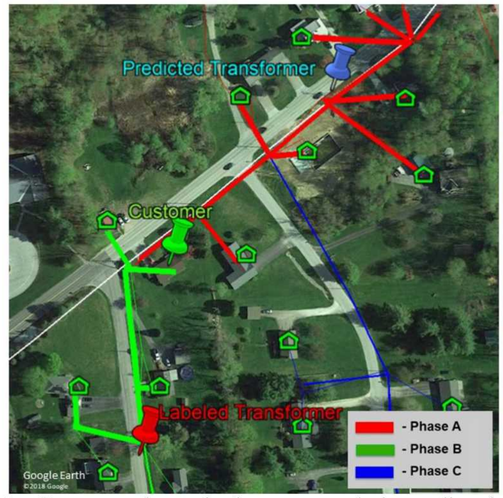

Figure 3 - Customer shown in the green pushpin predicted to be labeled on an incorrect transformer

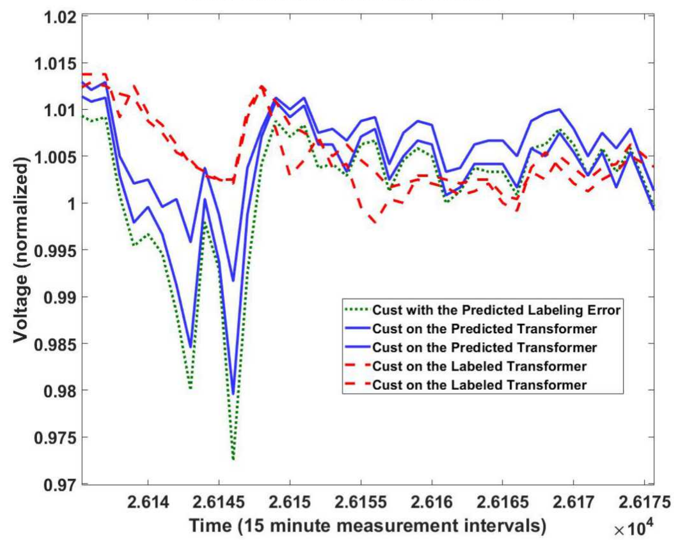

Figure 4 - Voltage profiles over time showing a predicted transformer labeling error

The next example is fully verifiable for transformer pairing using street view images. Looking at Figure 5 we see two transformers 60 and 61 and seven customers. Transformer 61 is labeled in the utility model as being two phase (BC), serving customers 6 and 8, and transformer 60 serving customers 1-5. Note that transformer and meter GIS locations are approximate, and the transformers are actually on either side of the street.

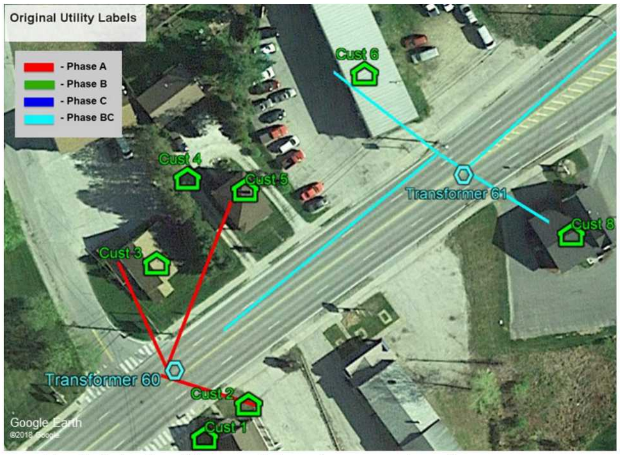

Figure 5 - Original utility model and connections between customers to transformers. The actual connections are shown in Figure 6.

This area was indicated to be a problem area by the phase identification algorithm and analysis of the correlation coefficients of voltage fluctuations along with imagery from Google Earth show different actual interconnections, Figure 6. Customers 6 and 8 were originally excluded from the phase identification task because they were listed as being multi-phase customers, however customer 8 is the most highly correlated customer to customers 3, 4, and 5. Customers 1 and 2 are highly correlated with each other but not with customers 3, 4, and 5. Inspection of the Google Earth imagery reveals that transformer 61 from Figure 5 is actually two transformers labeled 61 and 62 in Figure 6. Transformer 61 is connected to Phase B and transformer 62 is connected to Phase C, Figure 7. In Figure 8, we see the incoming Phase B from Transformer 61 and the Phase A connection for Transformer 60. In this example, this analysis identified two errors, first, what was labeled as a single transformer in Figure 5 is actually two different transformers, and second, customers 3-5 are actually connected to the same transformer as customer 8. This example of model errors illustrates meter transformer pairing errors, a single-phase customer which was labeled as a two-phase customer, and what was labeled as one two-phase transformer is actually two separate transformers serving single-phase customers.

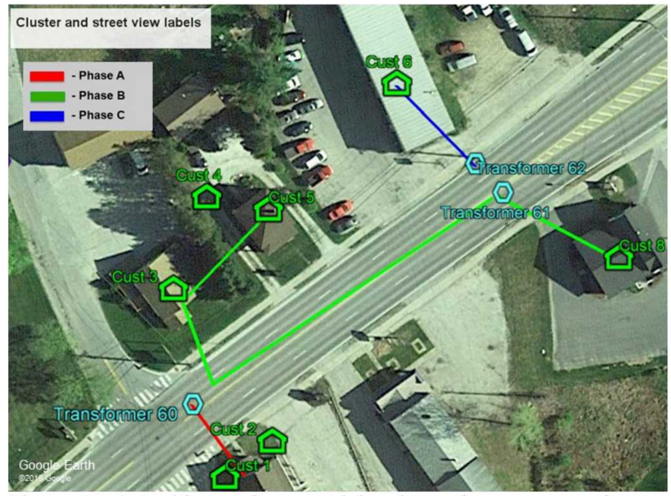

Figure 6 – Actual low-voltage model and transformer connections, verified in street view figures below.

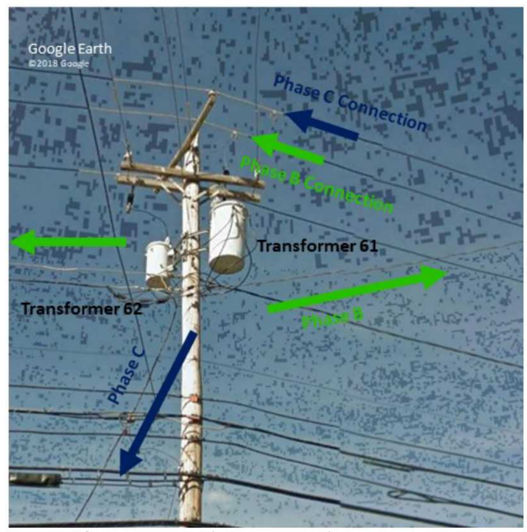

Figure 7 - Transformer 61 and 62 connections

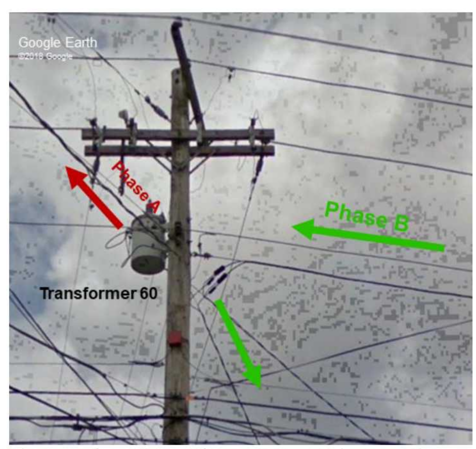

Figure 8 - Phase B from Transformer 61 serving another customer and Transformer 60 connected to Phase A

Although, the Google Street View images in this case are fairly conclusive as a validation method, it is also constructive to visually inspect the correlations associated with this analysis. Figure 9 shows a segment of voltage plotted over time for the customers shown in Figure 6. We can see that customers 3, 4, and 5 are indeed much more correlated with customer 8 than with customers 1 and 2. The work in [1], [4] demonstrated how similar correlation type analysis can be used to automatically detect and correct meter to transformer labels.

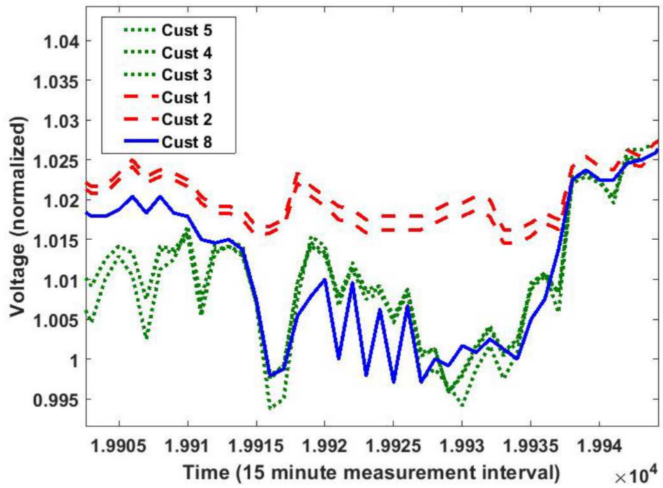

Figure 9 - Voltage plotted over time, indicating transformer labeling errors

D. Unlabeled Transformers

Figure 10 shows an example where the original utility labeling indicates three customers connected to Transformer 70. However, the customers in orange are highly correlated with each other but not well correlated with the customer in yellow. Inspection of the Google Earth imagery reveals an unmarked transformer shown in Figure 11. This example demonstrates a case where the error is not simply customers labeled on an incorrect transformer, but also a piece of equipment that is missing from the model. This type of model error has implications for service restoration scenarios as well as ongoing maintenance or maintenance projections for the utility.

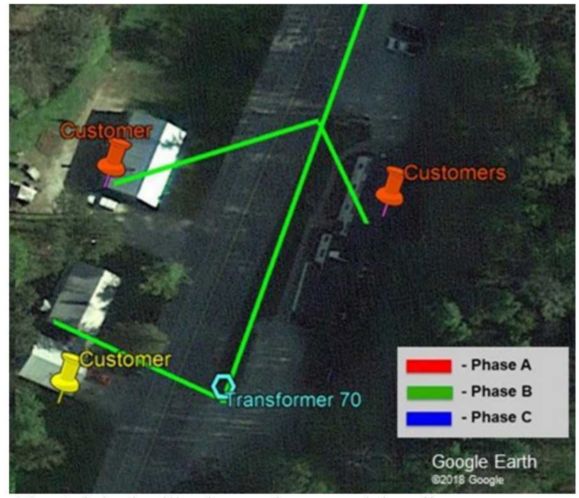

Figure 10 - Original utility low-voltage model, yellow customer not well-correlated with the orange customers. Actual model is shown in Figure 11.

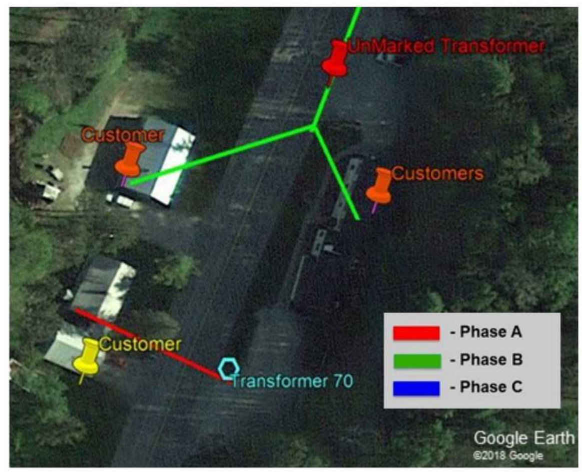

Figure 11 - Actual topology, validated with Google Street view showing an additional transformer not in the utility model.

E. Missing GIS Coordinates

Within this dataset there are a number of customers for which there is timeseries, AMI data, but the geographical coordinates within the GIS model and the pairing to a service transformer are lacking. Analysis of correlation coefficients can aid in identifying these customers within the GIS model. Figure 12 illustrates this; there are two customers shown that are lacking geographical coordinates (shown in green), and the most highly correlated customers to those two customers are shown in blue. It is plausible to hypothesize that those AMI time series match up with those two unknown customers. Figure 13 shows the voltage profiles over time for the customers shown in Figure 12. The two unknown customers are plotted with the dashed green lines, the blue lines are the highly correlated customers on the transformer shown in Figure 12, and the customer in red is a customer on an adjacent transformer, plotted as a reference. We can see that the green (unknown) customers and the blue customers are highly correlated, particularly relative to the customer on the adjacent transformer. This particular feeder alone has about 40 customers for which there is no matching GIS data, thus this type of analysis may be critical for improving the accuracy of existing models.

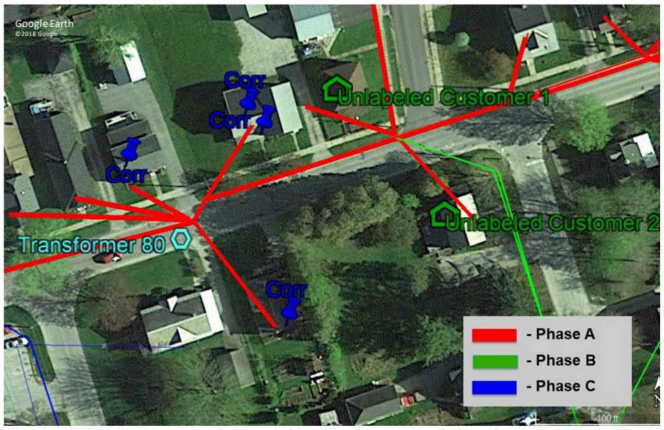

Figure 12 - Example of secondary system model going to two houses without AMI meters marked at the location

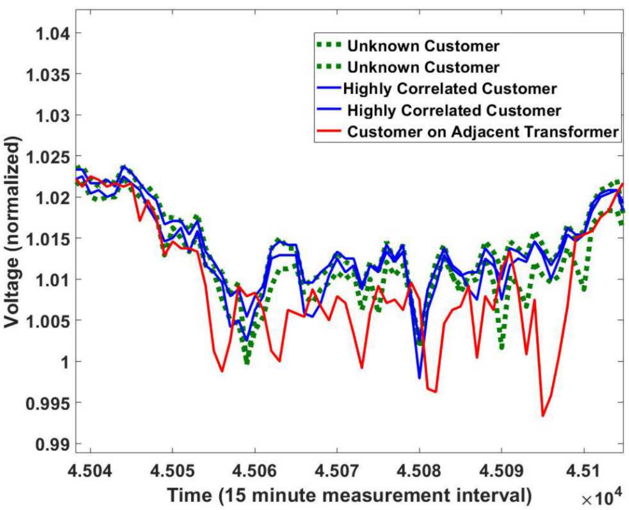

Figure 13 - Voltage profiles for two customers with unknown locations highly correlating with other customers on a transformer

F. Three-phase Customer Labeled as Single-phase

Figure 14 shows the satellite view for a possible three-phase customer which is labeled in the utility model as a single-phase customer. The street view images are inconclusive in this case, however the customer in yellow is adjacent to the substation, with the three-phase lines running down the street, and the building in question is not a residence. Generally plotting the most correlated customers to a specific customer results in customers which are on the same phase and nearby. However, in this case, plotting the most highly correlated customers to the customer in yellow results in customers in diverse locations and on differing phases. This suggests that this customer may be a three-phase customer mistakenly labeled as a single-phase customer. In general, analysis of 3-phase customers may be more challenging because there are fewer 3-phase customers, and there is uncertainty on what values (phase, line to line, or average) are being recorded.

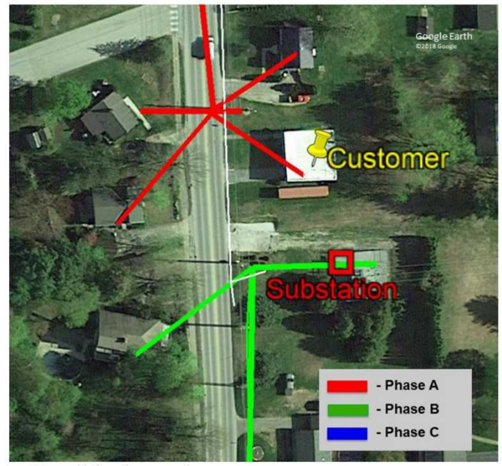

Figure 14 - Possible three-phase customer

G. Unlabeled PV Installations

Figure 15 shows an example of a residential customer with PV panels installed which are not marked in the utility model. There are many reasons why unmarked PV installations may exist in a utility model, including the relevant updates not being entered into the model in a timely manner (or were lost) and non-permitted installations [36].

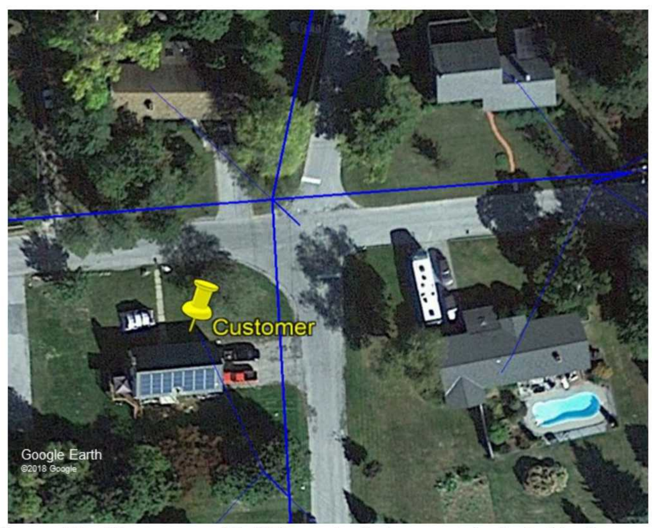

Figure 15 - Customer with PV panels that are not included in the utility model.

H. Incorrect Secondary System Line Lengths and Customer Position

Utilities often have little information about the conductor types or lengths between the service transformer and the AMI meters on low-voltage networks. Even in cases when this system is modeled, the precise distances and locations may be incorrect. In [37], secondary system parameter estimation is performed using linear regression. They also were able to leverage Google Earth images to verify selected results. Figure 16 shows the topology, as it was labeled in the utility model, of three customers connected to the same transformer. Figure 17 shows the actual topology, showing that Customer 3 is both marked in the wrong location relative to the transformer and is much farther away from the transformer. For more results and details, see [37].

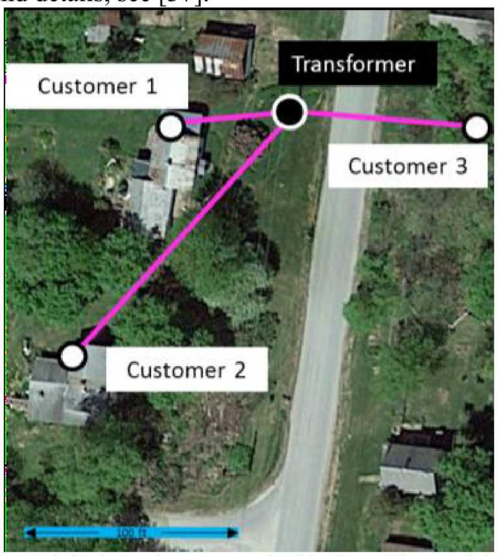

Figure 16 - Original topology as marked in the utility model with customer 3 marked too close to the transformer and where there is not a house [37]

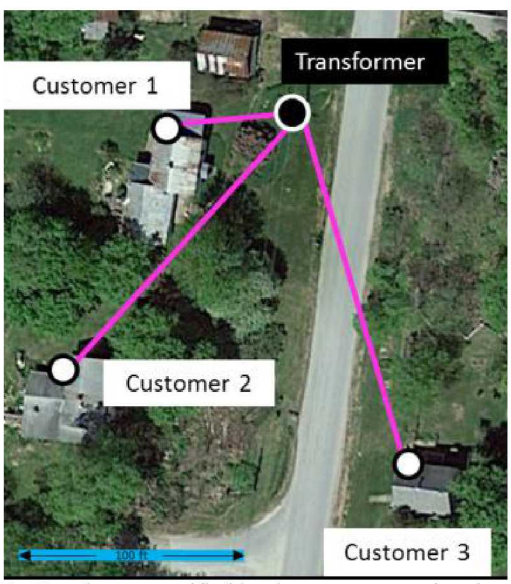

Figure 17 - Topology as verified by the parameter estimation algorithm and Google Street View images [37]

IV. Conclusion

This paper addresses some error types that can be expected in the GIS data and distribution system models built based on GIS data. This paper demonstrates the presence of these errors in a real utility distribution feeder and demonstrates the efficacy of using correlation coefficients to aid in determining both the error and potentially its solution. Examples shown include phase label errors, customer-transformer mapping/connection errors, single-phase customers marked as two-phase customers, unmarked transformers, customers lacking geographical coordinates in the model, unmarked PV installations, and three-phase customers marked as single-phase customers. Table 1 provides a non-comprehensive list of the error types that may be present in distribution system models as well as a selection of references demonstrating current work is those areas.

Understanding the types of errors that are typical in distribution system models, identifying the errors, and correcting those errors is critical in integrating growing penetration of DER into the distribution systems. Accurate distribution planning and operation applications, such as load flow and hosting capacity analysis rely on accurate distribution system models. Moving forward, integrating growing penetration of DER will require increasingly accurate and detailed distribution system models.

V. Acknowledgements

This material is based upon work supported by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE) under Solar Energy Technologies Office (SETO) Agreement Number 34226.

Sandia National Laboratories is a multi-mission laboratory managed and operated by National Technology and Engineering Solutions of Sandia, LLC., a wholly owned subsidiary of Honeywell International, Inc., for the U.S Department of Energy's National Nuclear Security Administration under contract DE-NA-0003525.

References

[1] W. Luan, J. Peng, M. Maras, B. Harapnuk, and J. Lo, "Smart Meter Data Analytics for Distribution Network Connectivity Verification," *IEEE Trans. Smart Grid*, vol. 6, p. 1, Jul. 2015.

[2] J. Peppanen, S. Grijalva, M. J. Reno, and R. J. Broderick, "Distribution System Low-Voltage Circuit Topology Estimation using Smart Metering Data," *IEEE PES Transm. Distrib. Conf. Expo. Dallas TX*, 2016.

[3] X. Zhang and S. Grijalva, "A Data-Driven Approach for Detection and Estimation of Residential PV Installations," *IEEE Trans. Smart Grid*, vol. 7, no. 5, pp. 2477–2485, Sep. 2016.

[4] R. Mitra *et al.*, "Voltage Correlations in Smart Meter Data," *ACM SIGKDD Int. Conf. Knowl. Discov. Data Min.*, pp. 1999–2008, 2015.

[5] B. Palmintier *et al.*, "On the Path to SunShot: Emerging Issues and Challenges in Integrating Solar with the Distribution System," *Natl. Renew. Energy Lab.*, vol. NREL/TP-5D00-65331, 2016.

[6] V. Schwarzer and R. Ghorbani, "Transient Over-voltage Mitigation: Explanation and Mitigation Options for Inverter-based Distributed Generation Projects," *Elect Veh. Transp Cent. Sch*

Ocean Earth Sci Technol Univ Hawaii Manoa Honol. HI USA, vol. Tech Report HNEI-02-15, Feb. 2014.

[7] 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," *IEEE PES Gen. Meet.*, 2014.

[8] P. Fairley, "Hawaii's Solar Push Strains the Grid," *MIT Technology Review*, [Online] Available: https://www.technologyreview.com/s/534266/hawaiis-solar-push-strains-the-grid/, Jan-2015.

[9] M. Ebad and W. M. Grady, "An Approach for Assessing High-Penetration PV Impact on Distribution Feeders," *Electr. Power Syst. Res.*, vol. 133, pp. 347–354, Apr. 2016.

[10] F. Katiraei and J. R. Aguero, "Solar PV Integration Challenges," *IEEE Power Energy Mag.*, vol. 9, no. 3, pp. 62–71, Jun. 2011.

[11] A. Nguyen *et al.*, "High PV Penetration Impacts on Five Local Distribution Networks Using High Resolution Solar Resource Assessment with Sky Imager and Quasi-steady State Distribution System Simulations," *Sol. Energy*, vol. 132, pp. 221–235, Jan. 2016.

[12] T. A. Short, "Advanced Metering for Phase Identification, Transformer Identification, and Secondary Modeling," *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp. 651–658, Jun. 2013.

[13] F. Olivier, A. Sutera, P. Geurts, R. Fonteneau, and D. Ernst, "Phase Identification of Smart Meters by Clustering Voltage Measurements," *Power Syst. Comput. Conf. PSCC*, 2018.

[14] L. Blakely, M. J. Reno, and W. Feng, "Spectral Clustering for Customer Phase Identification Using AMI Voltage Timeseries," *Power Energy Conf. Ill. PECI*, Feb. 2019.

[15] Y. Ma *et al.*, "Phase Identification of Smart Meters by Spectral Clustering," *IEEE Conf. Energy Internet Energy Syst. Integr. EI2*, Oct. 2018.

[16] W. Wang, N. Yu, B. Foggo, J. Davis, and J. Li, "Phase Identification in Electric Power Distribution Systems by Clustering of Smart Meter Data," in *2016 15th IEEE International Conference on Machine Learning and Applications (ICMLA)*, 2016, pp. 259–265.

[17] B. Foggo and N. Yu, "A Comprehensive Evaluation of Supervised Machine Learning for the Phase Identification Problem," *World Acad. Sci. Eng. Technol. Int. J. Comput. Syst. Eng.*, vol. 12, no. 6, 2018.

[18] M. Sheinin, Y. Y. Schechner, and K. N. Kutulakos, "Computational Imaging on the Electric Grid," in *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017, pp. 2363–2372.

[19] M. Lave, M. J. Reno, R. J. Broderick, and J. Peppanen, "Full-Scale Demonstration of Distribution System Parameter Estimation to Improve Low-Voltage Circuit Models," presented at the IEEE Photovoltaic Specialists Conference (PVSC), 2017.

[20] J. Peppanen, M. J. Reno, R. J. Broderick, and S. Grijalva, "Distribution System Model Calibration with Big Data from AMI and PV," *IEEE Transacation Smart Grid*, vol. 7, no. 5, pp. 2497–2506, Sep. 2016.

[21] Y. Liao, Y. Weng, M. Wu, and R. Rajagopal, "Distribution Grid Topology Reconstruction: An Information Theoretic Approach," *North Am. Power Symp. NAPS*, Oct. 2015.

[22] Y. Weng, Y. Liao, and R. Rajagopal, "Distributed Energy Resources Topology Identification via Graphical Modeling," *IEEE Trans. Power Syst.*, vol. 32, no. 4, Jul. 2017.

[23] A. Guzman, A. Arguello, J. Quiros, and G. Valverde, "Processing and Correction of Secondary System Models in Geographic Information Systems," *IEEE Trans. Ind. Inform.*, pp. 1–1, 2018.

[24] G. Cavraro, R. Arghandeh, K. Poolla, and A. von Meier, "Data-driven Approach for Distribution Network Topology Detection," *IEEE Power Energy Soc. Gen. Meet.*, Jul. 2015.

[25] A. J. Berrisford, "A Tale of Two Transformers: An Algorithm for Estimating Distribution Secondary Electric Parameters Using Smart Meter Data," *26th IEEE Can. Conf. Elctrical Comput. Eng. CCECE*, May 2013.

[26] J. D. Watson, J. Welch, and N. R. Watson, "Use of Smart-meter Data to Determine Distribution system Topology," *J. Eng.*, vol. 2016, no. 5, pp. 94–101, 2016.

[27] J. Peppanen, M. J. Reno, M. Thakkar, S. Grijalva, and R. G. Harley, "Leveraging AMI Data for Distribution System Model Calibration and Situational Awareness," *IEEE Trans. Smart Grid*, vol. 6, no. 4, pp. 2050–2059, Jan. 2015.

[28] P. Jokar, N. Arianpoo, and V. C. M. Leung, "Electricity Theft Detection in AMI Using Customers' Consumption Patterns," *IEEE Trans. Smart Grid*, vol. 7, no. 1, pp. 216–226, Jan. 2016.

[29] S. McLaughlin, B. Holbert, A. Fawaz, R. Berthier, and S. Zonouz, "A Multi-Sensor Energy Theft Detection Framework for Advanced Metering Infrastructures," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 7, pp. 1319–1330, Jun. 2013.

[30] R. Jiang, R. Lu, Y. Wang, J. Luo, C. Shen, and X. S. Shen, "Energy-theft Detection Issues for Advanced Metering Infrastructure in Smart Grid," *Tsinghua Sci. Technol.*, vol. 19, no. 2, pp. 105–120, Apr. 2014.

[31] R. Mohan, T. Cheng, A. Gupta, and V. Garud, "Solar Energy Disaggregation Using Whole-house Consumption Signals," *NILM Workshop*, Jun. 2014.

[32] D. Chen and D. Irwin, "SunDance: Black-box Behind-the-Meter Solar Disaggregation," *Proc. Eighth Int. Conf. Future Energy Syst.*, pp. 45–55, May 2017.

[33] S. Iyengar, N. Sharma, D. Irwin, P. Shenoy, and K. Ramamritham, "A Cloud-based Black Box Solar Predictor for Smart Homes," *ACM Trans. Cyber-Phys. Syst.*, 2016.

[34] "Smart Meters and Smart Meter Systems: A Metering Industry Perspective," *EEI-AEIC-UTC Wash. DC USA*, Mar. 2011.

[35] W. Luan, J. Peng, M. Maras, and J. Lo, "Distribution network topology error correction using smart meter data analytics," in *2013 IEEE Power Energy Society General Meeting*, 2013, pp. 1–5.

[36] P. Rosegg, "Heco Customers Asked to Disconnect Unauthorized PV System." [Online] Hawaiin Electric Available: https://www.hawaiianelectric.com/hawaiian-electric-asking-customers-with-unauthorized-rooftop-pv-systems-to-disconnect-to-ensure-safety-fairness-for-all, Sep-2014.

[37] M. Lave, M. J. Reno, R. J. Broderick, and J. Peppanen, "Full-Scale Demonstration of Distribution System Parameter Estimation to Improve Low-Voltage Circuit Models," presented at the IEEE Photovoltaic Specialists Conference (PVSC), 2017.