TOPOLOGY ESTIMATION FROM VOLTAGE EDGE SENSING FOR RESOURCE-CONSTRAINED GRIDS

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ABSTRACT

Electric grids are the conduit for renewable energy delivery and will play a crucial role in mitigating climate change. To do so successfully in resource-constrained low- and middle-income countries (LMICs), increasing operational efficiency is key. Such efficiency demands evolving knowledge of the grid's state, of which topology—how points on the network are physically connected—is fundamental. In LMICs, knowledge of distribution topology is limited and established methods for topology estimation rely on expensive sensing infrastructure, such as smart meters or PMUs, that are inaccessible at scale. This paper lays the foundation for topology estimation from more accessible data: outlet-level voltage magnitude measurements. It presents a graph-based algorithm and explanatory visualization using the Fielder vector for estimating and communicating topological proximity from this data. We demonstrate the method on a real dataset collected in Accra, Ghana, thus opening the possibility of globally accessible, cutting-edge grid monitoring through non-traditional sensing strategies coupled with ML.

1 INTRODUCTION

Climate change mitigation is a twin challenge: decarbonizing energy production and globally meeting energy needs. Electric grids play a central role in addressing this challenge, and must adapt to deliver electricity between new generation technologies and increasing consumer demand. Especially in low- and middle-income countries (LMICs)—where per capita energy consumption is expected to grow dramatically despite far less investment in grid infrastructure—this growth will require new levels of efficiency and responsiveness in grid operations. This new operating approach should maximize the longevity of existing infrastructure and precisely target costly upgrades.

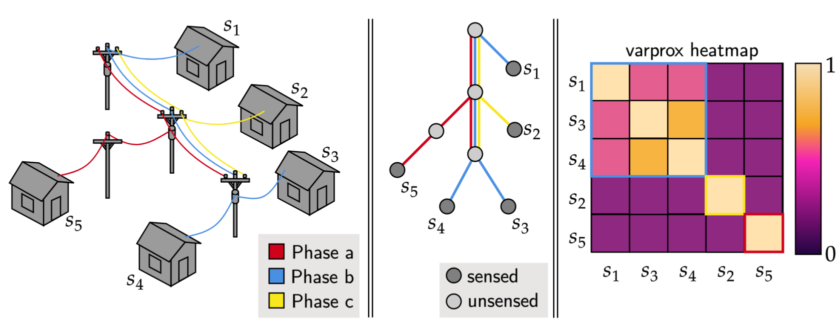

Figure 1: The proposed algorithm reconstructs grid topology using voltage measurements from sensors placed on the edge of the network, and produces a Fiedler vector-based heatmap visualization.

Efficient operation of an electrical grid requires evolving knowledge of the grid's state, of which topology—how points on the network are physically connected, including on which of three phases—is a key piece. Knowledge of grid topology can enable loss reduction by identifying connections for phase re-balancing, locating lossy equipment, and targeting load re-distribution to prolong equipment life. Topological awareness can help localize the root causes of outages for quicker restoration and reduced use of polluting backup generation. Unfortunately knowledge of distribution grid topology is often poor or erroneous, especially in urban areas of LMICs.

Existing solutions for topology estimation demand advanced sensing, such as smart meters or PMUs (Yuan et al. (2022); Cavraro & Kekatos (2018); Yu et al. (2017)); such devices are expensive to purchase, install, and operate and therefore largely absent from LMIC distribution networks. This work demonstrates topology estimation in LMICs by lowering the necessary sensing requirements. By proposing a modification of the transformation in Bariya et al. (2021) and a new visualization, we uncover rich topological information about the proximity of grid nodes from lower-cost, less-precise voltage magnitude sensors at the network edge (Klugman et al. (2021)). To our knowledge, this work presents the first real-world demonstration of topology estimation in the distribution grids of a LMICs from such an accessible data source.

We present an initial evaluation of the proposed method in three selected case studies. The latter case studies expand upon our base method by adding creative sensor deployment strategies and fusing auxiliary data types from the same sensor, including event-triggered point-on-wave snapshots. These case studies lay a promising foundation for topology estimation from low-cost sensor deployments that are designed for the constraints of LMIC grids.

2 Deployment and Data

Our topology estimation method is validated on a dataset from 1,276 PowerWatch sensors deployed in Accra, Ghana. The PowerWatch sensors cost $<1\,\%$ of commercially available PMU sensors that are traditionally used in topology estimation, and have been deployed at scale to monitor grid reliability in LMIC contexts (Klugman et al. (2021)). PowerWatch sensors plug into customer wall outlets and report voltage magnitude, frequency, and power state every two minutes. Due to limited GPS availability indoors, data is only provided with second-level timestamps, which precludes the use of topology algorithms that require precise time-synchronization across sensors. The sensors are deployed in groups of generally 3 but up to 20 sensors called "sites" to monitor a single transformer. As several hundred customers can be served by a transformer, this is an enormous but necessary undersampling, reflecting a reality for topology estimation in LMICs: comprehensive sensing of the distribution network is essentially impossible.

We present four case studies in Accra: two at densely deployed sites—named 59 and 78—with 15 and 20 sensors respectively, a third at many sites spread along Aburi Road, and a fourth at two sites around Darkuman Road. In the latter case studies, voltage magnitude data is compared with two other data types—outage data and point-on-wave (POW)—to demonstrate the value of data fusion for topology recovery. Outage data is obtained by consolidating individual sensor reports into estimated outages via clustering Klugman et al. (2021). We transform this into *outage overlap*: a proximity metric measuring the number of common outages experienced by a pair of sensors, normalized by the total number of outages. The POW data consists of two-second windows of high-frequency 4 kHz data of the *raw* voltage waveform immediately preceding an outage event.

3 Topological Proximity Estimation Algorithm

When measurements are available from only a small subset of grid nodes, complete topology estimation is impossible (Moffat et al. (2019)). Instead, we recover the relative connectivity/proximity of measured nodes, similar to Bariya et al. (2018). Although connectivity alone does not definitively identify topology, it can indicate grid structure and, when presented to a grid operator who has prior knowledge of possible configurations, can suggest the precise topology. Targeted, dense deployments of sensors can provide more precise structural insights, as we show in the site 59 case study.

To obtain a topological metric, we start with the variance of normalized voltage differences. Normalization is important because sensors are sparsely deployed, separated by significant line drop, and possibly under different transformers. This variance is converted to a pair-wise proximity metric $varprox$, bounded between 0 and 1: $varprox_{ij} = 1 - var(\bar{v}_i - \bar{v}_j)/4$ where $\bar{v}_i$ is a normalized voltage magnitude time series segment from sensor i. Voltages are driven by currents across the network; the more nearby the current, the larger the impact on voltage. Therefore, voltages at proximal nodes will track more closely and have a larger $varprox$ (Bariya et al., 2021). For n sensors, $varprox$ can be arranged into a symmetric $n \times n$ matrix with ones on the diagonal. To communicate these values, we propose a heatmap visualization ordered by the Fiedler graph projection. This projection is obtained by representing $varprox$ matrix as a graph with a node per sensor, connected by edges weighted by pairwise $varprox$ values (Horaud (2009)). Thus, two sensors closer together in the physical network are connected by a heavier edge. The Fiedler vector, derived from the graph Laplacian and containing one value per node, succinctly describes a graph's structure, with highly connected nodes given closer vector values. To visualize network proximity and geographic location simultaneously, sensor map locations are colored by Fiedler value.

4 Case Studies

As validation in the absence of ground truth topology, we present four case studies of topology estimation with the proposed method. Taken together, these initial results demonstrate large-scale structure learning, transformer-level connectivity discovery, detection of grid configuration changes, and phase identification, all from low-cost voltage magnitude measurements. All figures associated with the case studies are presented in Appendix A.

Aburi Road: Fig. 2 visualizes $varprox$ for sensors spread along Aburi Road. The Fiedler vector is used to order the heatmap and color sensors on the map. $varprox$ aligns with the spatial ordering along the road, reflecting the likely grid configuration of a line running along the road. There is a distinct proximity group in the south, possibly served by another branch of the grid. This structural information compellingly demonstrates the topological information present in the voltage data.

Darkuman Avenue: In Fig. 3, we compare proximity heatmaps of outage overlap and $varprox$ over several nearby sites served by different transformers. Both metrics show similar proximal sensor groups corresponding to spatial groups, though disagreement increases over smaller groups. The results suggest that outage overlap can be used to bolster voltage-based topology estimates over large regions, with the caveat that it requires a much longer timescale to obtain sufficient outages than to compute robust $varprox$.

Site 78: Fig. 4 visualizes the evolution of $varprox$ at site 78 over three months. The metric is strikingly consistent, revealing a largely stable grid configuration. This amount of topological consistency matches what we would expect over such a time frame.

Site 59: Consistency at this site is similar to site 78. The distinctive proximity change for sensor 10122 is visible even in raw voltage data (Fig. 5). POW snapshots captured just around an outage allows us to identify apparent phase groups: the outage moment allows us to precisely time align the individual waveforms, revealing $\sim 120^o$ shifts between phases. Comparing these groups with $varprox$ groups shows promising correspondence.

5 Conclusion

We present the first demonstration of topology estimation from accessible, outlet-level voltage magnitude data collected in a LMIC. We propose a statistical metric and associated graph projection-based visualization to uncover and communicate topological information. Our case studies on a real world dataset from Accra indicate that operationally valuable information encompassing structure and phase is present in the measurements. This coupling of accessible sensing strategies, thoughtful visualization, and ML algorithms holds the promise of bringing state-of-the-art but traditionally expensive grid monitoring capabilities to LMIC contexts to inform grid-operation.

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A Case Study Figures

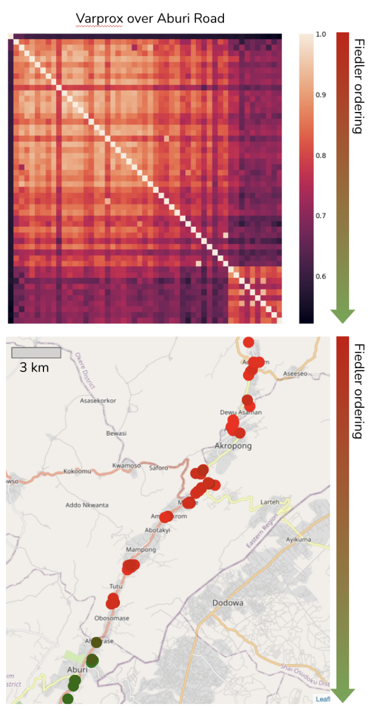

Figure 2: **Proximity along a line:** Fielder-ordered heatmap (top) and sensors colored by Fielder value (bottom) along Aburi Road. A distinct proximity group is visible in the south.

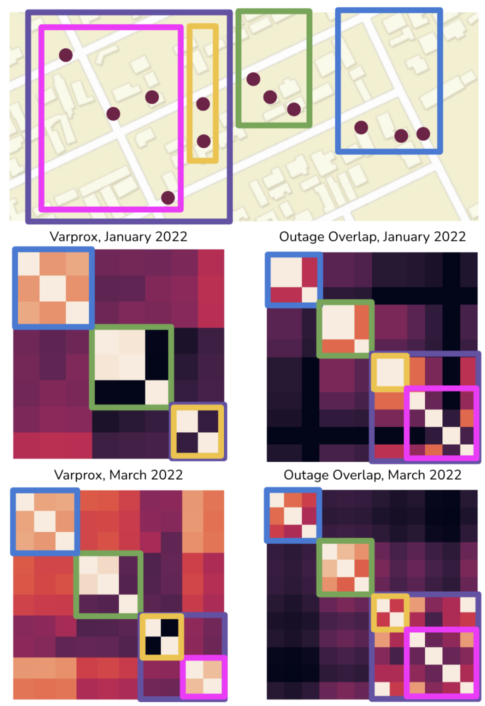

Figure 3: **Proximity under several transformers:** Comparing $varprox$ (left) and outage overlap (right) at Darkuman Ave. Outage overlap can augment voltage-based topology estimates.

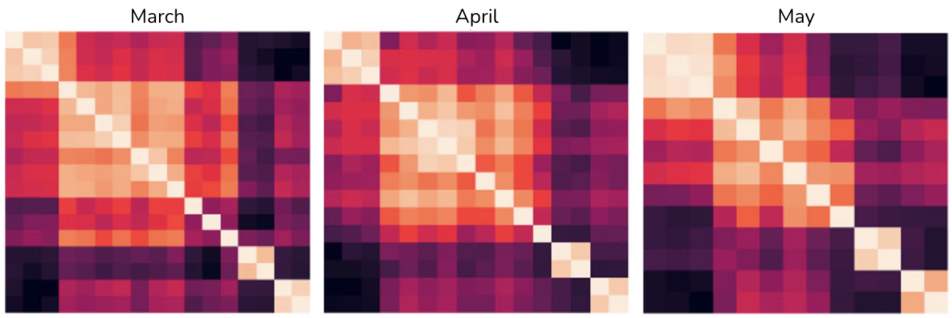

Figure 4: **Topological stability:** The consistency of $varprox$ is clear over three months at site 78.

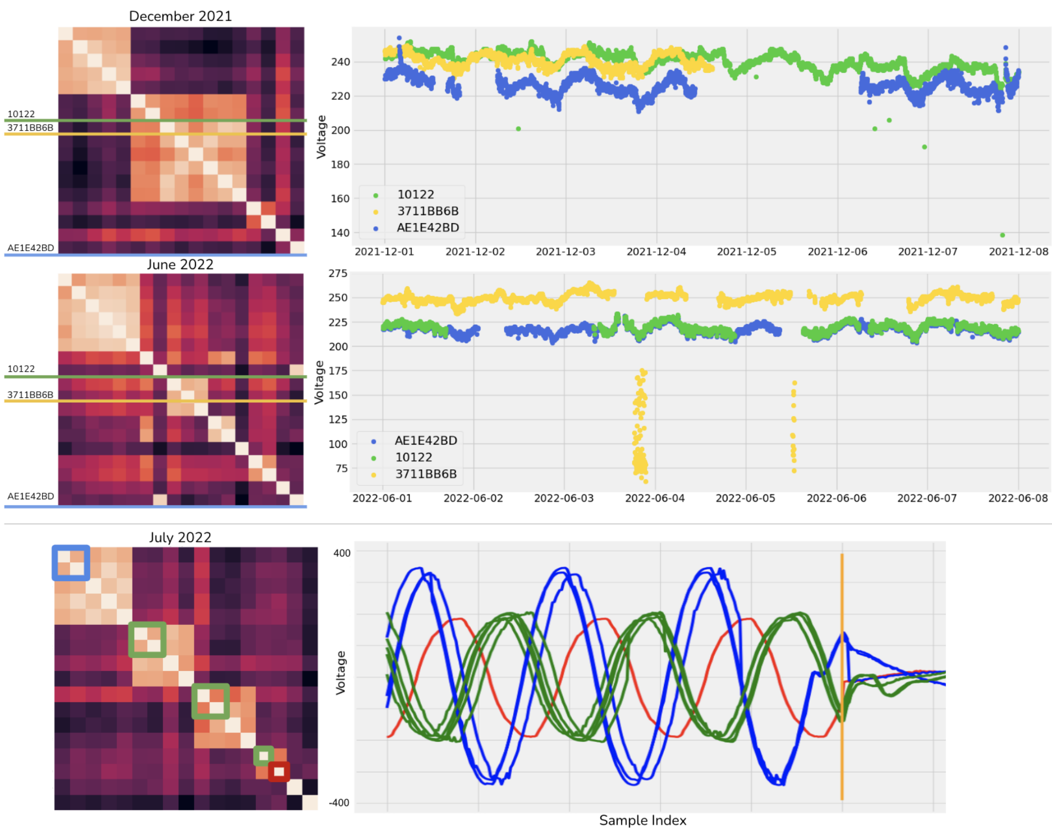

Figure 5: **A topological change and proximity within phases:** Between December and June at site 59, heatmaps of $varprox$ (left) reveal a connectivity change for sensor 10122 which starts proximal to 3711BB6B and shifts to be near AE1E42BD; this is evident in raw voltage data (right). A POW snapshot—precisely time-aligned by the outage event—reveals phase groups that show promising correspondence to $varprox$ groups.