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Learning-based Real-time Outage Location Identification in Power Distribution Systems with Sparse Sensors

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Abstract—**Real-time identification of outage locations in power distribution systems is an essential task for utilities to mitigate the negative impact of power system outages. In this paper, a learning-based model-assisted method is developed for identifying outage locations in power distribution systems in real time. Notably, the method utilizes primarily only a) sparsely located supervisory control and data acquisition (SCADA) measurements, and potentially b) last gasp signals from a small number of smart meters. The method exploits offline training of outage location predictors based on data simulated with synthetically generated load profiles and outage scenarios. The trained predictors can then be used in an online fashion to accurately identify outage locations in new scenarios in real time. With physical-model-based network partitioning, the offline learning is decoupled into training predictors for much smaller sub-regions so that the learning efficiency is much improved. Importantly, the trained predictors based only on SCADA measurements and entropy loss functions can be integrated with smart meter last gasp signals, *without loss of any optimality*, regardless of smart meter locations, outage scenarios, and performance evaluation metrics. Evaluation of the method based on real-world power distribution feeder and load data demonstrates high accuracy in outage location identification even using SCADA measurements only. We then demonstrated how having just a handful of smart meters with last gasp capabilities can further improve the outage location accuracy significantly.**

I. Introduction

One of the most fundamental tasks of utilities in maintaining high power system reliability is identifying outage locations. Identifying line outages in a *fast and accurate* manner can greatly improve utilities' outage management and restoration. Indeed, outage location identification is the first key component of the so-called FLISR (fault location, isolation, and service restoration) tasks. However, locating outages in real time remains a challenging task in utilities' practice. With the ongoing transformation of power distribution systems such as load eletrification and DER integration, real time outage location is even more important and challenging.

Traditionally, utilities rely heavily on customer calls to locate outages in their systems. Beyond this, there has been extensive research on outage location identification based on a variety of information sources. For power distribution systems with radial topologies, based on intermittently updated smart meter load measurements and real-time line sensor measurements, optimal algorithms are developed for outage location identification and line sensor placement [1] [2]. A generative adversarial network is used to detect outages in partially observable distribution systems by capturing anomalous changes in smart meter data [3]. A spectral clustering-based outage detection algorithm is proposed in [4]. [5] introduces a multiple-hypothesis method that utilizes data from smart meters and fault indicators to identify outage locations. A mathematical programming approach is employed in [6] to jointly estimate the topology of the distribution system and outages within the system. [7] employed a multi-label SVM approach to identify line outages in AMI-enabled distribution networks. Relaxing the real-time requirement of outage location identification a bit, a Bayesian network-based method is proposed for outage location in distribution systems by fusing data from multiple sources [8]. Notably, existing work exploiting smart meters for real-time outage identification all rely on the knowledge of actual smart meter measurements of physical quantities such as loads. In practice, however, real-time communications with these smart meters are often unavailable, except for outage-triggered "last gasp" signals that notify system operators when any metered households go into outages.

In this work, we develop a real-time outage location identification method that utilizes primarily only a) sparsely located SCADA sensors, and potentially b) last gasp signals from a handful of smart meters. As such, the developed method can be widely employed in practice. The method employs a framework similar to the spirit of [9]: it exploits offline learning based on simulated synthetic load, outage, and measurement data to train effective outage location predictors for online uses in real time. Several physical-model-based principles are utilized to reduce the dimension of the learning tasks by partitioning the power network into much smaller sub-regions without loss of any performance optimality. We further showed that the learning procedure can be conducted independently with potential subsequent incorporation of any smart meter last gasp signals, again without loss of any optimality. Evaluation based on real-world feeder and load data demonstrated that the developed method, even with SCADA measurements only, can identify outage locations with reasonably high accuracy. Moreover, with just a small number of smart meters providing last gasp signals, the identification accuracy can be further improved significantly.

II. System Model and Problem Formulation

Consider a power distribution system with single, two-phase, or three-phase distribution lines. During its operations, the

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circuit breaker statuses always satisfy that the network topology is radial. We assume that the topology and line parameters are known to the system operator. An illustrative example is depicted in Figure 1. In this example, buses connected by only a single phase line are denoted by the phase "A", "B", or "C" next to the bus index. Located on each bus are end users.

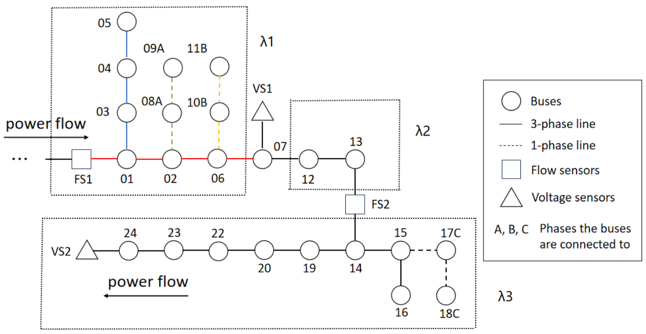

Figure 1: An illustrative diagram of a distribution system.

As typically present in supervisory control and data acquisition (SCADA) systems in power distribution systems, we assume that the following sensors exist in the system:

- A sensor located at the feeder head that measures the complex voltage and currents of all the existing phases at the feeder head. For short, we term sensors that measure both complex voltages and currents "flow sensors".
- Flow sensors located at connected circuit breakers that measure the complex voltages and currents of all the existing phases on the connected circuit breakers.
- Voltage sensors located at disconnected circuit breakers and capacitor banks that measure the complex voltages of all the existing phases at the buses connected to them.

These SCADA sensors provide *real-time* measurements updated every few seconds. Notably, the presence of SCADA sensors is often very *sparse*, thus providing real-time but only sparsely located measurements in the system.

In addition, there are potentially also smart meters present in the system. Notably, we do not make any assumption about their presence; in the extreme case, there could be no smart meter at all. In practice, a smart meter measures the nodal loads but does *not* communicate its measurements in real time to the system operator, (a typical communication schedule would be daily). Thus, unlike SCADA, we do not assume any real-time measurements from smart meters present in the system. Nonetheless, a smart meter often provides a "last gasp" signal in real time when the household it measures goes into outage. As such, such outage-event-triggered last gasp signal is the only assumed *real-time* information available from smart meters.

When a line outage occurs in the system, the objective of this work is to identify, in real time, the location of the line outage based on all the real-time information available, i.e., real-time measurements from SCADA sensors, and any last gasp signals from smart meters if they exist. It is important to note that the real-time nodal load information is *not* available for use.

III. Methodology

As we do not make any assumption about the existence and locations of smart meters, we consider the case *without any smart meter* as a "baseline" case, and then address the general case with arbitrary smart meter deployment. To be clear, such a baseline case is in fact the *most challenging* one in terms of achieving high performance, because any available smart meter last gasp signals would always help improve the performance as they reduce the set of possible line outage hypotheses.

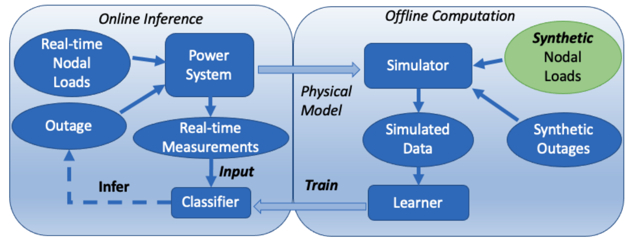

Figure 2: Offline training for online prediction.

For the baseline case, due to the typically very sparse presence of SCADA sensors, it is intuitively very challenging to identify the location of an outage based only on the SCADA measurements. The difficulty is especially compounded by the fact that the nodal load information is not available. It is thus perfectly possible that one outage under some geographical load profile can lead to SCADA measurements very similar to those observed with a different outage under some other geographical load profile. On the flip side, load profiles in practice are not arbitrary, and the statistical rarity of such "adversarial" scenarios could imply that a desirable accuracy of outage location identification may still be achievable. To fully capture and exploit the intricate relations between outages and the corresponding SCADA measurements, we employ a *data-driven* approach that trains predictors that take only SCADA measurements as inputs and output outage locations. The general steps are as follows:

- *Offline*: Generate synthetic load-outage-measurements data via extensive simulations.
- *Offline*: Train predictors based on the simulated data.
- *Online*: Utilize the trained predictors to produce real-time decisions of outage locations facing new load and outage scenarios.

An overall diagram of this offline-learning-from-simulation and online-prediction framework is depicted in Figure 2. We note that this framework resembles the "learning-to-infer" approach as developed in [9]. Under this framework, we exploit the *characteristics of the physical models* of the grid and sensors to simplify the learning process. In short, rather than training an overall predictor for an entire feeder that encompasses all the lines as potential outage locations, network partitioning can be performed so that outages across different partitions can be *perfectly distinguished* based on physical laws. As such, the learning needs only be performed with much smaller sets of hypotheses, and thereby the learning efficiency can be much improved. More details follow.

A. Synthetic Data Generation

Ideally, synthetic nodal load data should be generated following the same statistical distribution as the real-world load data. However, knowledge of the latter at a granular time scale (e.g., hourly or shorter) can only be available if smart meters are present. As smart meters are not necessarily available in practice, we cannot assume synthetic data can be generated

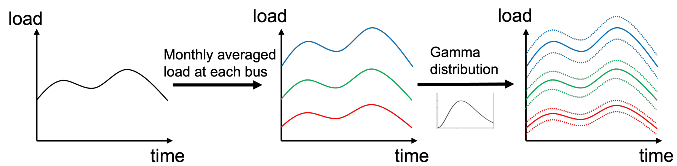

Figure 3: Synthetic load data generation. Left: hourly load profile in the entire region measured by flow sensors. Middle: baseline load profile at each bus scaled by monthly load. Right: random synthetic load profile generated by gamma distribution, with mean equals to the baseline load profile at each time.

as such. Indeed, we again make no assumption about the presence of smart meters when generating the synthetic load data. As such, our data generation process is widely applicable in practice.

Specifically, our synthetic load data generation only relies on information that all utilities have access to: a) time series of aggregate load measurements by SCADA sensors at feeder heads and circuit breakers, and b) individual customers' monthly total loads measured for billing purposes. Notably, the former is granular in time but aggregate in customers, while the latter is granular in customers but aggregate in time. In essence, we would like to utilize these two types of information to generate synthetic loads that are granular in both time and customers. The process is as follows (cf. Figure 3):

1) From the time series of aggregate loads and the individual monthly loads, we generate "baseline" loads at all the buses that a) share the same temporal profile as the aggregate time series, and b) have different magnitudes proportional to their monthly totals.
2) The synthetic load at each time and each bus is then randomly generated by passing the above baseline loads into the Gamma distribution as means. The reason of choosing Gamma distribution is that it faithfully characterizes load distribution based on the real-world data set we use.
3) The real power P and reactive power Q at each bus at each time are then generated as follows:
   a) P takes the value of the randomly generated load.
   b) Q is determined by P and the power factor (PF) of the load at the corresponding bus:

$$Q = P \times (\tan(\arccos(PF))).$$

   Without assuming smart meter data, the precise values of these PFs are unknown. We pick the PF values randomly between 0.9 and 0.99 for each bus at each time [10].

With the synthetic load data, we can then simulate line outages at all potential outage locations, and compute the resulting SCADA measurements from such outages and load profiles.

B. Network Partitioning

We now exploit the physical characteristics of the distribution system and the sensor locations to decouple an entire feeder into regions where outages from each region can be perfectly distinguished by physical-model-based logic rules. In short, we first partition the feeder into regions according to the locations of the circuit breakers and capacitor banks where flow and voltage sensors are deployed. Next, within each region, the network is further partitioned according to line phases. While the partitioning principles are theoretically proven as follows, we indeed observe that such partitioning is numerically 100% validated by our trained predictors. In other words, we observe that predictors trained in a completely data-driven fashion that are agnostic to the physics-based network partitioning principles can automatically distinguish outages among different partitions with 100% accuracy.

1) Network Partitioning by SCADA Sensor Locations: Consider there are M flow sensors, including the one located at the feeder head, in a distribution system with a *radial topology*. The distribution system is then partitioned into M regions, each again having a radial topology with a flow sensor located at its root and potentially other flow sensors at some of its leaves. An illustrative example is depicted in Figure 1 where the feeder is partitioned into two regions, $\lambda_1 \cup \lambda_2$ and λ_3. Outage detection in these two regions can then be independently performed (see [1] [2] for more details). Furthermore, with the voltage sensor, outages from λ_1 and λ_2 can be perfectly distinguished by simply examining whether each sensor measures anything non-zero.

2) Network Partitioning by Line Phases: Regions can be further partitioned into sub-regions based on line phases. For example, a three-phase line outage will create an impact on all the three-phase voltages and currents measured by SCADA sensors. In contrast, a single-phase line outage will only affect the currents and voltages of that specific phase. Another piece of information is again whether each SCADA sensor at one of the leaves of a region measures anything non-zero: if a SCADA sensor at a leaf measures a zero voltage, there must be an outage on the path from this leaf to the feeder head. Otherwise, there must be no such outage on this path. An illustrative example of such further partitioning into sub-regions is depicted in region λ_1 in Figure 1: each section of λ_1 in a different color represents a partitioned sub-region, and outages in different sub-regions can be distinguished from each other perfectly.

C. Offline Training for Online Prediction

Within each sub-region, we perform offline training of a multi-class predictor, with each class corresponding to a possible outaged line, based on the generated synthetic dataset. In particular, we employ the *entropy loss* as the training loss function. This implies that the trained multi-class predictor automatically produces the estimated *posterior probability* of each line outage hypothesis. As such, a *confusion matrix* can be computed that consists of, for each (i, j) pair, the probability of hypothesis i being declared when hypothesis j is the ground truth.

During testing in practice, the metric by which an outage location identification decision is evaluated can depend on real-world causes. One such practical metric is the average error distance (AED), i.e., the average *geographical distance* between the declared line outage and the true line outage. The shorter the AED, the less traveling overhead a repair crew would experience for finding and addressing the outaged line. Specifically, the expression of AED_i, i.e., the average error distance when line i is in outage, is as follows:

$$\text{AED}_i = \sum_{j=1}^{n} d_{ij} \times p_{ij} \tag{1}$$

where $D = [d_{ij}] \in \mathbb{R}^{n \times n}$ is the distance matrix across all the line locations, and $P = [p_{ij}] \in \mathbb{R}^{n \times n}$ is the confusion matrix.

Importantly, regardless of what practical metric is desired, the posterior probabilities are always *sufficient statistics* for optimizing any evaluation metric. Therefore, *it is sufficient to train the predictors using the entropy loss so that the posterior probabilities are estimated*, and the trained predictors can then be used, *without loss of optimality*, to make outage location identification decisions based on whatever practical metric (such as AED). In other words, there is no need to re-train predictors tailored to different metrics.

D. Incorporating Smart Meter Last Gasps

When a smart meter is deployed at a bus, (or more precisely, at one of the customers on that bus,) if this bus is in an outage, a last gasp signal will be sent from the smart meter to the grid operator. Therefore, whether a last gasp signal is received from a smart meter further changes the set of possible lines on which an outage could have occurred. As such, summarizing the snapshot of whether a last gasp signal is received from each smart meter present in the system, each partitioned sub-region can be *further reduced* to an even smaller set of outage hypotheses.

Notably, the impact of the smart meters on the outage hypotheses depends on not only a) the locations of the smart meters, but also b) the instances of last gasps signals. Both can change over time as a) the locations can evolve with new smart meter deployment, and moreover b) the actual last gasps signals can vary across different outage instances. Fortunately, we will show next that *it is again not necessary to re-train predictors* tailored to any specific reduced set of hypotheses based on last gasp signals. Instead, *it is sufficient to train predictors only for the baseline case without smart meters*, and optimal outage location identification decisions can be made by jointly utilizing the trained predictors and whatever last gasp signals there are.

Specifically, consider the posterior hypothesis probabilities provided by the predictor trained for a baseline case, denoted by $P(x = i)$ for all potential outage locations i in a sub-region. Consider that the last gasp signals reduce the set of possible outage hypotheses to a subset $\mathcal{S}$. The updated posterior probabilities given the last gasp signals can then be computed as follows: for $i \notin \mathcal{S}, P(x = i|x \in \mathcal{S}) = 0$; for $i \in \mathcal{S}$,

$$P(x = i|x \in \mathcal{S}) = \frac{P(x = i, x \in \mathcal{S})}{P(x \in \mathcal{S})} = \frac{P(x = i)}{\sum_{i \in \mathcal{S}} P(x = i)}. \quad (2)$$

As such, the updated posterior probabilities can be straightforwardly computed based on the "baseline" posterior probabilities $\{P(x = i), \forall i\}$ using (2). In other words, these baseline posterior probabilities are again *sufficient statistics*. As such, regardless of the actual smart meter locations and their last gasp signals, it is sufficient to just train a baseline predictor assuming no smart meter presence. This decoupling between the learning and the optimal decision-making based on smart meter last gasp signals greatly simplifies the outage location identification method.

IV. Data-Driven Evaluation

We evaluate the proposed method based on real-world data of a distribution system feeder in the Midwest U.S. with time series load data available at each bus [10]. We note that, since we make no assumption of smart meter presence, throughout our evaluation we do not assume that the system operator has any access to the nodal time-series load data. These load data are only used in *testing* for generating realistic testing scenarios.

A. Data Preparation

1) Synthetic Data Generation: Based on the method described in Section III-A, a total of $100,000$ samples of smart meter data are generated. The coefficient of variance (CV, i.e., standard deviation to mean ratio) used to generate random load on each bus is set as 0.7. This is higher than the real-world average CV of 0.43 so that the generated synthetic load data have good coverage of the real-world situations. With the generated load data, outage scenarios are generated for all the lines and AC-power flow is simulated in OpenDSS with which SCADA sensor readings are recorded.

Notably, the generated synthetic data are used for training and validation (with a 5-fold cross-validation). The testing data are based on *real-world* nodal load time series collected from this feeder. As such, none of the testing data is seen during training as the training is solely based on synthetic load data.

2) Estimating Real-world Bus Locations: To evaluate outage location identification performance with the AED metric (1), we would need the locations of all the buses. The real-world coordinates of the buses are however not available from the feeder data set. We reconstructed the approximate real-world system topology by estimating the bus locations based on line lengths as well as the relative directions between each bus provided in the system model. For example, after our reconstruction, the abstract topology of a part of the feeder as depicted in Figure 4 has the approximate real-world topology as depicted in Figure 6.

B. Predictor Model

Within each sub-region, we employ fully connected neural networks (FCNNs) with skip connections to train a predictor for the multi-class classification problem of outage location identification. The FCNN with skip connections is a predictor model architecture that enhances the model's ability to capture both local and global dependencies within the data. By incorporating skip connections, the model can effectively propagate information from earlier layers to later layers, allowing for the preservation of valuable features throughout the network. Rectified Linear Units (ReLUs) are employed as the activation function. As we conduct semi-static power flow simulations, the input to a predictor consists of SCADA measurements at *two* time instances: one is right before an outage and another is right after the outage. The outputs are the posterior probabilities of the outages on all the lines in the sub-region.

C. Line Outage Location Identification

We first evaluated our proposed method on a region consisting of 48 buses from the original 240-bus system. The two blue blocks indicate flow sensors on the connected circuit breakers, and the three orange circles indicate voltage sensors on the capacitor banks and disconnected circuit breakers. The subsets of lines of different colors are the partitioned sub-regions of this region (cf. Section III-B). We present the line outage location identification accuracy achieved with the trained predictors for the *baseline case without any smart meter*. In Figure 4, the color-coding of the line indices represents the accuracy of outage

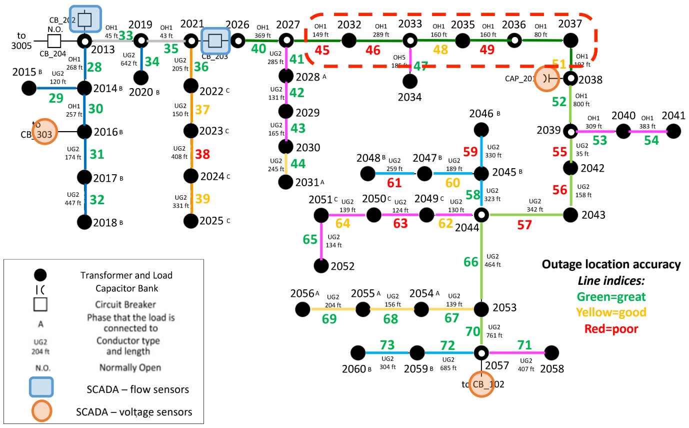

Figure 4: Outage location identification accuracy map, SCADA only.

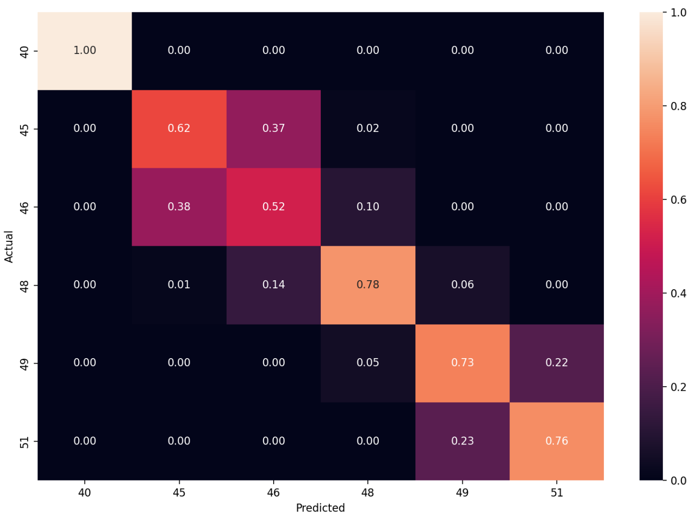

Figure 5: Location identification within one hop of the true locations.

detection. A green index indicates an identification accuracy above 95%. A yellow index indicates an accuracy above 75%. A red index indicates an accuracy below 75%. We see that, even without any smart meter, only based on very sparsely located SCADA sensors, very accurate outage location identification can already be achieved. For those line outages with low identification accuracy (i.e., the red-colored line indices), we nonetheless observe that the inferred outage location is almost always *within one hop* of the true outage location. For example, for the upper sub-region of the feeder enclosed in the red dashed box, we further plot its confusion matrix in Figure 5: the observed *banded structure* clearly indicates the within-one-hop localization performance even if the inferred outage location is not exactly the actual one.

In addition to the identification accuracy plot, we further plot the average error distances (AEDs) computed based on the approximate real-world locations of the buses. As depicted in Figure 6, each line is plotted with a bubble that indicates the AED when an outage occurs on this line. Smaller bubbles indicate better outage localization performance. We note that the line outages with above 95% identification accuracy can have bubbles that are almost invisibly small. This bubble plot again

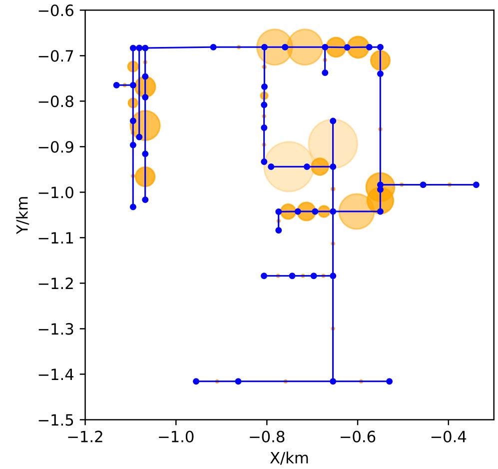

Figure 6: Average error distance map, SCADA only.

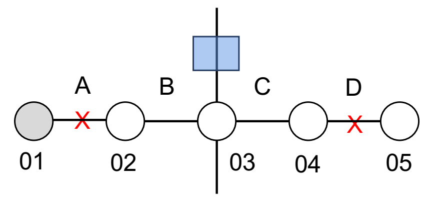

Figure 7: A smart meter that breaks the indistinguishability.

demonstrates the great outage localization accuracy achieved even with SCADA measurements only.

D. Incorporating Smart Meter Last Gasps

Next, we note that there are cases where it is *fundamentally difficult* to distinguish between different line outages using only SCADA measurements. A conceptual example is depicted in Figure 7: if two exactly the same loads (buses 1 and 5 in this case) are symmetrically connected to lines that join at a bus (bus 3 in this case), even with a flow sensor as depicted above bus 3, there is still fundamentally no way to distinguish between the shedding of either of the two loads (i.e., outages of line A vs. D). Indeed, we have numerically verified that the voltages and currents measured at the flow sensor under the two outage scenarios always read exactly the same values. Such fundamentally indistinguishable cases can indeed occur in practice. In Figure 8, we plot the topology of another region of the 240-bus system, consisting of 75 buses in total. In the sub-region encircled by the red box, an outage in the upper section can be mistakenly detected as one in the lower section (and vice versa) if the load sheds due to the two outages are similar. In Figure 9 (left panel), the bubble plot of AEDs achieved using only SCADA measurements is depicted. We observe that line outages that are far away but fundamentally indistinguishable can lead to large AEDs.

As discussed in Section III-D, smart meters can provide last gasp signals which can effectively address the aforementioned fundamental indistinguishability. To illustrate this, consider that a single smart meter is placed at bus 1 in the above example (cf. Figure 7). If an outage occurs in line A or B, a last gasp signal from bus 1 will be received, whereas an outage in line C or D will not result in a last gasp signal. As such, the two previously indistinguishable outages (A and D) are now perfectly distinguishable. Based on this insight, by deploying

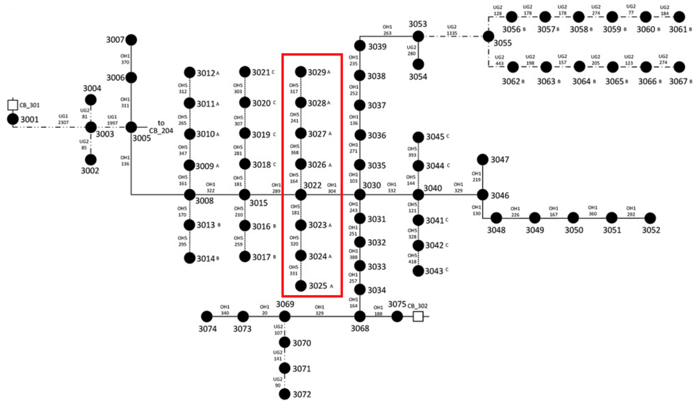

Figure 8: A region with a sub-region having fundamentally indistinguishable outages.

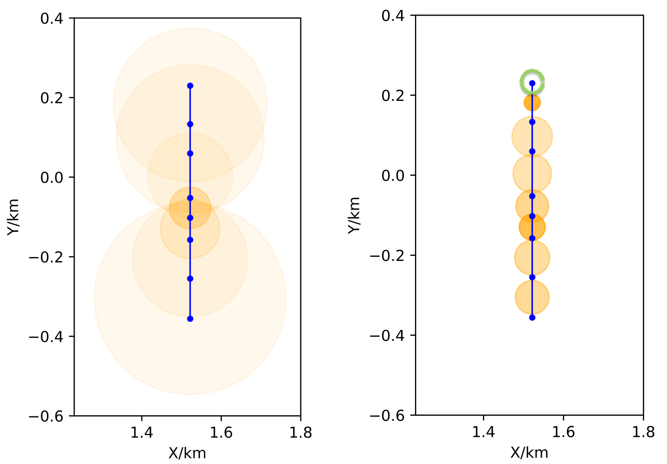

Figure 9: Average error distances before (left) and after (right) installing just one smart meter at the top bus.

just a single smart meter at the leaf of the upper section of the encircled sub-region in Figure 8, much reduced AEDs can be achieved as depicted in Figure 9 (right panel). In general, the AEDs of this entire region based on SCADA measurements only is plotted in Figure 10, and that with just *four* smart meters' last gasp signals is plottied in Figure 11. Significant performance improvement can be observed.

V. Conclusion

We developed a highly effective data-driven model-assisted method for identifying outage locations in power distribution systems in real time. The method utilizes primarily only a) sparsely located SCADA measurements and potentially b) last gasp signals from a small number of smart meters, and is hence broadly applicable in practice. The method exploits offline learning from simulated data based on synthetically generated loads and outage scenarios. Importantly, by exploiting physical model characteristics, the dimensions of the learning tasks are much reduced with network partitioning without any potential loss of performance. Moreover, predictor training needs only be performed with SCADA measurements, and any potential last gasp signals from smart meters can be incorporated with the trained predictors regardless of smart meter locations, outage scenarios, and evaluation metrics, *without loss of optimality of detection decision making*. Based on evaluation with real-world feeder and load data, high performance of the developed

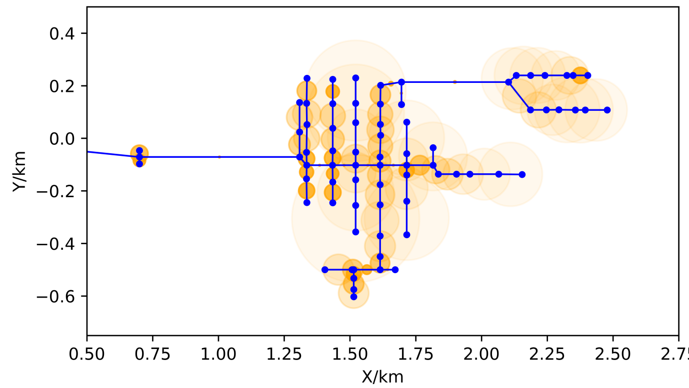

Figure 10: Average error distance map, SCADA only.

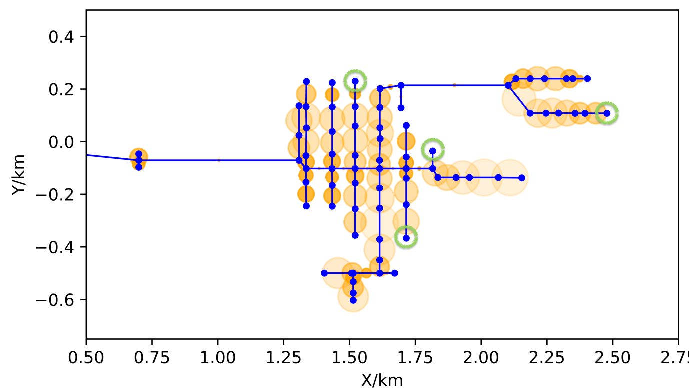

Figure 11: Average error distance map, with 4 smart meters.

method is demonstrated even with SCADA measurements only. Significant performance improvement can be achieved with just a small number of smart meters providing last gasp signals.

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