Loss Estimation and Visualization in Distribution Systems using AMI and Recloser Data

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***Abstract*—Distribution system losses account for a large percentage of energy losses from generation to customer; however, utilities still have limited possibilities to determine or analyze losses in their networks. There is little or no awareness of current loss conditions in the system, and traditional loss studies typically focus on peak load scenarios. This lack of awareness is disadvantageous as losses convey information about system efficiencies and could indicate existing or impending outages. The approach proposed in this paper relies on already deployed AMI and recloser infrastructure and is used to evaluate distribution system losses over time and divided by load areas. The results are displayed in multiple ways in order to allow operators to assess the system state and to examine anomalies attributable to distribution losses. The paper presents the application of the developed algorithm to a real-world circuit.**

***Index Terms*—advanced metering infrastructure (AMI), big data, data visualization, distribution system losses, loss estimation, situational awareness, visual analytics**

I. Introduction

The advent of advanced metering infrastructure (AMI) and sensors throughout the distribution system has led to increased situational awareness for utilities, including in areas such as billing, outage management, and asset management. Traditionally, these functions were carried out manually by utilities, and were thus inefficient as utilities were unable to capture the actual state of the distribution system at a particular point in time. More recently, AMI, SCADA and higher number of sensors in the distribution system have provided opportunities to monitor system parameters such as voltage, current, power consumption, and losses, in real-time due to the large amount of data available from these sources.

Typically, utilities estimate distribution system losses by comparing wholesale power purchase bills with manual meter reading from customer sites. This approach is laborious and error-prone; with increasing AMI penetration, automated procedures are being explored. With increased AMI penetration at the distribution level, real-time and spatially resolved estimations of distribution losses, which have long been a promise of the smart grid, can now become accessible to utilities [1], [2]. This is demonstrated for example in a method proposed by Triplett et al. to evaluate losses for an entire distribution circuit using AMI and GIS data [3].

Losses are of paramount importance to utilities, as they indicate inefficiencies in their networks, which in turn translate into lost revenues. Detailed information would allow utilities to monitor the impact of replacing old and inefficient equipment, and to identify where increased losses with an associated rise in temperature could lead to accelerated ageing of devices in the distribution network [4], [5]. Thus, losses may convey information about impending equipment failure in addition to current network conditions.

Several studies have been conducted on the value of big data analytics in distribution systems for load forecasting, state estimation, and outage management and prediction [6]–[8] yet most research concerning outages was focused on outages due to weather, animals and vegetation [9]–[13]. Hence, this paper describes a novel technique for loss estimation and visualization in distribution systems using data collected from various sources in the circuit. These sources include advanced metering infrastructure (AMI), recloser power measurements, geographic information systems (GIS) and electrical circuit models.

Automated data analytics is one way to cope with the sharp increase in available data, but it is also essential that a human be placed in the loop at the right place and time. Visual analytics leverages human perceptive and pattern recognition skills such that the right visual interface leads to effective and situationally aware users who can discover relevant items and turn them into decisions [14], [15]. This paper presents results from the developed loss estimation technique and its application to a real-world distribution circuit together with the resulting loss visualizations.

The rest of the paper is structured as follows. Section II describes the available data sources and the process developed to evaluate losses in the distribution system. Section III presents the application of the described techniques to a real-world distribution circuit. Section IV presents possible ways to visualize the generated loss data. Section V summarizes the work presented and its role in the vision for increased situational awareness of distribution systems via visual analytics. It also gives an overview of future research opportunities.

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II. Loss Estimation using AMI and Recloser Data

This paper leverages the comprehensive measurements now available in the distribution system due to widespread adoption of AMI. This study also incorporates data from reclosers with measurement capabilities installed in the circuits under study. Combining these two data sources allows for loss estimations in circuit sections confined by the reclosers. The resulting loss data vary in time and space and can be visualized in various ways, such that the user can then identify spatial, temporal and categorical patterns in the losses.

A. Data Sources and Data Cleansing

The AMI dataset contains real and reactive power measurements for distribution transformers in the investigated circuits. The meter readings are aggregated per transformer in order to obfuscate load patterns of individual households, thus mitigating data privacy concerns. The recloser dataset includes recloser measurements of line voltages, currents, phase angles and harmonic distortions. These measurements along the main feeder facilitate the partition of the distribution network into distinct load areas with computable power inflows. In this study, a load area refers to a part of the distribution network bounded by two reclosers. In a case where a recloser has no downstream recloser, the load area refers to the part of the network downstream of that recloser. Fig. 1 shows the load areas for the distribution system used for this study.

Location information about all equipment under consideration is listed in the GIS dataset, where latitude and longitude coordinates are assigned to every network device. The circuit topology data specify all network elements along with their mutual electrical interconnections and represent the information basis from which the load areas can be extracted.

The provided data is preprocessed before integrating the heterogeneous information sources. At the most fundamental level, access to the raw data is not given due to specific proprietary file formats used by vendors of distribution network equipment. It was therefore necessary to convert those files to an open and standardized file format. For this work, the IEEE COMTRADE format [16], commonly used for transient power system analysis, was chosen.

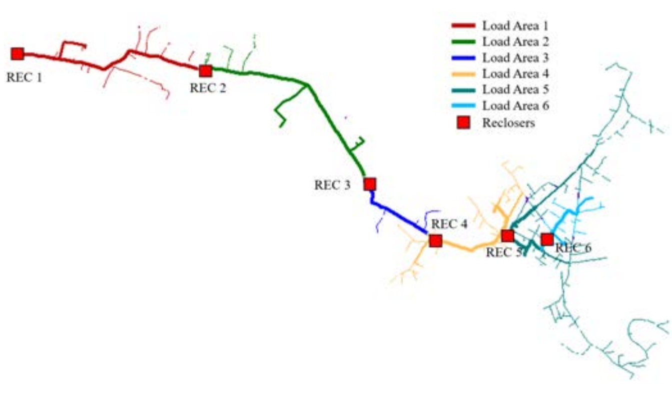

Fig. 1. Distribution system under study, depicting location of reclosers (PCRs) and load areas

Another challenge typical to distribution systems is ensuring time synchronous measurements from different monitoring devices. This time-synchronization includes establishing a common time zone for AMI and recloser data, and integrating data sources with measurements at different points in time. To resolve this, one time series is resampled during preprocessing employing linear interpolation in order to match the sample times of the other time series.

B. Loss Estimation

At the core of the presented loss estimation technique lies the partitioning of the distribution circuit into distinct load areas, each confined by reclosers capable of measuring power flow at their respective locations. Since a manual allocation of distribution transformers to those load areas would be cumbersome for initial investigations and would prohibit analysis of more extensive circuits, an algorithm was developed for this task.

Starting from the circuit head, this algorithm performs a depth-first search, during which each discovered node can be either a load contained in the current load area or an intelligent recloser, which marks the boundary to the next area. The resulting circuit structure containing a list of all encountered areas can then be exported for further loss analysis. The power flow within a given load area is calculated using (1) below:

$$P_{\text{in}} = P_{\text{REC, in}} - \sum_{j \,\in\, O} P_{\text{REC, j}} \tag{1}$$

where P_{in} is the power inflow to a load area, $P_{\text{REC, in}}$ is the power measured at the entry to the load area, $P_{\text{REC, j}}$ is the power measured at the exit recloser(s), and O represents the set of outbound reclosers.

With all the loads for a specific load area given by the circuit partitioning, the transformer power data is to determine the overall power consumption within that area given in (2):

$$P_{\text{Consumption}} = \sum_{i \,\in\, T} P_{\text{AMI, i}} \tag{2}$$

where $P_{\text{Consumption}}$ is the power consumption calculated by the transformers, T, and $P_{\text{AMI, i}}$ is the sum of real power measurements from all AMI meters, within the load area under consideration. Equation (2) is based on the assumption (true for our test case) that all customers are connected to the circuit using smart meter devices.

Subtracting power consumed by customers located inside the load area from the power flow into that area, as measured by the confining reclosers, results in the section loss estimate given in (3) below:

$$P_{\text{Loss}} = P_{\text{in}} - P_{\text{Consumption}} \tag{3}$$

The losses within each load area consist of the primary and secondary line losses as well as load and no-load distribution transformer losses and should therefore follow a regular pattern. Spikes in losses or other deviations indicate abnormal conditions, which can hint at problematic system states or events.

Since the circuit partitioning is based on reclosers with measurement capabilities as load area boundaries, an increased number of such reclosers naturally leads to finer spatial resolution for the loss estimate. This in turn could prove beneficial for analysis purposes and for localizing error sources in case of noticeable increases in losses within a load area.

The loss estimation method is based on the assumption that all the loads within the examined load area are connected using smart meters. Missing AMI data pertaining to a transformer listed in a load area would therefore be interpreted as an additional loss of significant magnitude. Even though the loss estimation algorithm could provide an educated guess for this absent record based on data related in space or time, the missing data could then go unnoticed. Lack of such data points is of interest for the utility as they could indicate similar problems during the billing process.

The loss estimation algorithm assumes constant boundary conditions for the distribution network. This assumption could be erroneous in case of protection events; for this reason, measurements following such disturbances must be filtered out or adjusted to be comparable to nominal state values.

III. Case Study

The loss estimation algorithm described in the previous section is applied to a real-world distribution system which comprises AMI, recloser, GIS, SCADA and OMS/DMS data spanning over one month. The two circuits considered for the loss estimation and visualization consist of single-phase and three-phase overhead lines and underground cables. The network characteristics are listed in Table I.

TABLE I
CASE STUDY NETWORK DETAILS

	Circuit A	Circuit B
Total Area	56.2 sq mi	
Conductor Length	49.5 mi	99.6 mi
Number of Transformers	423	728
Total Transformer Capacity	15.2 MVA	18.4 MVA
Number of Reclosers	6	10
Loading Conditions		
Minimum	637 kW	1055 kW
Maximum	3275 kW	7655 kW
Average	1616 kW	2453 kW

As the distribution system losses vary in space and time, they are best visualized using an interactive plot. In this paper, time series with a fixed location and network representations at a specific point in time are presented. Since the distribution losses consist of both load-dependent and independent components, some variation over time is to be expected. This time dependency is depicted in Fig. 2, which shows the plots of power inflow, power consumption and losses for load area 4 over a 7-day period. The loss peaks coincide with respective peaks of power demand and supply; the same is true for points of minimal loss. In spite of this obvious relation, not all characteristics of the loss curve are proportional to the power inflow and consumption in the load area, possibly indicating other loss mechanisms.

Some loss variations not explained by the change of load are depicted in Fig. 3, which shows power inflow, consumption and losses in load area 6 over a 24-hour period. Around 1 AM, losses rise significantly, even though power inflow and consumption in the area decrease at the same time. Conversely, at 10 AM the same day, losses drop with no discernible correlation to the load, prompting further investigation into possible explanations. It is also interesting to note a periodical pattern in both power inflow and consumption during the depicted timeframe, possibly indicating behavior of specific circuit elements.

Table II shows the loss distribution across the different load areas for circuit A, at 5pm on a summer weekday. Also included in this table is the percentage of total consumption for each load area. It is worth noting that load area 5 accounts for more than half of the losses in the circuit. This can be attributed to the number and length of lines within that load area (see Fig. 1).

The results show a strong correlation between losses and consumption in each load area (expressed as percentages of the total). Again, this dependency is explained by the load-dependent components such as copper losses in conductors and distribution transformers. No-load transformer losses are also captured in the percentage of total power consumption metric, as the amount of transformers increases with the relative share of electricity demand. Loss components independent of the local power consumption can consist of longer conductors to more remote costumers, or higher core losses of distribution transformers of larger, but untapped capacity.

TABLE II
LOSSES IN LOAD AREAS OF CIRCUIT A

Load Area	Losses (kW)	Losses (% of Total)	Power Consumption (% of Total)
1	9.87	7.4	5.5
2	6.75	5.0	2.9
3	1.36	1.0	3.6
4	20.79	15.6	19.1
5	76.23	57.0	53.5
6	18.75	14.0	15.4

Simulation-based verification of the system losses was conducted using the available AMI data to generate representative load models at specific times. Examining the loading conditions using CYMDIST [17] showed similar results for light loading conditions, but considerable differences with increasing load. Some part of this divergence can be attributed to missing transformers in the AMI dataset, but the main cause of the difference in losses is that the CYMDIST circuit model does not include detailed information about the customers connected to the distribution transformers. In the circuit model, distribution transformers have their aggregated loads directly

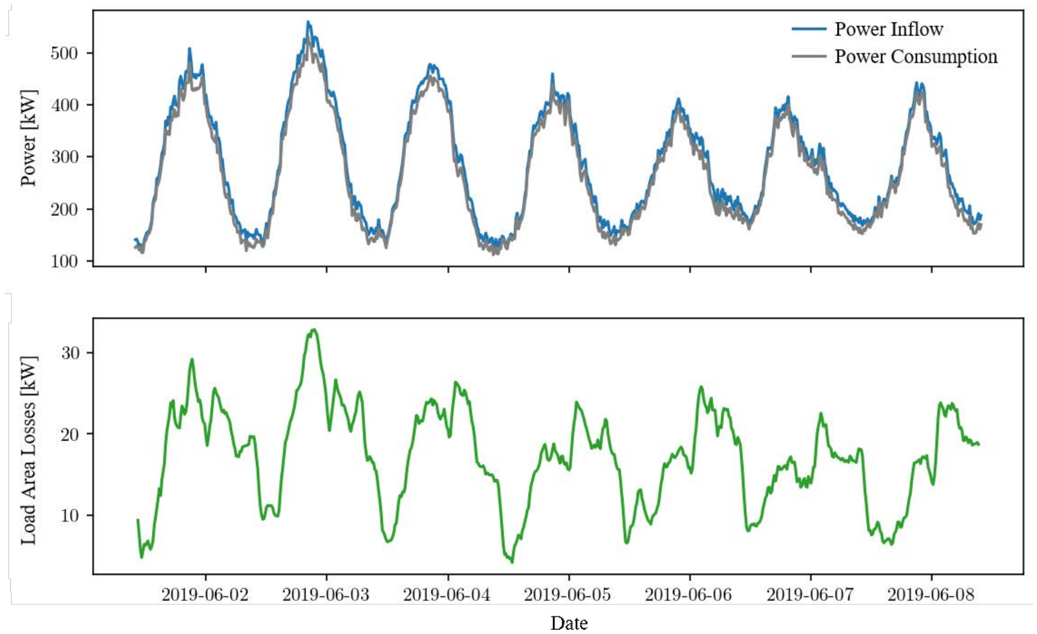

Fig. 2. Power inflow, consumption and losses over time for load area 4

connected, which prohibits any meaningful statements about secondary losses.

The reclosers deployed in the example circuits are equipped with Rogowski coils for three-phase current measurements. Together with their voltage sensors, the reclosers are able to capture the present power flow with an accuracy of 1% of reading or less. The AMI devices are certified as revenue-grade equipment and should therefore not be of concern regarding accuracy, even though recent studies have shown possible misreadings in case of highly distorted currents [18]. Together, this measurement accuracy is sufficient to provide significant loss numbers. Nonetheless, upstream feeder section results could prove less reliable as a result of higher recloser power throughput, and thus higher per reading deviations.

IV. Visualization of Distribution System Losses

The loss data generated by the estimation algorithm varies both in space and time and is therefore hard to analyze by a human operator if presented in a tabular format. To better perceive the current state of the distribution system losses, the data needs to be visualized in an interactive manner.

Several options exist to visualize the generated loss data. The most concise overview can be obtained by constructing a graph representation of the load areas and their interfacing reclosers. Relevant information can then be expressed using color-coded graph edges and by displaying the metrics next to each associated graph node as shown in Fig. 4. The graph visualizes the percentage of loss to power consumption within

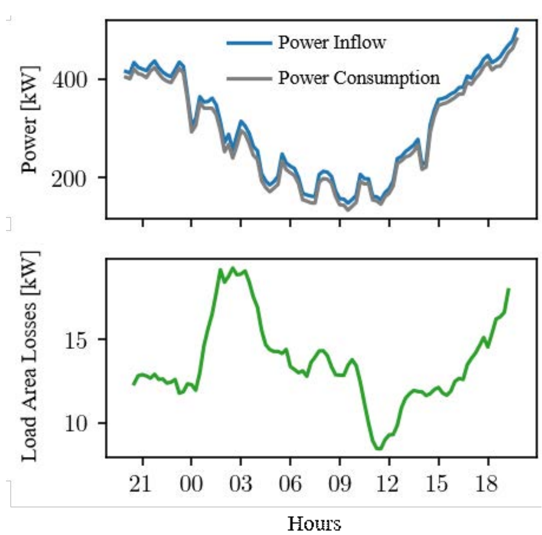

Fig. 3. Detailed view of losses (kW) in load area 6

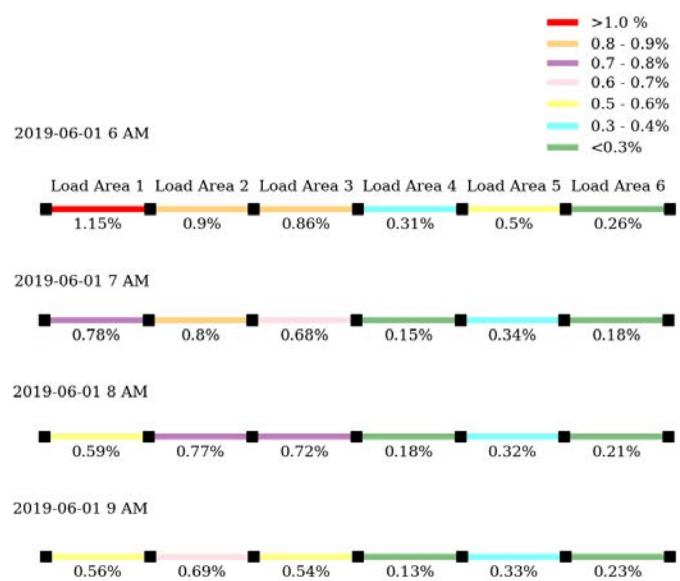

Fig. 4. Graph visualization of circuit A

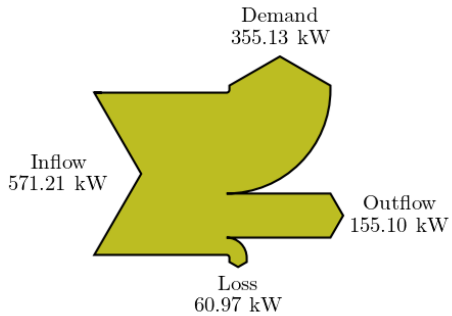

Fig. 5. Sankey diagram for load area 5

the five load areas in circuit A over a 3-hour period. If the geographic distribution of the network losses is of interest, the actual circuit topology can be used as background with the time-dependent losses as heat map overlay as demonstrated in a previous work in [15]. This way, network operators can also identify the physical location of loss anomalies, which might help to ascertain root causes of the losses. Another visualization alternative consists of highlighting the power flow and the allocation of real power consumption using a Sankey flow diagram as displayed in Fig. 5. The Sankey flow diagram shows a comprehensible breakdown of power flows into downstream demand, customer demand and losses for load area 5.

In each case, the extent of the available datasets provides multiple possible quantities to display. The most evident to show are the losses per load area, but as these depend on the number of connected customers, it can also be helpful to relate the losses to load area or downstream demand. Considering that line losses and transformer load losses both depend on the loading conditions of the network, it can also be practical to show the power flow in each load area. Especially in situations with unexpected loss behavior, additional measurements such as temperature and harmonic distortion can help to determine and narrow down possible explanations.

V. Conclusion

Loss information is essential for assessing distribution equipment efficiencies, visually evaluating the state of the distribution system and could be an important indicator for imminent device failures. In this paper, an approach for estimating distribution system losses by load area over time is presented. Already deployed infrastructure is utilized to obtain the necessary data and resulting loss information is presented in multiple visual representations.

Future work will focus on applying the estimation algorithm to bigger datasets and integrating existing outage information in order to evaluate possible equipment failure prediction schemes. Pattern recognition approaches can be used to discern between possible causes for loss such as vegetation, energy theft or eventual equipment failure. Although outage prediction based on losses is not covered in this paper, the data generated using the presented load estimation approach will be used for that purpose as part of an ongoing project.

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