

# Inferring Non-Outage Events Using Meter Voltage Data

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## ABSTRACT

Power distribution utilities incur significant expenditures due to field operations. While restoration efforts following outages lead to truck rolls in order to identify and rectify faults, there exist several non-outage events that also result in generation of work orders and crew visits. In this paper, we discuss a new problem in the smart grid domain wherein data-driven approaches may be used to improve field operations and customer experience by minimizing the time required to diagnose, locate and rectify non-outage faults. In particular, we discuss how voltage datastream from customer smart meters can be leveraged to pre-inform the crew about such faults and proactively generate work orders. We also conduct a preliminary investigation based on meter data obtained from a large electrical utility in North America.

## Keywords

Smart Meter Data, Electrical Utilities, Data Analytics

## 1. INTRODUCTION

Service crews of power distribution utilities are continually engaged in field operations for asset maintenance or repair activities and customer restoration efforts following faults, outages, and system disturbances. While restoration efforts following storms and outages result in truck rolls and crew visits to the fault location, a significant number of work orders are also generated due to non-outage events or faults. For instance, when a tree branch touches an overhead conductor leading to persistent flickering of lights, customer complaints may pour in from a neighborhood and field service crews are sent out to identify, localize, and rectify the issue. Similarly, customers may complain of dim lights or partial outage when one leg of a conductor connecting the service transformer deteriorates. Some complaints also result in multiple field visits as the crew is unable to identify or localize the fault in one visit. Utilities in North America spend thousands of dollars every year on such non-outage events as truck rolls are expensive (USD 50-100). Therefore, improving the efficiency of field operations by providing in-

sights to the crew beforehand about the location and type of faults can yield significant savings, improve customer experience, and reduce diesel emissions. [1, 2, 3]

With the advent of smart grid deployments, utilities now have the opportunity of leveraging smart meter data for purposes other than billing and reap value from meter investments. While smart meters can report last gasp notifications during outages, signatures corresponding to partial or non-outage events are not always recorded or well-defined at the level of an individual customer meter. Moreover, without sufficient customer calls, the outage management system (OMS) is unable to localize faults accurately, leading to longer crew time in the field. In this paper, we propose that voltage data-stream from multiple customer meters may be used as signals to detect the occurrence of non-outage events and help utilities minimize the time taken to diagnose, localize, and rectify faults in the field. We highlight the data required for addressing such problems and conduct a preliminary study. The next section discusses the data requirements while Section 3 presents our study conducted over voltage data and non-outage events belonging to a large utility in North America. The last section concludes the paper.

## 2. DATA REQUIREMENTS

This section presents requirements in terms of data and models needed to detect and localise non-outage events.

**AMI Voltage Data:** Voltage data from customer smart meters significantly improves observability in the medium and low voltage networks. Generally, voltage drops along the length of the distribution feeder and varies continuously as a function of total load. Since system disturbances and faults impact the voltage of downstream customers, meter voltage time-series can help in detecting and localizing events that may lead to customer complaints. Smart meters commonly record average RMS value of voltage at time resolutions of 1-15 min. Sometimes measurements also include min/max values and voltage sag/swell information. Depending on the IT system, this data is transmitted to utility servers at regular short intervals. Common applications of meter voltage data include volt-var optimization, maintaining power quality, and integrating distributed generation. Recent work has also shown that meter voltage data may be used to correct the connectivity model of the network, leading to improved reliability and better customer outage experience [4].

**Connectivity Model:** The connectivity model (CM) of a distribution network specifies the electrical connectivity between devices, assets and customers downstream of a substation. Therefore CM provides information not only of which customers are connected on which feeders, but also which

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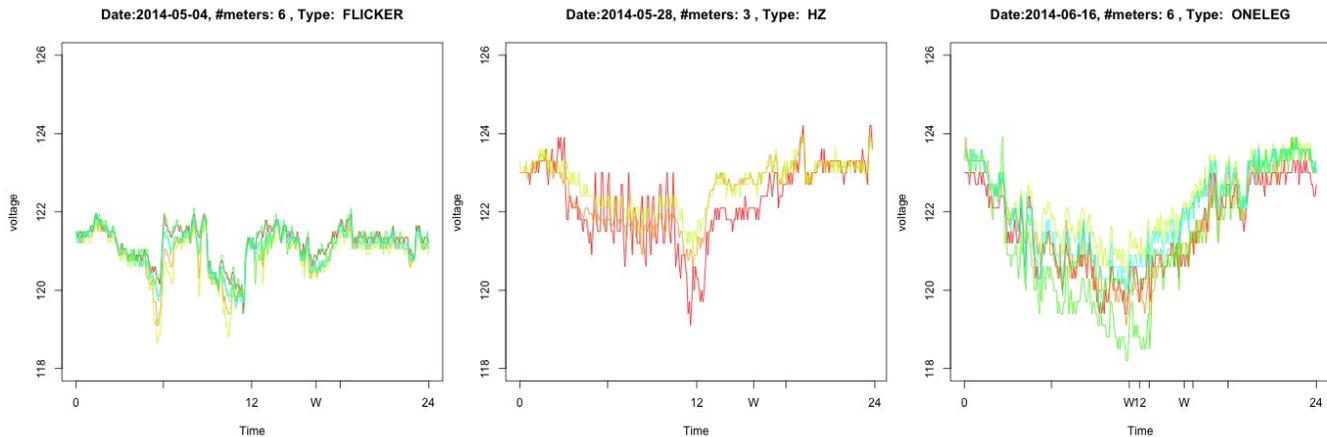


Figure 1: Voltage time-series of customers groups impacted by different non-outage faults/events.

Type	Description
TrWire	Tree on wire
OneLeg	Partial outage
Flicker	Flickering voltage
PPWD	Pole to pole wire down
HZ	Hazardous
Arc	Visible arcs

Table 1: List of different types of work orders

distribution transformer powers a customer and on which phase of the feeder. CM is required to both detect and localize non-outage events using voltage data. When a fault occurs on the line, voltage of customers downstream of the fault is affected. Therefore, when voltage data of a customer group shows evidence of a possible event, CM is needed to narrow down the fault location and provide appropriate information to field crew. Additionally, CM is required to weed out noise caused by sporadic voltage fluctuations and distinguish them from valid faults or events.

### 3. CORRELATION OF HISTORICAL WORK ORDERS WITH AMI VOLTAGE DATA

Customer complaints following disturbances or faults generally result in work orders generated by the OMS, based on which, a truck roll is initiated and field crew visits one or more locations to resolve the issue. Upon return, they also update work orders with additional information if needed. Generally, work orders contain the basic details such as time-stamp, type of the problem, and ID of the device where the problem is identified.

We conducted a preliminary study based on historical work orders and meter voltage data collected from a large electrical utility in North America. Our dataset was sourced from 4 feeders, each containing about 300 distribution transformers and serving 2000 customers on average. In particular, we used voltage time-series data from customer smart meters that recorded RMS values at 5-min resolution for a period of 2 months. The list of work orders corresponding to non-outage events on these feeders for the same time period was also available. Table 1 lists the relevant types of work orders available in the dataset.

Against this background, we propose that non-outage events leading to such work orders could be detected proactively and in real-time by jointly analyzing voltage patterns of dif-

ferent customer groups. These voltage patterns can act as signatures of events in two ways: (i) towards detecting and localizing a potential event, and (ii) identifying the type of event and proactively generating appropriate work order(s) in advance of customer calls. Fig 1 shows the voltage time-series of customer subsets which were affected during 3 random work orders picked from the dataset. The x-axis represents the 24-hour time period on the day the work order was generated; ‘W’ marks the exact time at which the work order was generated in the system. Y-axis plots the voltage for the set of customers downstream of the device listed in the work order. We observe that in each case, there exist clear voltage signatures prior to or around the time-stamp of the work order, mainly manifesting in the form of sudden drops. Moreover, fluctuations of different work order types have distinguishing features compared to each other.

### 4. CONCLUSION

In this paper, we introduced a new problem in the smart grid domain which can be solved using data-driven approaches. In particular, we discussed how voltage data from customer smart meters can be leveraged to improve the efficiency of field operations leading to lower costs of field visits and improved customer experience. This can be achieved by detecting non-outage events when they occur through voltage signals and identifying the type and location of the underlying problem. This preemption of work orders is possible by applying machine learning techniques on the voltage time-series data. Such approaches need to take into account both the spatial and temporal nature of events in order to detect the occurrence of events before they are reported by customers to the utility.

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