Power Quality Grid Monitoring At Scale

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Abstract*— With nearly 400,000 sensors deployed across the United States Grid, Whisker Labs has observed and documented over 150,000 grid events over the last two years. These recorded events occur when multiple sensors across a geographic region simultaneously capture identical signals unique to the event. The paper examines several events that have revealed misoperating capacitor banks, failed power lines, and more. While identification and analysis of these events have been good for post-mortem analysis, the ability to correlate these events and their characteristic data with other external data sources has provided deeper insight into the grid's resilience. Future work will produce predictive models, which could be especially important in high-fire-risk areas.*Keywords—power quality, grid events, sags, swells, surges, fire**

I. Introduction

A high-density, smart home power quality network records high-resolution voltage data [1]. Experience with this voltage data has led to the identification, localization, and resolution of thousands of residential power quality problems across the U.S. Within the home, these problems range from damaged, loose, or missing neutral connections to out-of-range base voltage. On the grid, the problems include grid interruptions, sags, swells, and arcing from failing utility equipment.

II. Sensor specifications

A. Sampling Rate

The sensor is a passive monitoring device. It plugs into an ordinary receptacle within the home. The system monitors arcing by using a 30-megahertz sampling rate. A second channel measures power quality phenomenon by sampling at 30 kilohertz. The sensor employs artificial intelligence to identify known signals in the 30-megahertz data. Data is streamed back to the cloud, where the system performs additional high-speed machine learning to correlate data from multiple sensors.

B. Network Reach

The sensors have been deployed to nearly 400,000 homes in the U.S. Presently, the network is growing at a rate of 40,000 to 50,000 sensors per month. There are over 425,000 home years of monitoring data. Figure 1 shows the density map of the sensor network.

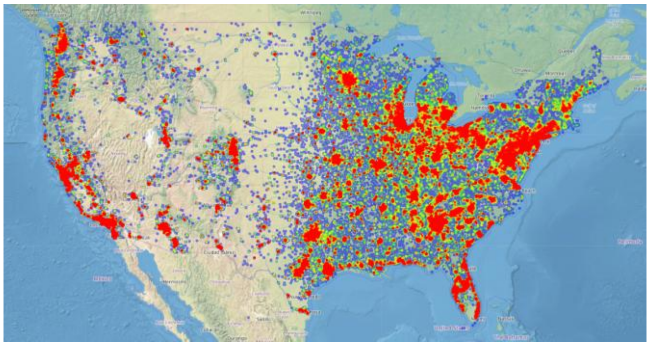

Figure 1 - Sensor Density Map

III. Synchronized measurements

The sensors are not equipped with a global positioning system (GPS) clock. Rather, measurements between devices are time-synchronized using a proprietary protocol. The protocol keeps the measurements from all the sensors correlated to within ten milliseconds. In Figure 2, several sensors reported a voltage sag. As shown in the figure, the timestamps for the start time of the ten sensors below are within about 10 ms of each other. However, there are three groupings of measurements: those centered on a start time ending .897 +/-2 ms, those centered on .905 +/- 1 ms, and those centered on .917 +/- 1 ms. Presently, there is no phase information. The random distribution of sensors suggests that the time differences result from being on different phases.

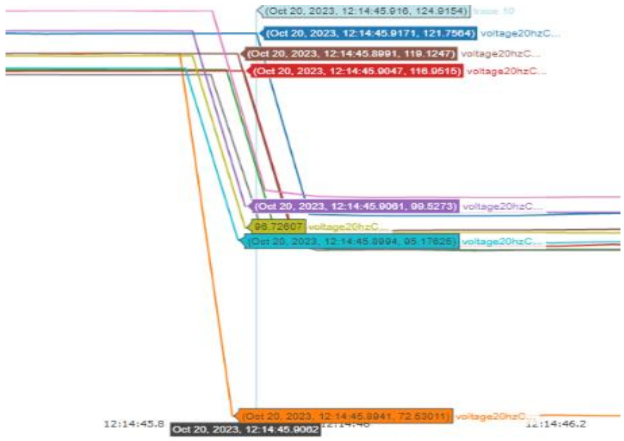

Figure 2 - Voltage Traces Showing Start Time of Event

IV. Event Definitions

For the scope of this paper, there are three primary categories of events: electrical fire hazards (EFH), utility fire hazards (UFH), and grid events. The combined rate of EFHs and UFHs is roughly 1 in 68 homes per year [2]. This paper focuses on Grid Events. Over 6,200 potential home fires (combined EFH and UFH) have been prevented. The electrical fire prevention efficiency has been computed to be 80% [3].

A. Electrical Fire Hazards Defined

Electrical fire hazards are dangerous conditions originating from homeowner devices, appliances, home systems, and electrical wiring. EFHs occur at a rate of approximately 1 in 123 homes per year.

B. Utility Fire Hazards Defined

Utility fire hazards are dangerous conditions introduced into the home by electric utility infrastructure, most commonly loose neutral connections on the utility side of the meter. Compared to EFHs, UFHs occur at a rate of 1 in 154 homes per year.

C. Grid Events Defined

The system detects thousands of grid events every day. Figure 3 shows a 4-hour window from October 20, 2023. The system detects interruptions, sags, swells, arcing, frequency perturbations, and arcing. The events are color-coded by type.

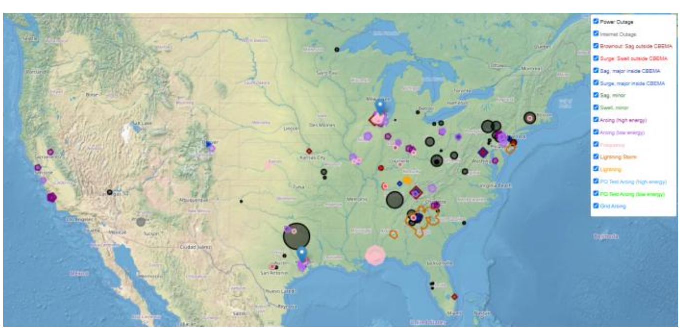

Figure 3 - Event Map

To be considered a grid event, sensors must be more than 30 meters apart but within 10 km of each other. With the exception of power and internet outages, all events require a minimum of 5 independent sensor measurements, and the event times must be within 200 ms of each other. The following rules dictate the classification of the event type:

- Power and Internet Outage: Outage in at least three sensors with event times within 3 seconds.
- Brownout: Voltage sag below 108 V outside the CBEMA curve. At least two sensors measured a Sag outside CBEMA.
- Surge: Voltage swell above 132 V outside the CBEMA curve. At least two sensors measured a Swell outside the CBEMA curve.
- Sag Major: Voltage sag below 108 V, major event inside the CBEMA curve.
- Swell Major: Voltage swell above 132 V, major event inside the CBEMA curve.
- Sag, Minor. Voltage change less than -3 V.
- Swell, Minor. Voltage change more than 3 V.
- Arcing (high energy). Jump in the high-frequency measurement with a voltage grid event at the same time. Events with lightning flashes in the past 6 minutes have been removed.
- Arcing (low energy). Jump in the high-frequency measurement with NO voltage grid event at the same time. Events with lightning flashes in the past 6 minutes have been removed.
- Lightning. Jump in the high frequency measurement and lightning flash within a second previous to the event.
- Lightning Storm. Five or more lighting grid events within 30 minutes.
- Grid Arcing. Four of more low-energy arcing events within 120 minutes and within 50 km.

The size of the symbol represents the magnitude (number and geographic distribution of the sensors). For example, the large black circle in Texas means a larger area is impacted than the smaller black circle in Ohio in Figure 3.

This approach to detecting grid events provides multiple benefits. First, the loss of a single sensor does not negatively affect the detection of events. Similarly, universal coverage is not required to detect grid events effectively. Finally, timestamps do not require microsecond precision, which allows the sensors to be produced more cost-effectively.

V. Grid Events Detected

A. Using Voltage

The sensors that detect a particular event are grouped, and the extent of the event is displayed. Correlation to weather like lightning is performed to quickly identify likely causes of the event. Ultimately, the system allows users to see the voltage or frequency trends associated with the event. Figure 4 shows the voltage trace from 10 of the 36 sensors that detected the event.

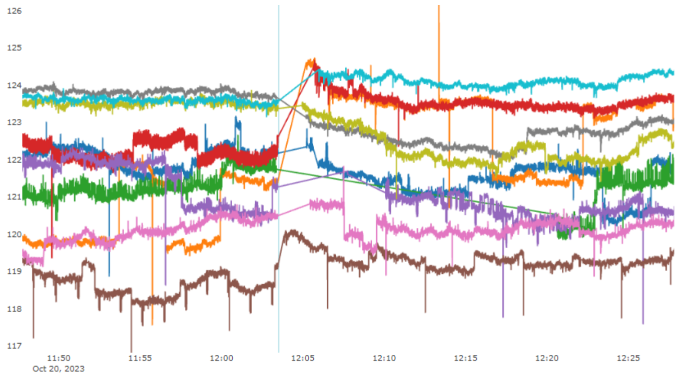

Figure 4 - Voltage Traces During Power Outage

Figure 5 shows a summary of the specific event. The sensors that observed the event are shown in the detailed map. In addition, a summary of the severity of the event is displayed. In this case, since this was a power outage, the average, minimum, maximum, and median values of the voltage were 0. Additionally, 17 sensors detected the event. Finally, no lightning was detected during the event time.

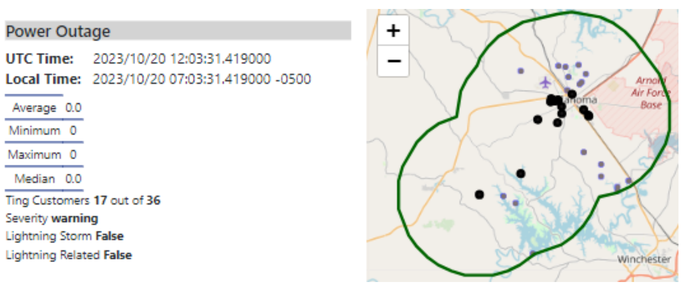

Figure 5 - Outage Information

B. *Using Arcing*

In addition to voltage, the sensors report back a proprietary feature sensitive to nearby arcing signals. When the voltage is perturbed simultaneously with the arcing signal, this is called a high-energy arcing event. When the voltage is not perturbed in the presence of an arcing signal, this is called a low-energy arcing event. In the case of the power outage above, several sensors detected arcing prior to the outage, which suggests some misoperating grid equipment was likely the cause. Notice the deflections in the arcing signal starting at about 11 am in Figure 6.

Figure 6 - Arcing Signature

VI. Reporting Grid Events

As the sensor network has become more widely deployed, the sensor data is used to produce a monthly Consumer Power Quality Index (CPQI). This index compares utility companies' performance related to sags, swells, and interruptions [4]. Figure 7 shows the CPQI for September 2023.

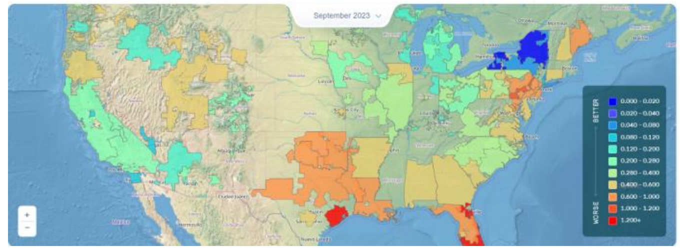

Figure 7 - CPQI Map

The event types can be trended over time to see if they are getting better or worse. Figure 8 shows a trend of the P.Q. index over 18 months. The per capita events dramatically increased in the last few months even though the sensor network deployment remained relatively constant. The increase in activity suggests that the grid is having some performance-related issues.

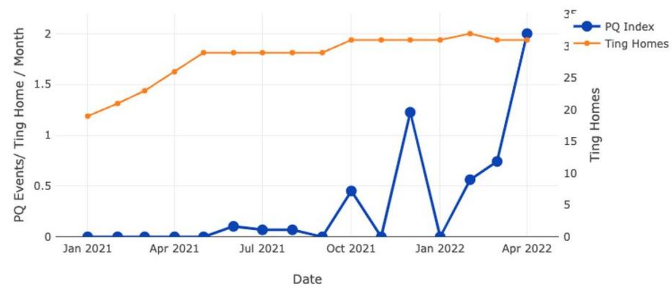

Figure 8 - Trend of CPQI Showing Increased Grid Activity

Since the sensor locations are known, the grid events can be analyzed by geographic area. As grid areas begin to perform more poorly, grid maintenance staff could be deployed to perform more frequent inspections. Figure 9 shows a heat map where a wildfire ignition point, where the ignition was potentially caused by utility grid fault(s). As can be seen, the grid square and its neighbors have an increased number of events.

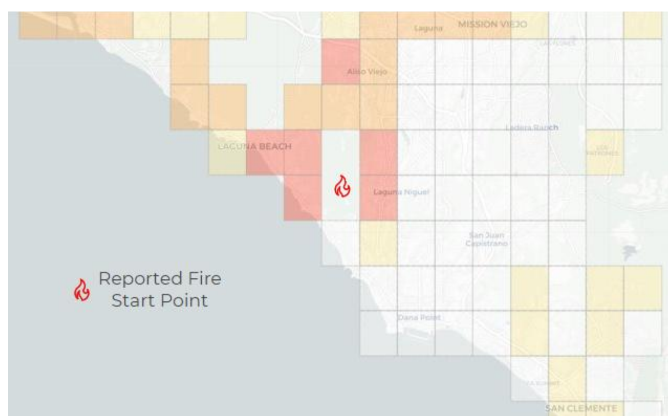

Figure 9 - Map of events by grid square

VII. Predicting Grid Events

Since the events are correlated by type (e.g., sag, swell, interruption) and time, a heatmap can be developed to identify if the condition is improving or worsening. As the number of arcing events increases across a group of sensors, the probability of a piece of grid equipment failing also increases. Figure 10 shows the increased number of arcing events across a group of sensors. A burned insulator on a nearby capacitor bank switch was identified as the source.

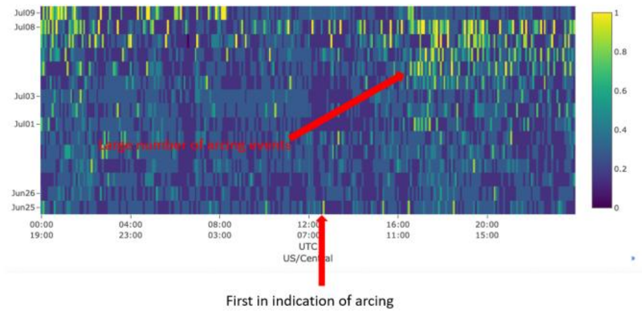

Figure 10 - Arcing Heatmap

VIII. Locating Grid Events

The system can estimate the location of the fault source. The location is calculated using a triangulation method without knowledge of the utility network topology. Naturally, the error is higher when this approach is used, but it can be useful for locating the general area of the fault location. Figure 11 shows the original fault location reported by the system without topology. The actual location was about .6 miles away.

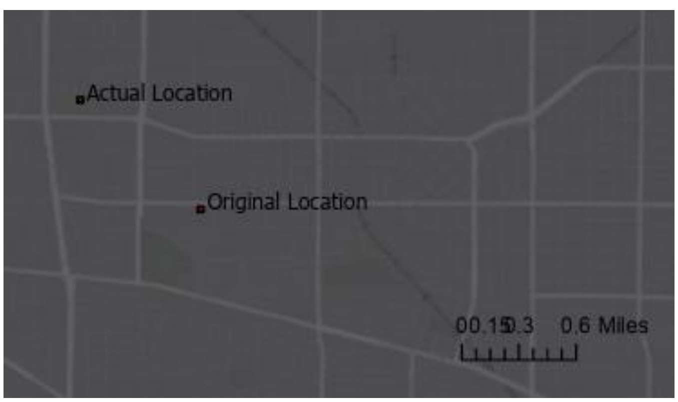

Figure 11 - Fault Location Without Topology

Using the revised topology yielded a dramatic improvement in the fault location. Figure 12 shows the revised fault location with topology in use. In both estimates, the location is on the correct feeder. There are two estimates because the data converged on two locations, which likely has to do with the sensor location.

Figure 12 - Fault Location with Topology

IX. Case Study – Hawaii

In August of 2023, Maui experienced devastating fires. The sensor network had been deployed to about 300 homes within Hawaii, including the island of Maui [5]. Several grid events were detected prior to when the fire was first reported. At approximately 10:47 pm, a San Diego Zoo Wildlife Alliance video showed a large flash. At the same time, the sensor network detected a grid fault that coincided with the video. The voltage trace is shown in Figure 13.

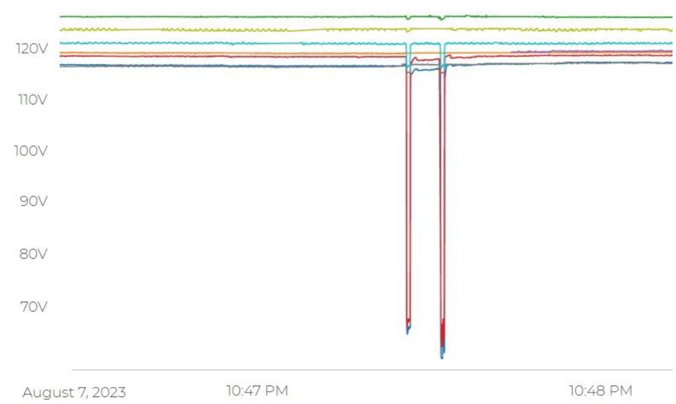

Figure 13 - Voltage Sag at 10:48 pm

A different grid event was detected at approximately 11:38 pm on August 7 (local time). Figure 14 shows several events were recorded during this time.

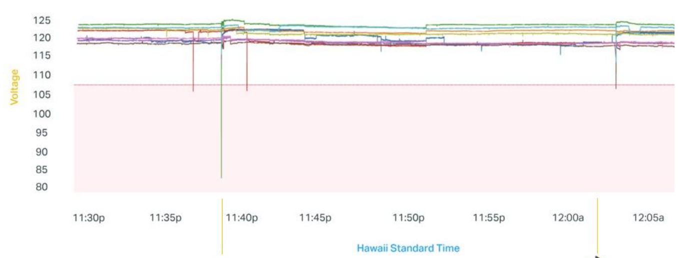

Figure 14 - Voltage Sags at 11:38 pm

In Figure 15, the high-resolution data shows that the grid was responding to the event. Nearly every sensor on the island showed the exact same measurements.

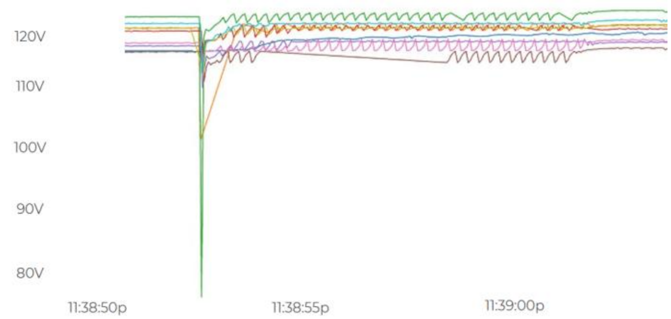

Figure 15 - High-Resolution Voltage Sag Data

In Figure 16, an analysis of the sensors around the town of Lahaina on Maui shows a heatmap of events as recorded by the sensors. Events started to appear as early as 1 pm local time on August 7, well before the fires were reported. After the fires started, there was a significant uptick in events until the power went out around 5 am.

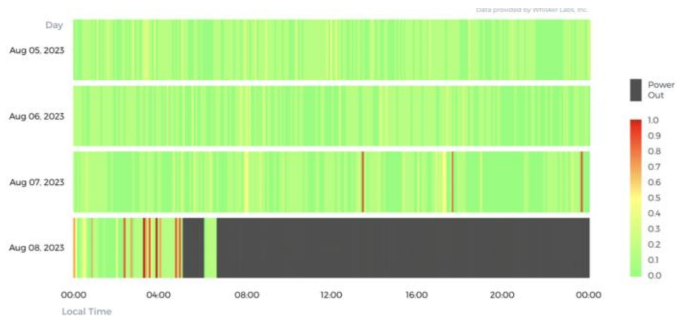

Figure 16 - Heatmap of Sensor Data

X. Conclusions

A low-cost, distributed sensor network has been deployed through insurance agencies to reduce home fires ignited by electrical faults within the home. When a sufficient density of sensors is reached in an area, the sensors can be used to monitor grid events. The network is effective at detecting, predicting, and locating faults on the grid.

XI. References

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