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Mobile Edge Computing Sensors and Cloud Machine Learning Enable Grid Predictive Maintenance

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SUMMARY

The resiliency of the nation's electric grid is under continuous stress. Impacts of weather, wear and tear, and the age of the grid all contribute to a decline in reliability and an increase in power outages. Aged and deteriorated electrical equipment produce characteristic radio frequency (RF) emissions. Fixed sensors to monitor the condition of all grid equipment would be expensive and create an enormous data-handling problem. Mobile Edge Computing sensor (MECS) technology that can discriminate and locate the equipment that produce pre-failure RF emissions would enable equipment replacement before flashover or catastrophic failure causes an outage. Rebuilding or replacing the 5 million miles of the U.S. transmission and distribution grid is not an economical alternative. Maintaining the grid through a strategy of predictive conditions-based maintenance results in improved grid performance, fewer outages, and addresses a worldwide problem with substantial economic impact.

KEYWORDS

Mobile edge computing, Grid resiliency, Equipment condition assessment, Predictive maintenance

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Introduction:

The electric grid is an interconnected web of facilities and equipment that supplies energy to the world's users at a residential, commercial, and industrial level. As shown in Figure 1, the grid can be segmented into three distinct areas: Generation, Transmission, and Distribution.

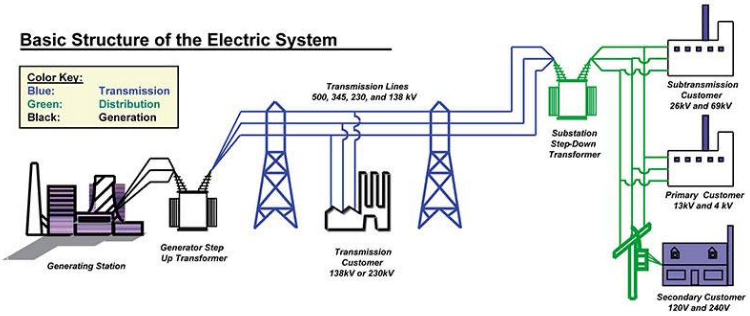

Figure 1: The Electric Grid.

Grid resiliency refers to the continuous operation of the grid. Impacts of climate change, agriculture, and road deicing impact grid resiliency by causing deterioration of the grid.

The Problem:

There are 245 million power outages annually in the U.S. alone and 94% of these outages involve the 4.5 million miles of distribution grid. Power outages in the U.S. cause an annual $110 Billion economic impact on the nation's economy [1]. Wholly, 21% of outages are due to major weather events. Of the remaining outages, 31% or 60 million annual outages are related to the failure and deterioration of electrical equipment.

In the U.S. alone there are over 5 million miles of transmission and distribution power lines. The grid includes an estimated 150 million structures, and over 2 billion pieces of energized equipment. To illustrate the impact of reducing the number and severity of equipment related outages, consider the case when there is just 1 deteriorated part for every 6 miles on the 5-million-mile grid. This represents 834,000 pieces of electrical apparatus on the grid that will cause an outage. It will cost an estimated $417 million to repair the grid (average repair cost of $500 per unit). If the $110 Billion annual cost of outages is reduced by only 10%, an improvement of $11 Billion annual savings would be realized with an ROI = $11 Billion/$417 Million = 2,638% [2, 3]. This review supports the need for understanding, forecasting, and reducing the number and duration of outages.

To address the issues of grid conditions-based maintenance, a low-cost, low-power, battery operated, weatherproof, mobile edge computing sensor that includes the measurement of environmental conditions was developed. The sensors mount on fleet vehicles that move throughout the city on a regular basis, collect the sensor grid evaluation information daily, and analyze this data using machine learning models. The machine learning models add other data sets to the sensor data, like weather and grid loading as examples, to develop the ability to forecast conditions that will cause power outages. The prognostic data that results will allow the grid to be better maintained, and to enable the forecasting of impending grid issues that impact grid resiliency.

Technical Challenges:

There were several technical challenges that are addressed in the project. The first was to develop a sensor that is robust and low cost. The sensor must survive continuous outdoor exposure and operate without interaction from the vehicle driver and require only minimal care and maintenance. The sensor design requires advanced analysis algorithms that are greatly simplified and integrated to operate in a low-power environment, yet they must be effective in the discrimination and location of deteriorated equipment RF emission sources.

Sensor Algorithm Design:

The sensor analysis algorithms are a phase-locked-loop-based (PLL) version of the existing field proven FFT based detection and analysis algorithms [4]. The main objective is to eliminate the harmonics in the voltage signals resulting from the collected data and to estimate the phase without relying on complex computations. This method results in accurate harmonic estimation while also reducing the computational complexity. Again, the method is to first eliminate the harmonics and estimate the phase of the voltage signal from the PLL. This phase estimate is then used to estimate the harmonics.

The voltage signal may have even or odd harmonics. The algorithm uses different approaches to eliminate the even and the odd harmonics. The single-phase voltage distorted with n^{th} order harmonics can be expressed as:

$$v(t) = V_1 sin(\omega t + \emptyset_1) + \sum_{k=2}^{n} V_k \sin(k\omega t+\emptyset_k)$$

where V_k, $k\omega$, $\emptyset_k$ are the magnitude, frequency, and phase of the k^{th} harmonic component. The even harmonic components can be eliminated by applying the single operation:

$$v_0(t)=v(t)- v\,(t - \tfrac{\pi}{\omega}).$$

Unlike the even harmonics, odd harmonics cannot be eliminated by a single equation. Eliminating each odd harmonic needs a separate operation. To remove the h^{th} harmonic we use:

$$v_{0-h}(t)=v(t)- v\,(t - \tfrac{\pi}{h\omega}).$$

The proposed algorithm is applied to the voltage signal of Figure 2, which is detected from the power lines. From Figure 3, it can be observed that the fundamental frequency is 120Hz, and that the signal has both odd and even harmonics. Applying the proposed method to the voltage signal to reduce the harmonics yields the harmonic-free signal shown in Figure 4.

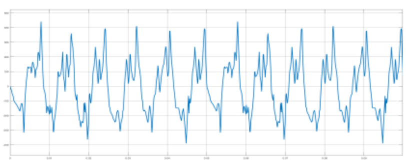

Figure 2: Demodulated RF Emission.

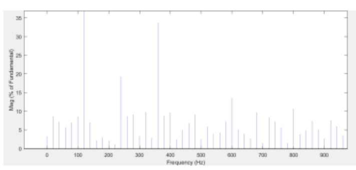

Figure 3: FFT of RF Emission Voltage.

After eliminating the harmonic components, the harmonic free signal is converted into the reference rotating frame and thereafter the PLL locks the phase of the signal. The phase is then used for the harmonic estimation, as illustrated in Figure 5.

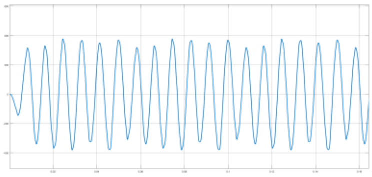

Figure 4: Harmonics-free Signal.

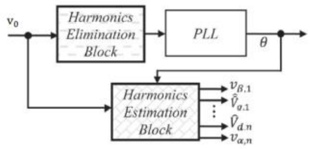

Figure 5: Phase Estimation.

The voltage harmonics can be estimated in the rotating reference frame. According to second order generalized integrator method, sine and cosine signals are produced for each harmonic component; that is,

$$u_{ck} = U_k cos(k\omega t);\ u_{ck} = U_k \sin(k\omega t)$$

where U_k is the amplitude of the k^{th} harmonic. Suppose that the voltage in the power line is:

$$v_o = \sum_{k=1}^{n} [V_k \cos\emptyset_k \sin(k\omega t)] + [V_k \sin\emptyset_k \sin(k\omega t)]$$

$V_{d,k}$ and $V_{q,k}$ are the estimates for $V_k \cos\emptyset_k$ and $V_k \sin\emptyset_k$ to represent the estimation in the reference frame. The mixed estimation error integral (MEEI) method is used to estimate the harmonics as shown below in Figure 6, where:

$$v_{err,k} = v_o - \hat{V}_{d,k} \sin(k\theta) = V_{d,k} \sin(k\theta) - \hat{V}_{d,k} \sin(k\theta)$$

$$\Delta_{k\theta} = (V_{d,k} - \hat{V}_{d,k}) sin^2(k\theta) = \frac{1}{2}(V_{d,k} - \hat{V}_{d,k}) - \frac{1}{2}(V_{d,k} - \hat{V}_{d,k}) \cos(2k\theta)$$

For the k^{th} harmonic, the MEEI block is shown in Figure 7 with both sine and cosine components for accuracy. The overall harmonic estimation block is shown in Figure 8.

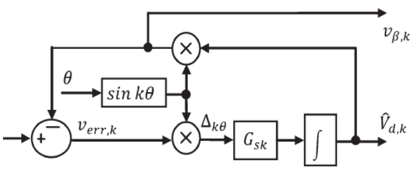

Figure 6: Basic MEEI Estimator.

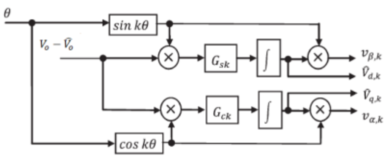

Figure 7: MEEI Estimator Block for k^{th} Harmonic.

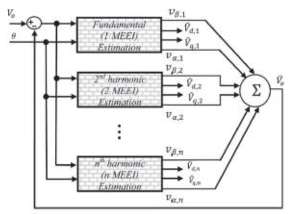

Figure 8: Harmonic Estimation Block.

Sensor Confirmation Test:

The sensor was mounted on vehicles and driven near known electric grid problems. An analysis will be completed by comparative sensor performance. The new sensor was able to detect additional locations of deteriorated equipment when compared with the results of the original sensor. These locations were field verified using ultrasonic acoustic detection equipment that registered the partial discharge signal.

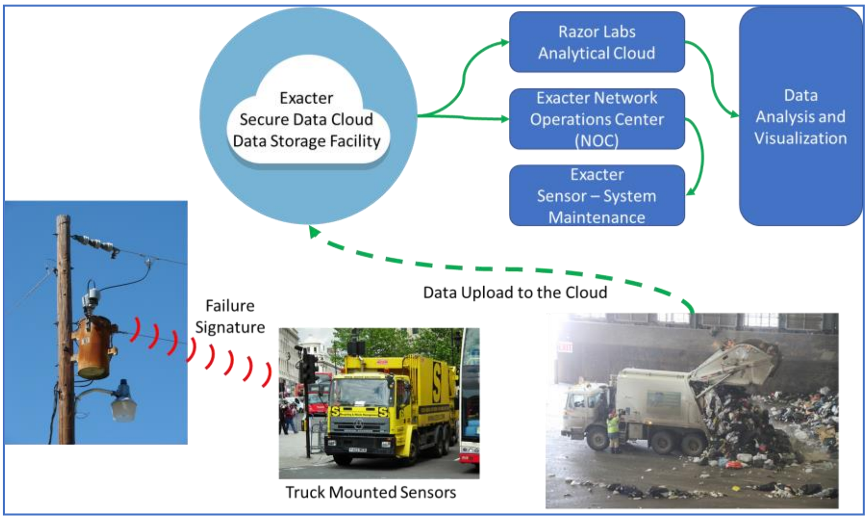

Figure 12: Data Collection and Data Routing Plan.

Conclusions:

The algorithm for the analysis of RF emissions from deteriorated electrical equipment was developed for quick response and low-power requirement. The field tests of the mobile edge computing sensor confirmed it to be effective in discriminating and locating the source of failure signature emissions from grid equipment. The deployment of the sensors on a city garbage truck fleet will continue as a demonstration program through mid-2021.

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