Asset Monitoring using Smart Sensing and Advanced Analytics for the Distribution Network

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***Abstract*—As the electric grid transitions into a highly distributed and intelligent grid, electric utilities are becoming increasingly concerned with monitoring the health and performance of their distribution assets. As Internet of Things technologies and data analytics become inexpensive and ubiquitous, low-cost asset monitoring becomes more feasible. Moreover, using edge analytics, computations can be off-loaded to these intelligent sensors to report only actionable information to the cloud. This needs to be done in a highly distributed manner using non-intrusive sensors and device physics that seamlessly integrates with legacy infrastructure. This paper reviews existing sensor based solutions, identifies t heir issues, proposes a novel solution by exploring the required attributes and proposes an approach for low-cost distribution transformer health monitoring.**

***Index Terms*- Asset monitoring, cloud computing, distribution grid, edge computing, non-invasive sensor, transformer health.**

I. INTRODUCTION

The power grid is the biggest infrastructure designed by man. It is currently facing major challenges as the grid is moving from a centralized, unidirectional and deterministic system to a decentralized, bidirectional and stochastic system. Many of these changes are being implemented on the distribution side of the grid through increased penetration of electric vehicles (EVs), rooftop photovoltaics (PVs), smart inverters etc. The network was not initially designed for these changes and thus it becomes imperative for grid operators to have high visibility into the network to maintain and improve reliability standards.

A distribution network feeder typically has many critical assets as shown in Fig. 1. These include service transformers, capacitor banks, reclosers, sectionalizers, etc. which serve specific purposes and require different monitoring and instrumentation strategies. In recent years utilities have taken major efforts to monitor distribution assets. However, this has proved to be challenging due to the low cost of assets with relatively high cost of sensing. Many assets are left un-monitored and utilities often follow a 'run to failure' strategy. Moreover, these devices tend to be geographically dispersed with a long life of $40-50$ years, providing utilities low incentive to operate expensive sensor and communication networks.

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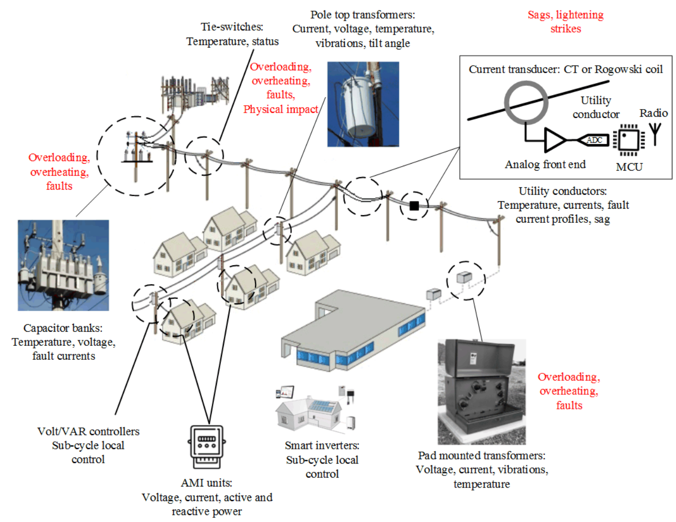


Fig. 1. Distribution system assets on a typical feeder, with stresses indicated in red.

A low-cost sensor that can directly or indirectly monitor distribution asset health and allow utilities to proactively deal with deteriorating or failing devices is crucial from utility operations' perspective. Currently Advanced Metering Infrastructure (AMI) units are the most widely deployed grid-edge sensors which have vastly improved utility's visibility, especially into secondary distribution networks. With time-stamped, granular voltage, and power data, AMI has enabled numerous high-value operational and planning capabilities beyond consumer billing, such as outage management, load forecasting, topology and phase identification, rooftop PV and EV detection, load dis-aggregation etc. [1], [2]. However it is difficult to utilize AMI data for asset monitoring as it cannot capture important parameters like asset temperature, geo-locations, mechanical vibrations, etc. which indicate different aspects of an asset's degradation cycle. Thus the adoption of AMI does not guarantee a fully autonomous and 'aware' system.

Moreover, AMI based technology has a high cost; upwards of \$300 per end-point [3], in addition to installation and communication costs, which significantly inhibit wide adoption of AMI. This forces most utilities to use AMI primarily for billing and metering purposes, making it an expensive Automatic Meter Reading (AMR) implementation. As of 2016, only 52% of the 152 million electricity customers had smart meters with only $1,372$ out of the $2,344$ utilities in the US using AMI in their distribution systems [3].

Low-latency centralized awareness systems work well for generation and transmission networks, where infrastructure and assets are few, and mission-critical. The challenge arises when similar solutions are applied for distribution networks, where on the one hand, the assets are diverse, more in number, and distributed across geographical regions, while on the other hand, each individual asset has a low cost. This paper talks about sensing for condition based asset monitoring in distribution systems, not to be confused with sensing and controls used for grid operations.

Consider the most common utility distribution system asset - the service transformer. A typical North American mid-sized utility serving more than 3 million customers would have between $400,000$ to $500,000$ pole-mounted transformers in the field. A single transformer can cost between $\$1,000$ - $\$2,000$ whereas existing sensors range between $\$400-\$600$. This high cost does not justify monitoring every asset. However, with more than 50 million distribution transformers, the overall loss of revenue from transformer failures and unplanned outages is significant [4]. This creates an opportunity for savings through proactive condition based maintenance. For instance, Hydro Quebec replaces $3,000$ transformers annually. A monitoring sensor system becomes viable only at low cost points as compared to the distribution asset.

The pace with which renewables, DERs and EVs are being adopted is adding unforeseen stress on grid assets. Moreover, utilities are seeking to increase reliability standards by reducing SAIDI/SAIFI indices and to adopt a more proactive approach prior to equipment related failures and outages. The recent fires in California are examples of power equipment failure and their catastrophic consequences. Reports claimed that many of these fires were likely due to poor maintenance and monitoring of grid assets, making it a high-risk liability issue [5].

The contribution of this paper is to show why distribution asset monitoring is a vital piece of the smart grid, to identify requirements of such a monitoring system and recommend a plausible solution if current technologies or approaches are insufficient. Section II illustrates the state of the art and its challenges. Section III describes the requirements for the sensor network and data analysis. Section IV provides details of an actual platform for distributed asset monitoring. Section V discusses ancillary benefits of such a sensor network and section VI concludes the paper.

II. State of the Art

Many sensor solutions for monitoring distribution system assets have been proposed in literature which are summarized in Table I.

Recently, with statistical and machine learning tools, it has become easier to monitor transformer overloading based on available data. Seier *et al.* have proposed a data-driven thermal model for service transformers, which can be coupled with the incoming data from AMI units [14]. The approach combines the loading information from residential AMI with local weather information to predict transformer internal temperatures for mitigating the detrimental effects overloading caused by EVs. A similar approach has been presented in [15]. Qian *et al.* have recently proposed 'AI at the Edge' solution for real-time fault detection in highly critical operations such as dynamic control of rotating machines [16]. All capabilities such as signal acquisition, feature extraction, and fault identification were embedded with the edge node. While this paradigm offers a strong solution for time sensitive fault diagnosis, it requires embedded sensors within the asset and a high computation capability. However, with the power of edge computing, certain features can be extracted and decisions can be made fast and locally, without having to send massive amounts of data to the cloud.

III. Sensor System Requirements

A careful look at the issues of approaches discussed in section II shows the following attributes are needed from a viable distribution system asset monitoring solution-

1) Low-cost, high-value sensor: With millions of distribution system assets, individually, the sensor component costs must be minimal. However, with the sensed parameters and data being generated, a collective deployment of these devices must bring high value to the utility asset management programs.

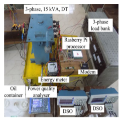
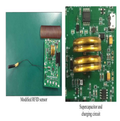
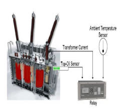
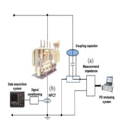
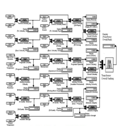
2) Low-cost communications: It is critical to connect all end points to the cloud in an inexpensive manner. While cellular networks or solutions like Wi-Fi, LoRaWAN, 6-LoPAN exist [17], the cost per end node is not sustainable when scaled to millions.

3) Data measurement: A non-invasive sensor can only monitor certain parameters such as device temperature of the outer casing, ambient temperature, device vibration, etc. These variables may directly or indirectly impact the asset's health or be an indicator of degradation. The data and analysis techniques required to extract information depend on the physics of the asset class. Sensors should intelligently detect abnormal operating conditions.

4) Edge intelligence: With every new sensor, the data generated, transmission bandwidth and cloud computing requirements increase significantly [20], [21]. It is difficult to send high frequency time-series data to the cloud via low bandwidth networks. In edge computing, intelligence and computational power are embedded within the sensor that can process data locally and extract necessary features, to report only the actionable information to the cloud. This reduces the overall bandwidth requirement and amount of data sent to the cloud. However, there is a trade-off between computational power and cost.

5) Data analysis and cloud computing: Cloud computing is an excellent technique for evaluating historical performance of assets by collecting and sending *big data* to the cloud. Data

TABLE I
SENSOR SOLUTIONS PROPOSED IN LITERATURE

Solution	Image	Description	Advantages	Issues
Online condition monitoring system for substation and service transformers [6]		Raspberry-Pi and several sensors used for extracting health-index.	Standard IoT-like components used.	Impractical to actually deploy in the field: Expensive and complicated sensors (e.g. - top-oil sensors), internet access point required.
Soft sensors for distribution transformers [7]		Non-intrusive sensors for coupling thermo-electrical models with smart meter measurements.	Easy installation, enables monitoring of top-oil, hotspot temperature, ageing rate while without the need for specialized sensors.	Cellular or Wi-Fi access point required for getting data back to the cloud.
Advanced distribution transformer load monitoring [8]		Sensor that monitors pole-top transformer loading, demonstrated in five locations in Thailand.	Provides additional visibility into the distribution grid.	Uses 433 MHz custom RF network, along with a GSM based backhaul.
Self-powered RFID sensors [9]		Self-powered vibrational sensors.	Self-powered and stick on sensing approach.	Solution uses RFID, and needs a customized backhaul to push data to the cloud.
Itron Grid 20/20 OptaNODE [10]		Encircling CTs for current measurement, customized backhaul solution.	Asset management platform with advanced visibility into the distribution network.	Expensive solution, complicated installation, need for managing custom communication network.
Transformer protection based on thermal loading [11]		Suggests thermal loading and contingency mitigation techniques for power transformers using IEEE $C57.91-1995$ std.	Creates dynamic ratings and guidelines for loading transformers. A microprocessor relay is used for protections, warning system alerts operators of possible temperature violations.	No information about integrated sensing. Protective relays are expensive and complicated to operate and need custom communication network.
Smart transformers [12]		High frequency CTs used for detecting PDs along with signal processing for online condition monitoring.	Online system using feature extraction and pattern recognition.	Solution can be expensive as it uses a customized DAQ and PD measurement system. Needs a custom communication network.
Fuzzy logic approach for transformer management & decision making [13]		Data driven approach for real-time, online condition monitoring of power transformers.	Model provides decision making ability based on multiple inputs like DGA, partial discharge, winding integrity, insulation deterioration etc.	Purely data-driven approach, no information regarding actual sensing hardware provided.

analysis techniques that require historical context and high computing power are most suited for this implementation.

6) Reliability: The degradation of a transformer occurs over several years. Sensors and electronic equipment installed on the transformers must be able to perform for many years with minimal maintenance.

7) Cybersecurity: Cybersecurity is the foremost concern in utility grid operations and asset management. Each device in the field must have a secure communication channel with the cloud, and every possible attack vector must be analyzed and countered with appropriate design elements.

8) Easy installation process: Considering the number of distribution assets such as service transformers currently in use in USA, a sensor for monitoring this huge fleet must be designed to have minimal field installation effort. Ideally, these sensors must be hot-stick compliant, so that they can be installed and commissioned within minutes, keeping the overall costs low.

Thus, an effective architecture that optimizes the advantages of both cloud and edge computing to maximize awareness and visibility across distribution assets while keeping sensor cost low is required.

IV. PROPOSED APPROACH- DISTRIBUTED, LOW-COST INTELLIGENCE AT THE EDGE

Several internet-of-things solutions [17] have tried tackling these issues, but few have successfully addressed all requirements. Primarily, it is difficult to scale centralized 'data gathering' paradigms at the scale that electric utilities are targeting. There is a strong need for adopting a decentralized approach, that can help in the process of making decisions locally, and sending only actionable information to the utility cloud, se-

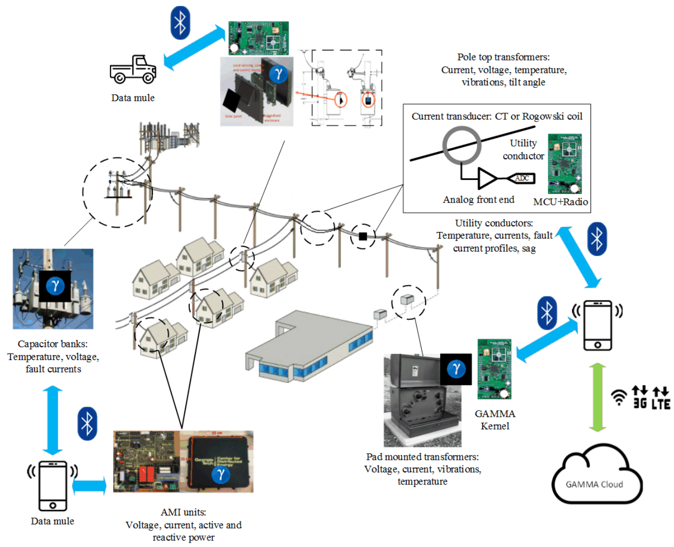


Fig. 2. A distribution feeder with asset monitoring sensors enabled by GAMMA platform. The mobile phone and utility service trucks are data mules, and act as gateway devices between sensors and the cloud.

curely, at an ultra-low cost, at a scale that can support millions of devices that can operate from anywhere in the world. This can be achieved by 'edge intelligence' helping the system to function autonomously, without relying on low-latency communication, while responding to local events in near-real-time.

Authors have shown that such distributed intelligence at the grid edge, can help in decentralized awareness in smart grid applications [18]. The solution - GAMMA (Global Asset Monitoring, Management & Analytics) platform uses autonomous 'end-nodes', capable of sensing, computation, signal processing, data storage, actuation (if required), energy management, in a \$4 device. It integrates a long range Bluetooth Low Energy (BLE) radio and a fleet of 'data mules' to create a low-cost sensor network that can be deployed anywhere in the world. Data mules are devices like smart phones, drones, utility trucks, etc. that can move around in a geographical area and opportunistically connect to distributed assets and act as a gateway device between the end nodes and the cloud. The data packets are a few kBs in size and are encrypted end-to-end with unique AES$-$128 keys for cybersecurity.

The advantage of such a sensor network is that it can be globally deployed, at a minimal cost enabling secure, low-cost distributed sensing and high latency applications. This allows different applications to be rapidly developed around it, as shown in Fig. 2. For example, an approach to implement AMI functionality using GAMMA platform has been discussed in [19]. This platform can also enable asset monitoring at a low cost, for example, monitoring distribution transformers.

Grid assets degrade over time primarily due to over-loading causing excessive heating and sudden impacts such as fault currents and lightning strikes that quicken the degradation process. Fig. 3 conceptually illustrates how shocks can cause an electrical asset to reach its end of life sooner than expected. The proposed approach utilizes low-cost, non-invasive sensors

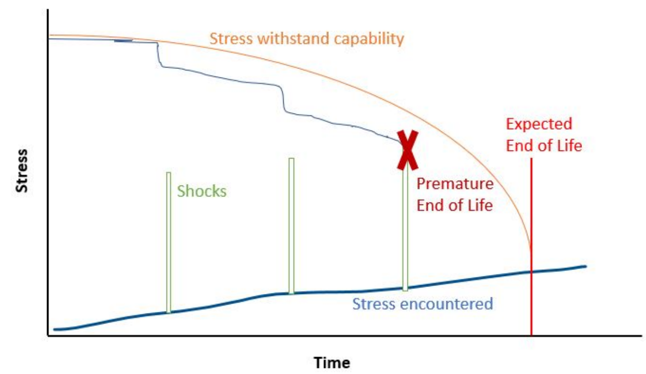


Fig. 3. An asset's ability to withstand stress over time.

that can be easily installed on the grid assets, and can monitor parameters of interest that can contribute to the overall asset degradation.

The subsections below elaborate how two variables, namely asset temperature and external shocks, can be monitored in a low-cost and reliable manner to provide insights into the asset's health. The proposed approach focuses on distribution transformers as examples but can also be applied to other assets such as capacitor banks.

1) Fault Current Sensors: Every time a transformer undergoes shocks in the form of fault currents, lightning surges, etc. it can experience significant insulation degradation and winding distortion [22]. Tracking such extreme events for each transformer will provide utilities with more insight into transformer health and failure causes.

Low-cost current sensors capable of capturing and classifying fault current profiles can help in trouble-shooting and diagnostics during post-event analysis. Processing data locally using edge computing on the sensor can help mitigate the overload of highly granular data on the cloud.

Studies have shown [23] that fault current waveform data, can be used for analyzing the types of faults and detect symptoms of degrading assets. An illustration of this concept is shown in Fig. 4. With low-cost current sensors and edge intelligence, it is possible to record waveform data and perform sequence extraction or harmonic analysis, to gain more insight

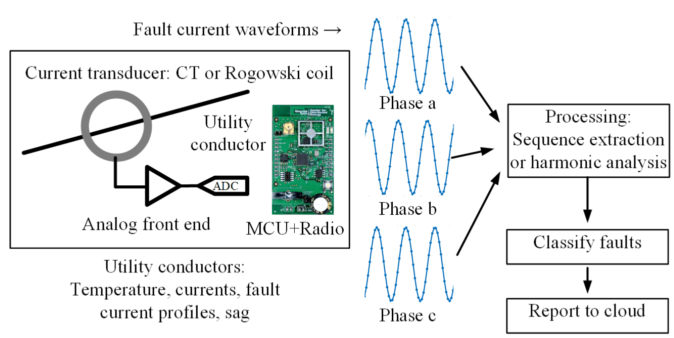


Fig. 4. Fault current waveform capture and processing using edge intelligence.

into the type of faults (single line to ground, symmetrical fault, etc.). This helps in analyzing failure modes on the distribution network assets.

By using novel manufacturing techniques (3-D printing or new PCB structures), it is possible to develop these sensors at ultra-low cost (less than \$5 in volume), making this approach economically viable.

2) Transformer Temperature: Transformer aging-related insulation degradation is a function of temperature, moisture and oxygen [24], of which temperature has the greatest impact on insulation and overall life. Continuous overloading can cause excessive heating and the part that is operating at the highest temperature, usually known as the hot spot will experience the most deterioration. Based on fluid flow and thermal dynamics, the IEEE loading guide C57.91 $-$ 1995, Clause 7 developed [24] empirical equations to determine top-oil and hot-spot temperature as well as the aging rate as a function of temperature and current as given by (1) - (4). However, not only were these equations developed for large power transformers, on-line monitoring of hot-spot temperature for an in-service transformer is expensive and difficult.

Work has been done to use load data from smart meters and ambient weather from weather sensors in the IEEE C57.91 $-$ 1995 equations to estimate transformer hot-spot [15]. However, the empirical constants recommended for these equations such as n & m can vary widely in real life. Moreover, certain parameters depend on the type and make of the transformer which is not always recorded accurately in the utilities database or might be difficult to obtain from transformer manufacturers. While the IEEE C57.91 $-$ 1995 equations can be used to derive average life estimates of a fleet of transformers, they fail to detect excessive overloading or degradation on a particular transformer.

$$A(t) = A_0.exp\left\{\frac{-\alpha}{\theta_h(t)+273}\right\} \tag{1}$$

$$\theta_h = \theta_{amb} + \Delta\theta_{top} + \Delta\theta_h \tag{2}$$

$$\Delta\theta_{top} = f_1(\Delta\theta_{topR}, R, K_i, K_u, n, t, \tau_{top}) \tag{3}$$

$$\Delta\theta_h = f_1(\Delta\theta_{hR}, R, K_i, K_u, m, t, \tau_w) \tag{4}$$

where A is aging rate, θ_h, θ_{top} & θ_{amb} are hot-spot, top oil and ambient temperatures, τ_w & τ_{top} are winding and oil time constants, R is the ratio of rated to no-load loss, n & m are empirically derived exponents, K_i & K_u are ratios of initial and final loads with rated load.

By placing an external temperature sensor on the transformer tank and employing advanced techniques such as non-linear least square estimations, the thermal dynamics including time constants for each transformer can be learned overtime: i.e. a mapping between case temperature, loading and ambient temperature [25]. The aging equations can then be written in terms of case temperature to provide a better estimate of life and indicate which transformers are being overloaded (5) - (6).

$$A(t) = A_0.exp\left\{\frac{-\alpha}{\theta_c(t)+273}\right\} \tag{5}$$

$$\theta_c = g(\theta_{amb}, K_i, K_u) \tag{6}$$

where θ_c is transformer case temperature.

As the cost of a temperature sensor is less than \$1 this approach fits well under the low-cost distributed asset monitoring paradigm. An added advantage is the ability to compare the case temperature of a fleet of dispersed distribution transformers normalized with respect to load and ambient temperature and prioritize which assets might need further monitoring.

V. Ancillary Functions and System Level Benefits

Deploying several such low-cost sensors on the medium voltage feeder provides a number of ancillary benefits that can be accrued through data analytics. A few such use cases have been elaborated below.

A. *Correction of Feeder Connectivity Models*

Utilities might have incorrect or incomplete network feeder models in their database. Usually these models are updated manually when a new connection is made allowing for human error to creep in. With voltage and power data measured along the feeder lines, it is possible to verify the connectivity model of the feeder and determine phase connections as illustrated in Fig. 5. This is based on the assumption that nodes connected closer to each other or on the same phase will have a higher correlation between their time-series voltage data than between nodes that are far apart [28].

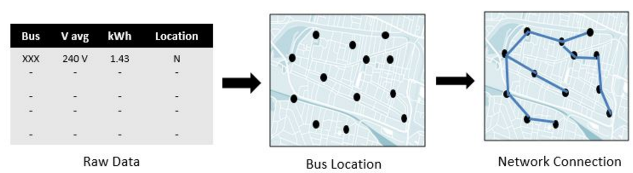


Fig. 5. Extracting feeder connectivity from time series sensor data

B. *Feeder Voltage Analysis*

The additional voltage and power data points can be used for more accurate power flow analysis and state estimation. This would allow utilities to detect areas of low voltage along the feeder, identify potential locations for DER injection and so forth. Moreover, this data can also be used to detect existing photo-voltaic connections on the grid [29].

C. *Load Forecasting*

A critical requirement in power grid operation and planning is the ability to forecast expected loads. With the deployment of sensors at the edge of the grid, consumer level load can be forecast accurately instead of aggregated feeder level load. Literature shows several machine learning based algorithms can be used successfully using time series power data [1].

D. Fault Detection and Analysis

Utilities have made significant advancements in their ability to locate faults and restore power after an outage occurs. As the industry shifts from reactive to proactive management, post fault analysis also becomes a key responsibility. Grid edge sensors can be programmed to send magnitude and frequency details of flickers, temporary faults and over-voltages, etc. that might otherwise go undetected. This information is extremely valuable in diagnosing outages or predicting them even before they occur.

VI. Conclusions and Future Work

As the power grid undergoes major transformations, it is important for system operators to gain visibility into the distribution networks in an economical fashion. Particularly, asset monitoring applications can enable better insights into the stresses that devices undergo. So far, it has been difficult to deploy sensor networks that could economically provide these insights to system operators due to the high component costs, as well as overheads in operating dedicated communication networks.

There is a need for intelligently processing sensor data at the edge to help reduce cloud computing, data storage and the requirements of on-demand, bandwidth-intensive connectivity options. With edge-intelligence, data can be processed locally to only report actionable insights to the cloud. This paper proposed using a decentralized, edge intelligence platform using 'data mules', enabling multiple asset monitoring applications as well as ancillary capabilities. This approach provides full digitization of distribution grids and makes the grid observable while supporting the decentralized smart grid paradigm.

Future work involves a pilot demonstration of the transformer sensors on two feeders with Southern Company and development of additional applications such as power quality analysis, fault classification, and assets failure prediction as well as to support data-driven and automated applications such as asset management and network planning.

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