Situational Awareness using Edge-Computing Enabled Internet of Things for Smart Grids

MD. Abul Hasnat[1], MD. Jakir Hossain[1], Adetola Adeniran[1], Mahshid Rahnamay-Naeini[1], Hana Khamfroush[2]

{hasnat@mail.usf.edu, mdjakir@mail.usf.edu, mahshidr@usf.edu, bolade@mail.usf.edu, khamfroush@cs.uky.edu}

[1]Electrical Engeeniring Department, University of South Florida

[2]Department of Computer Science, University of Kentucky

***Abstract*—Edge computing provides an ideal platform to enable many critical and time-sensitive applications in monitoring and operation of critical cyber-physical systems, such as smart grids. In this paper, we consider one of the key operations for smart grid's reliability, which is situational awareness and discuss the role that the edge computing can play to enhance this operation by providing distributed state estimation (DSE) locally at the edge nodes. We specifically focus on the network of the phasor measurement units (PMUs) as an example of the industrial internet of things in smart grids and discuss the edge-computing platform architecture to enable data analytics for DSE using the PMU time-series. We discuss that it is important to consider the physics of the smart grid in designing the edge-computing layer. As an example, we present a data-driven method for detecting power line trips using the PMU data and the designed physics-aware edge-computing platform.**

Keywords—Internet of Things, Smart Grids, Edge Computing, Fog Computing, Energy Data Analytics, Situational Awareness, State Estimation

I. INTRODUCTION

Smart grids are examples of a critical Cyber Physical System (CPS), which provide the essential electricity service to the society. Efforts toward making smarter grids are leading to a large scale Electric Grid of Things (EGT). The EGT can be divided into two layers: (1) The general Internet of Things (IoT) layer with general IoT needs, which are mostly deployed close the edge (customers) of the smart grid such as smart homes for energy management and customer profiling. (2) The Industrial Internet of Things (IIoT) layer with more strict requirements on latency, security and connectivity. This layer is a part of utility infrastructures and is deployed in distribution, generation (including renewable sources) and transmission layers of the system with mission-critical and real-time applications for monitoring and control of smart grids. For instance, advance metering infrastructure in the distribution layer used for network planning and demand response management is an example of IIoT. Another example of IIoT layer in smart grids is the network of PMUs for situational awareness, which is the focus of this paper.

In general, the EGT has the goal of enhancing the performance, reliability, and security of the grid and to do so it relies on the ubiquitous large-scale information acquisition, communication, storage, and processing capabilities. Therefore, EGT needs to be accompanied with communication and computation technologies that enable such capabilities. The need for such a computation and communication platform as well as the applications and operations that can benefit from it in smart grids, have been discussed in literature [1-14]. For instance, communication capabilities, including wireless communication networks based on 5G cellular networks for IoT in smart grids are discussed in [11]. For the computational capabilities, cloud computing has been introduced as a potential platform for processing and storing energy data from EGT [12]. However, large latency limits the use of the cloud platform for critical low latency applications in the IIoT layer of EGT, such as, for reliability related monitoring and control of the smart grid. The limitations of the cloud as the computation platform for IIoT has motivated the use of edge/fog computing that pushes the computation and storage services to the edge of the communication network (such as base stations) to reduce the latency and the traffic in the core network by localized computations, processing and storage capabilities. The application of edge computing and IIoT for critical functions and operations in smart grids is an emerging topic.

One of the key operations for smart grid's reliability is situational awareness performed with the help of the wide area monitoring system (WAMS). This operation relies on sensors collecting data from the system and thus relies on IIoT. State estimation, especially with new methods based on data-driven approaches, is a critical real-time operation of WAMS, which is sensitive to communication delays and has high computational complexity for processing of large volume of PMU data. The reliable operation of the smart grid largely depends on accurate and real-time estimates of the state of the system. Many of the conventional and data-driven state estimations are traditionally performed centrally at a central control system (e.g., using Supervisory control and data acquisition-SCADA) and when necessary using the cloud computational resources. However, centralized state estimations will not be effective and adequate for future smart grids with high penetration of renewable energy sources and strict reliability requirements. Such requirements suggest the need for dynamic and distributed state estimations (DSE). The edge platform is a suitable environment to implement the critical, time sensitive DSE. DSE and condition monitoring using edge computing can reduce the latency of such critical, time-sensitive operations by providing local estimates that can generate early warnings when necessary to improve the reliability of the smart grid. In addition, local warnings and estimates can notify multiple control centers and enhance the reliability by adding redundancy in case a system or server fails in one region and center. A recent major blackout event on June 16, 2019 in Argentina, Paraguay and Uruguay, left 48 million people without electricity [15]. An EGT based early warning system may improve the situational awareness over such large geographical region and allow operators more time to take preventive measures to mitigate the effect of failures and risks of large blackouts.

In this paper, we discuss the edge-computing platform architecture to enable data analytics for DSE in smart grids. We specifically discuss that it is important to consider the physics of the smart grid in designing the edge-computing layer. To show how the physics of the system can be used in designing the edge platform, we use a data-driven method to exploit the information about the dynamics of component interactions embedded in the PMU time series and design the architecture of the edge layer based on such information. We show that using such edge architecture, we can provide local state estimates and early warning for events in the smart grid.

II. Related Work

A large body of work has been emerging on the application of IoT, cloud computing, edge/fog computing and big data analytics in smart grids (examples include the works in [1-14]). In this paper, we briefly review the works on edge computing in smart grids as they are closer to the topic of this work.

The majority of edge computing applications in smart grid have been focused on supporting applications that are close to the customer level (close to smart homes) or in the distribution layer of the smart grid. Examples of such applications include customer profiling, energy scheduling in smart homes [6, 13] and advance metering infrastructure [4, 6, 7]. For instance, the work in [6] discusses the residential energy storage planning and the work in [6] demonstrates energy management as a service over the Fog computing platform both in the home level and microgrid level. The edge computing platform has also been proposed to support intelligent electric vehicle services in smart grids [5]. The work in [4] discusses a microgrid framework that uses a energy storage and fog data system to provide reliable power to critical and emergency loads.

The application of edge computing for mission-critical and real-time applications, such as monitoring and control of smart grids, is an emerging topic and needs more attention. Among the few works that discuss critical smart grid operations using edge platform is the work in [14], which proposes a platform for condition monitoring (e.g., monitoring the health of machines in the system including electric motor (A.C), DC motors, or generators) based on statistical analysis of time series from various machines using the edge platform. In [14], a database-dictionary system small enough to fit into the memory of edge data-analytic devices is developed, which reduces the communication for exchange of energy data to the cloud. Using the proposed platform, only fault report and recommendations from the edge layer will be sent to cloud. In general, huge data generation in the IIoT layer of the EGT and real-time decision-making requirements make energy data analytics one of the key applications on the edge computing layer of the system [14, 16] for smart grids. Big data aspects of the energy data and the need for platforms for handing such data has also been discussed in literature [9].

Another example of critical smart grid operations using edge platform is presented in [11], which proposes two distributed state estimation methods for the smart grid that can be deployed over a distributed architecture based on edge computing. Moreover, the work in [13] discusses caching mechanisms to optimize the organization and utilization of the limited cache size for situational awareness applications in smart grids.

Although the edge computing paradigm is still gaining its grounds in the industry, some works have emerged on methods to improve this platform for smart grid applications. For instance, the work in [5] introduced the use of a Fog computing coordinator into the fog computing architecture at the Fog layer for IoT applications in smart grid to aim at a better coordination of the distributed fog nodes in order to reduce delay. Nazmudeen et al., in [17] focus on improving communication metrics among smart meters for AMI with the use of an intelligent router as a fog device while using data aggregation approach.

III. Architecture of Edge-Computing Enabled EGT

In this section, we discuss the architecture of the Edge-enabled EGT to support critical applications in smart grids. We specifically focus on the edge platform architecture that can support the state estimation operation in the smart grid to be discussed in Section IV. The edge-enabled IoT for smart grids can be divided into physical layer, IoT layer, edge layer and central computing and control layer (Fig. 1). Each of the layers are discussed next.

The *physical layer* of the system includes the utility's electric infrastructure, including generators, substations, transmission and distribution lines, transformers and storage devices (i.e., electrical components). The physics of electricity, demand and generation variations and the operations policies determine the dynamics of the state of these components.

The *IIoT layer* includes sensors and actuators ranging from smart appliances and smart meters to synchronized phasor measurement units (PMUs) for measuring voltage and current phasors at various points of the system, field-bus control and legacy Remote Terminal Units (RTU) as the actuators in the system. In this work, we mainly focus on the PMUs in the IIoT layer as the application of interest for this work is state estimation using PMU time series.

The *edge layer* of this system includes edge nodes and edge coordinators. The edge nodes provide processing and storage requirements to support the critical operations of the smart grid (in this case state estimation). Edge nodes and coordinators are distributed geographically over the system and thus the operations need to be developed in distributed approach. The connectivity among the edge nodes and coordinators and the components of the IIoT layer (in this case PMUs) is a part of the architecture that needs to be designed. This aspect of the architecture has been discussed in the next section and the presented design considers the physics of the smart grid in such connectivities.

In addition to the connectivity structure among the edge nodes and the things (i.e., PMUs), a key component of the architecture is the communication technology enabling the exchange of information among the components. The performance of the edge computing platform highly depends on the performance of the communication system. The fifth generation (5G) communication networks and the introduction of massive machine-type communication (mMTC) services will enable deployment of large number monitoring devices, suitable for PMU deployment. Critical services related to reliable operation of the smart grid require ultra-reliable low-latency communications (URLLC) [11, 18] communication services.

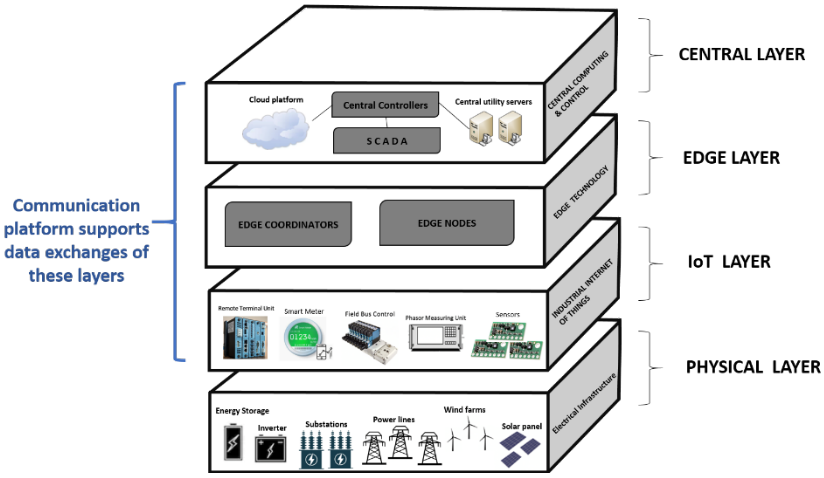

Fig. 1. Layers of the edge-enabled IoT for smart grids.

However, to meet the stringent URLLC requirements of these services, current URLLC communication platforms are not sufficient and thus the new data acquisition, communication and processing architectures are the focus of many researchers. For instance, one of the communication network technologies that can improve the performance of the network is Software Defined Networking (SDN). SDN is defined according to [19] as an emerging network architecture where the forwarding (data) plane is physically separated from the network control plane, while the latter controls several devices. By segregating the control plane from the data plane, flexibility is introduced into management for network operators. Moreover, R. Vilalta et al., in [20] introduced a network of an edge node enabled SDN/NFV technology for IoT services with the ability to act as a fog node while providing storage, computing and networking services. SDN has been proposed as a technology for the communication layer of IIoT layer of the EGT [21].

The *central computing and control layer* include the control center systems (e.g., SCADA system and central utility's computational servers) as well as the cloud platform to support computational and storage needs for less time sensitivity and delay tolerant applications. While devices at the edge have data storage and processing capabilities, data is sent routinely to the central computing and control layer as well as the cloud. In the case of state estimation application, in addition to the PMU data, the edge layer will send local state estimates and early warnings processed in the edge layer to the central control systems. The central control layer can use such early warnings for identifying critical events that can threaten the reliability of the system. In addition, the centralized state estimation will be performed in the central computing and control layer using more computational resources to provide more accurate system-wide state estimations using PMU data.

IV. SITUATIONAL AWARENESS USING EDGE-BASED EGT

The edge platform is an ideal environment to implement DSE. In general, for DSE the smart grid is partitioned into several non-overlapping subsections [22]. The DSE is performed in individual subsections, where the local estimates can be found with the help of the edge nodes. In the second stage, the central controller combines the local estimates and computes the overall state estimations of the whole grid.

A. *Edge Computing Architecture considerations to support situational awareness in Smart Grid*

To enhance situational awareness using local state estimation and an early warning system, one needs to design the edge-computing layer while considering the physics of the smart grid. Specifically, in addition to the geographic and computational resource considerations, the state dynamics of components that are connected to each edge node will affect the accuracy of the local state estimates and needs to be considered. In this paper, we discuss the architecture of the edge layer that connects the PMUs for this purpose based on power system considerations. The goal of the edge layer design is to identify which PMUs need to connect to which edge nodes and how many of the edge nodes are required to provide the best local state estimates.

This problem is formulated as following. We assume that the power grid components are equipped with PMUs that are connected over a communication network to the edge layer. We denote the set of PMUs in the smart grid by $\mathcal{P} = \{P_1, P_2, P_3, \dots P_M\}$. In the edge layer, we assume there are N edge nodes $\mathcal{E} = \{E_1, E_2, E_3, \dots E_N\}$, where each E_i collects and processes the time-series from a subset of the PMUs, denoted by $\mathcal{P}_{E_i} \subset \boldsymbol{\mathcal{P}}$. The goal of this problem is to identify the subset $\mathcal{P}_{E_i}$ for each E_i such that the E_i can provide the best local estimate for the state of the power components associated with PMUs in $\mathcal{P}_{E_i}$. The size of $\mathcal{P}_{E_i}$ for various edge nodes are not fixed and need to be identified. Another aspect of this problem is to identify the required number of edge nodes or N. To this end, we assume that the physical layer of the system and the PMUs and their locations are given and we would like to design the edge layer by identifying number of edge nodes and their PMU connections.

In our previous work [23], we have shown that certain components can provide more information about the state of other components based on the dynamics of the power flow in the system. The relations and influences among the components have been characterized using various techniques in literature such as their correlations, stochastic influences and electrical distances [24]. In this paper, we will use the relations among the components of the power system based on the correlation among their states to design the edge layer as following.

Designing the architecture of the edge layer must include two factors: 1) the members of $\mathcal{P}_{E_i}$ have to be geographically close to the position of the edge node E_i, and 2) the members of $\mathcal{P}_{E_i}$ should have strong correlation among themselves. The first one ensures practical feasibility for connecting the PMUs in $\mathcal{P}_{E_i}$ to the edge node E_i and the second one ensures that all the buses under the supervision of each edge node have correlated power dynamics so that state of a component can be estimated using other members of $\mathcal{P}_{E_i}$. Therefore, we can formulate the design of the edge architecture as an optimization problem.

We denoted the geographical distance from the edge node to PMU $k_i \in \mathcal{P}_{E_i}$ by $D(E_i, k_i)$. We put a threshold limit for $D(E_i, k_i)$ denoted by D_{th}, otherwise, it would not be practically possible to connect the selected PMU $k_i \in \mathcal{P}_{E_i}$ to edge node E_i. We denoted the correlations among the members of $\mathcal{P}_{E_i}$ by $C(k_i, l_i)$, where k_i, $l_i \in \mathcal{P}_{E_i}$. As discussed earlier, we want to minimize $D(E_i, k_i)$ while maximizing $C(k_i, l_i)$. Therefore, we can write the edge layer design as a constrained optimization problem as follows:

$$arg \min_{\mathcal{P}_{E_i}} \sum_{i=1}^{N} \left\{ \sum_{k_i \in \mathcal{P}_{E_i}} D(E_i, k_i) - \lambda \sum_{k_i, l_i \in \mathcal{P}_{E_i}} C(k_i, l_i) \right\}$$

$$s.t. D(E_i, k_i) \leq D_{th}.$$

For the faster convergence with an acceptable level of accuracy, we consider solving the above optimization problem with a heuristic approach instead of the straight forward solution. In our approach, we assume that the number of edge nodes N and their positions are given and fixed. Variable N and their positions are other parameters that can be optimized but; however, in this work, we assume $N = 4$ and the position of the edge nodes are given over the system as shown in the example in Fig. 2. We, initialize the set $\mathcal{P}_{E_i}$ based on the distance from each PMU from the edge node, i.e. $k' \in \mathcal{P}_{E_i}$ iff $D(E_i, k') < D(E_j, k')$, where, $i \neq j$. We consider the constraint $D(E_i, k_i) \leq D_{th}$ for ensuring practical implementation in initializing the $\mathcal{P}_{E_i}$. In each iteration of the optimization process $\mathcal{P}_{E_i}$ is updated by maximizing the correlation among all $k_i \in \mathcal{P}_{E_i}, \forall\, i$, with data. If $\mathcal{P}_{E_i}$ does not significantly updates within certain number of iterations for all $\forall\, i$, the partitioning will be finalized.

B. Localized PMU Event Detection based on Edge-enabled EGT

Using the proposed architecture, in this section we present an example of a data-driven early warning system for detecting anomalies in smart grids. For the implementation of this method, we consider the data-stream from each of the PMUs as a time-series. However, the whole set of PMU data under any subsection can be modeled as a multivariate time series. To demonstrate the application of DSE over the edge-enabled EGT, we focus on the event of line tripping in an area and the state estimation that can help generate early warning for that based on the PMU time-series locally.

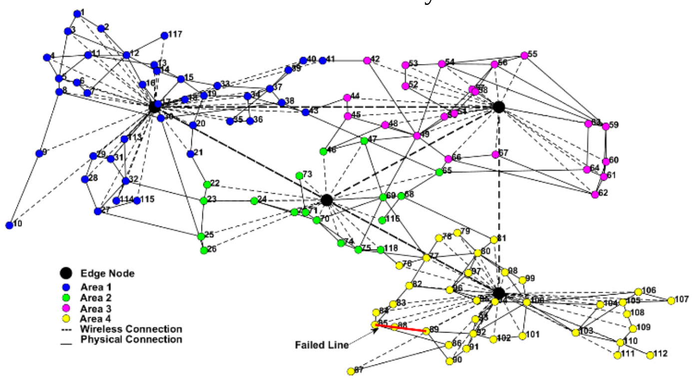

Fig 2: Simulation schematic of event detection based on Edge-enabled EGT over IEEE 118 bus system.

In our simulation, we have considered that the grid is fully equipped with PMUs, therefore, we have PMUs in all the buses. Fig. 2, represents the schematics of the physical structure of the IEEE 118 bus system. We assume a PMU at every node of this figure, which they represent the buses of the system. The black nodes represent the location of the four edge nodes. We have used the optimization method in the previous section to identify the group of PMUs connected to the four edges. The groups of PMUs for each edge node are depicted with different colors. Note that in this test system we only assumed four edge nodes for demonstration purposes; however, for real system with large geographical expansion the number of edge nodes will be higher.

Although PMUs provide the measurement of bus voltage phasor, injected current phasor and the instantaneous frequency, here in our algorithm, we only used the voltage angles from all the buses. We denote the voltage angle time-series from bus number, b as $\theta_b(\mathrm{t})$. At time instant t, all the PMU data from the connected PMUs to the edge node E_i comprises the vector, $\underline{\boldsymbol{\theta}}(t) = [\theta_1(\mathrm{t}), \theta_2(\mathrm{t}), \dots, \theta_n(\mathrm{t})]^T$, where n is the cardinality of set $\mathcal{P}_{E_i}$. However, all the voltage angle PMU time series at edge node E_i constitutes the multivariate time series, $\underline{\boldsymbol{\theta}}(t)$. In our experiment, the multivariate time series have been obtained from the power flow solution in MATPOWER 6.0 [25] according to the hour-long load profiles from NYISO [26]. Since NYISO has load profiles for only 11 regions, synthetic load profiles have been created for 91 load buses of IEEE 118 system according to [27]. The measurements have been recorded at a sampling rate of $0.033Hz$ and an SNR of $50dB$.

In this work, we propose a simple real-time method to detect and locate the anomalies in smart grids using the system states obtained from DSE using PMUs connected to the edge nodes. As an example of anomalies in smart grids in this paper, we present how a single line failure can be detected and its location can be identified locally at the respective edge node from the PMU time-series if the PMUs are connected to the right edge node. Here, we have considered the tripping of the Branch#136, which is the transmission line connecting BUS#85 and BUS#89 in the IEEE 118 bus system. According to our edge-layer architecture discussed in the previous subsection, both the

PMUs associated with BUS#85 and BUS#89 are connected to the edge node, E_4. Our goal is to detect and locate this line trip locally at the edge node, E_4 only with the time series of the PMUs connected to E_4.

In Fig. 3, we observe the voltage angle signals from some of the PMUs connected to the edge node E_4 to understand the effect of the line trip. As the effect of line trip at $t = 0.5$ hour (12:30 am), the value of the normalized voltage angle drops abruptly from 0.78 to 0.65 at the PMU at BUS#85, which is connected to the tripped branch. Similar change (0.13 decrease) occurs at the PMU at BUS#84, which is geographically close to BUS#85. A sharp decrease has also been observed at the PMU at BUS#78 but the magnitude of the decrease is small compared to the previous two. Although BUS#89 was connected to the tripped line, the effect is not intelligible from the time series of that PMU. Also, the geographically distant PMUs from the tripped branch do not show significant effects. From the above case study, it is clear that the analysis of the multivariate time-series at the edge node E_4 can detect and find the location of the failure and can provide early warning locally before central state estimation at the central controller and with the help of the cloud.

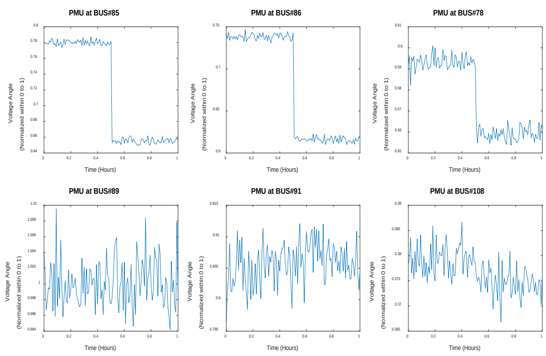

Fig. 3: Examples of the effect of a line trip on some of the PMU time series connected to the edge node E_4.

Several techniques can be applied to detect the sharp changes in time-series to provide warning in case of such scenarios. A simple method is the linear predictive filter similar to [28], [29]. In our work, we have applied linear predictive filtering to the multivariate voltage angle time-series. The one-step-ahead predicted value at time t is given by:

$$\hat{\boldsymbol{\theta}}(t|t-1) = \sum_{k=1}^{p} a_k \hat{\boldsymbol{\theta}}(t-k)$$

When the difference between predicted vector at time t, $\hat{\boldsymbol{\theta}}(t|t-1)$ and the actual vector obtained from the measurement $\boldsymbol{\theta}(t)$ exceeds a certain threshold, (i.e.$\left\|\boldsymbol{\theta}(t) - \hat{\boldsymbol{\theta}}(t|t-1)\right\|_2 \geq \epsilon$), the edge node generates alarms for an anomaly and send them to the central controller. In our simulation, we consider $p = 2, a_1 = 0.8$ and $a_2 = 0.2$. Therefore, $\hat{\boldsymbol{\theta}}(t|t-1) = 0.8\,\hat{\boldsymbol{\theta}}(t-1) + 0.2\,\hat{\boldsymbol{\theta}}(t-2)$. We empirically set ϵ to be 0.1. In our simulation, we showed that a single line trip, for example, tripping of the Branch # 136 (transmission line connecting BUS # 85 and BUS # 89) can be detected from the multivariate voltage angle time-series $\boldsymbol{\theta}(t)$ from all the PMUs connected to the edge node E_4. In Fig. 4, only the actual PMU signal from PMU#85, its one-step-ahead predicted version $\hat{\theta}_{85}(t|t-1)$ and their difference signal are shown for better visualization; however, in our algorithm, we have used the whole multivariate time-series $\boldsymbol{\theta}(t)$, its one-step-ahead predicted version $\hat{\boldsymbol{\theta}}(t|t-1)$ and the l_2 norm of their difference vector for detecting and locating a single line trip event at edge node E_4. From Fig. 4, we can observe, a sudden change in the value of the voltage angle, at time $t = 0.5\ hours$ (12:30 am) due to the tripping of the Branch # 136. Our method can detect this phenomenon and raised the alarm. The same type of method can be used to provide an early warning at the edge node in case of other similar physical failures and certain types of cyber-attacks.

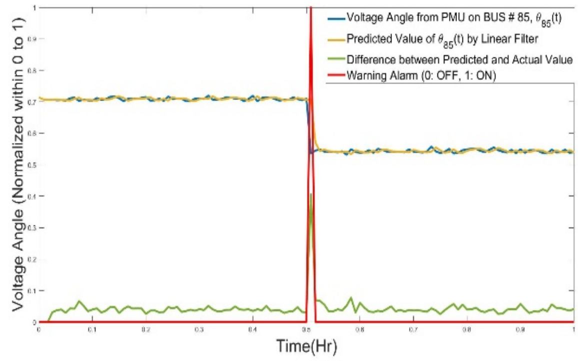

Fig. 4: The alarm for anomaly. Only one PMU data has been shown for better visualization.

For determining the location of the attack, we have to find at which PMU the difference between the predicted value and the actual value is the largest when the alarm is raised. Let, t_a be the time instant when the alarm is set to 1 (indicating the raised alarm). We find the location of the failure by determining the component of the vector $\boldsymbol{\theta}(t_a) - \hat{\boldsymbol{\theta}}(t_a|t_a-1)$ with the largest magnitude.

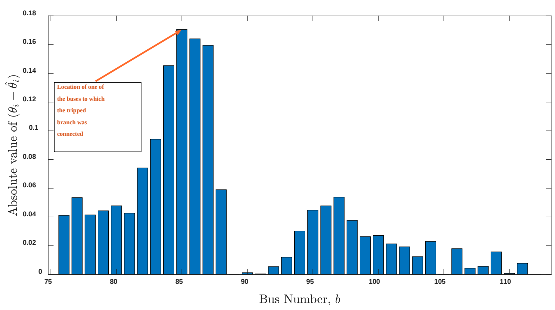

Fig. 5: $\theta_b(t_a) - \hat{\theta}_b(t_a|t_a-1)$ for all the PMUs connected to edge node E_4.

If in PMU number b, the difference is the largest, then $\theta_b(t_a) - \hat{\theta}_b(t_a|t_a-1)$ is the component with maximum magnitude of the vector $\boldsymbol{\theta}(t_a) - \hat{\boldsymbol{\theta}}(t_a|t_a-1)$. Therefore, we have to find such b that,

$$\left\|\theta_b(t_a) - \hat{\theta}_b(t_a|t_a-1)\right\| = \left\|\boldsymbol{\theta}(t_a) - \hat{\boldsymbol{\theta}}(t_a|t_a-1)\right\|_\infty$$

For our simulation, in Fig. 5 the values of $\left\|\theta_b(t_a) - \hat{\theta}_b(t_a|t_a-1)\right\|, \forall\, b$ have been presented in the bar diagram. It is observed that the values in the geographically adjacent PMUs of the tripped line (BUS#84-BUS#87) are higher than the values in all other buses. In fact, the maximum is for BUS#85, which is connected to the tripped line.

V. CONCLUSIONS

Smart grids, as examples of critical CPSs, are incorporating new technologies to enhance their operation and reliability. The application of cloud and edge computing in smart grids have been discussed in literature; however, their application in support of critical and time-sensitive operations has been limited. The distributed and localized communication, storage and processing capabilities of edge computing provides new opportunities for enhancing smart grid operations such as situational awareness. In this paper, we discussed an edge-enabled electric-grid of things that can provide a great platform for providing DSE. We specifically focused on the network of the PMUs as an example of the industrial internet of things in smart grids and discussed the edge-computing platform architecture to enable data analytics for DSE using the PMU time-series. We discussed that it is important to consider the physics of the smart grid in designing the edge-computing layer and we considered the correlation among time-series of the PMUs as an indicator of power dynamics interactions among smart grid components. We then presented a data-driven method for detecting power line trips and detecting their location using the PMU data and the designed physics-aware edge-computing platform. We showed that using the edge platform, system could generate localized early warnings for events in the system to enhance the reliability of the smart grid.

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