IoT-Based Data-Driven Fault Allocation in Microgrids Using Advanced μPMUs

Author(s): Kavousi-Fard, Abdollah; Nikkhah, Saeed; Pourbehzadi, Motahareh; Dabbaghjamanesh, Morteza; Farughian, Amir

Title: IoT-Based Data-Driven Fault Allocation in Microgrids Using Advanced µPMUs

Year: 2021

Version: Author accepted manuscript

Please cite the original version:

Kavousi-Fard, A., Nikkhah, S., Pourbehzadi, M., Dabbaghjamanesh, M. & Farughian, A. (2021). IoT-Based Data-Driven Fault Allocation in Microgrids Using Advanced µPMUs. *Ad Hoc Networks* 199. https://doi.org/10.1016/j.adhoc.2021.102520

IoT-Based Data-Driven Fault Allocation in Microgrids Using Advanced μPMUs

Abdollah Kavousi-Fard*[1], Saeed Nikkhah[1], Motahareh Pourbehzadi[1], Morteza Dabbaghjamanesh[1], Amir Farughian[2]

1-Electrical and Electronics Engineering Department, Shiraz University of Technology, Shiraz, Iran. (kavousi@sutech.ac.ir)

2-School of Technology and Innovations, University of Vaasa, Vaasa, Finland (amir.farughian@uva.fi)

Abstract- The ameliorations in high-precision phasor measurement units (μPMUs) and synchrophasor units have accommodated the distribution grid with peculiar visibility. Therefore, investigating the challenges of uncertainty consideration on precise fault detection in microgrids has become a new research milestone. This paper presents an effective data-driven stochastic method that justifies the adoption of only two μPMUs that are communicating under an IoT-based umbrella to detect and allocate irregularities in a microgrid. The proposed method has the ability to operate under a variety of case studies and scenarios including but not limited to the capacitor bank switching, distributed energy resources (DERs) diversity and high impedance fault occurrence, whilst considering the uncertainty in load, without installing individual sensors. Furthermore, a two-point estimate approach is utilized to model the uncertainties of the problem. Not only does the proposed stochastic framework benefit from the voltage magnitude measurement, but it also utilizes its angle in event allocation, which manifests better performance compared to ordinary voltage and current sensors. The simulation results on the proposed microgrid indicate the high accuracy and a sound success is obtained under a variety of case studies. The results show the high accuracy and applicable aspect of the proposed data-driven approach for fault allocation using a few μPMUs in the IoT context.

Index Terms--Fault Location, Internet of Things (IoT), Microgird, Micro-PMUs (μPMUs), Uncertainty Modeling.

I. NOMENCLATURE

Symbol	Description
$E(Y_{ij})$	j^{th} moment of the i^{th} uncertain parameter
f_{qi}	probability function for each member of Q
fa	faulty operation status
i	indicating bus number $i \epsilon \Omega^{bus}$; $\Omega^{bus}=\{1,\ldots,m\}$
I_i	current of i^{th} bus (A)
$I_{i,fa}/V_{i,fa}$	Current/voltage of the i^{th} faulty bus (A)
$I_{i,I}$	current of a constant current load at i^{th} bus (A)
$I_{i,no}$	current of the i^{th} bus in normal conditions (A)
$I_{i,P}$	current of a constant power load at i^{th} bus (A)
$I_{i,Z}$	current of a constant impedance load at i^{th} bus (A)
k	indicating the number of faulty bus
no	normal operation status
P_i	power of i^{th} bus (kW)
Q	uncertain parameters Q ϵ $\Omega^{uncertain}=\{Load_{bus1},\ldots, Load_{bus1m}\}$
$q_{i,K}$	estimated locations of i^{th} uncertain parameter
R_L	resistance connected to the DC source (Ω)
R_{TH}/V_0	Thevenin equivalent resistance (Ω)/ voltage (V)
$T1\text{-}g$	Uplink time of the g^{th} μPMU from upstream g $\epsilon\{1,2,3,4\}$
V_i	voltage of i^{th} bus (V)
V_s	voltage source (V)
$V_{i,no}$	voltage of the i^{th} bus in normal conditions (V)
y	nonlinear function relating uncertain parameters to output variables

Y_i	admittance of i^{th} bus (Ω^{-1})
Z_{down}	downstream impedance (Ω)
$Z_{m-1,m}$	impedance between buses 'm-1' and 'm'
Z_{up}	upstream impedance (Ω)
ΔI	current change (A)
ΔI_{down}	current change in downstream (A)
ΔI_{up}	current change in upstream (A)
ΔR	change in resistance (Ω)
ΔV	voltage change (V)
$\Delta Vdown$	voltage change in downstream (V)
$\Delta V_{m,b}$	voltage change of backward voltage calculation of m^{th} bus (V)
$\Delta V_{m,f}$	voltage change of forward voltage calculation of m^{th} bus (V)
ΔV_{up}	voltage change in upstream (V)
$\sigma_{qi}/\zeta_{i,K}$	standard deviation/location of i^{th} uncertain parameter

Symbol	Description
μ_{qi} /$\Psi_{i,3}$	mean/ skewness value of input i^{th} uncertain parameter
$\omega_{i,K}$	weighting factor of i^{th} uncertain parameter
φ_i	indicating the difference of forward and backward voltage calculations of i^{th} bus (V)

II. Introduction

In order to realize the application of synchrophasor technology in power systems, high-precision phasor measurement units or Micro-PMUs (µPMUs) have paved their way into the measurements of the distribution power systems [1]. In addition to their lower costs compared to commercial power measurement units (PMUs), their applicability to smart distribution systems and high sampling rates (120 samples per second) have led the operators to utilize µPMUs for accurate voltage and phase measurements [2]. As the distribution system has different *X/R* ratio values compared to the transmission system, the installed measurement units need to be more accurate and sensitive than the present PMUs. The distribution system is subject to a variety of events such as load fluctuations, capacitor bank switching, distributed energy resources' (DERs) existence and fault occurrence. Therefore, "*figuring out the source and location of every event*" is of high importance. Addressing the abovementioned point will improve the visibility, reliability and robustness of the distribution system. The results will be attractive to researchers who are active in the fields of islanding detection [3], security improvement and fault detection [4], postmortem analysis [5], voltage stability [6] and reliability analysis, state estimation [7] and protective relaying [8]. Moreover, the modeling of uncertain parameters and providing a rapid and secure communication infrastructure among µPMUs whilst resolving these events will provide more accurate results in faulty or inconsistent situations. Therefore, the present paper's main goal is to model the uncertain parameters that affect the event allocation in distribution systems while the µPMUs are locating the events' source and location using an IoT-based infrastructure. Table I presents a comprehensive comparison of PMU and µPMU technologies

A. Literature Review

The existing literature review in regards to PMUs are mainly focused on solving the Optimal PMU Placement (OPP), post-fault actions, state estimation, measurement data handling and increasing system security. To the best of authors' knowledge in most cases either the distribution system has not been taken into account or a variety of events, a modern communication infrastructure i.e. Internet of Things (IoT), uncertain parameters' modeling or a combination of them have been disregarded. Also, despite the fact that the PMU research area has a rich background, most of the preexisting researches are not related to µPMUs.

The multi-objective optimization problem of metering systems' planning, considering PMU existence, to gain maximum observability and minimum investment costs is described in [9]. Since the investment costs of PMUs are high, researchers have analyzed Wide Area Measurement Systems (WAMS) to improve their situational awareness whilst minimizing PMUs' quantity [10].

OPP is one of the main concerns in regards with PMUs' operation. The OPP problem has been modeled linearly in [11] in full and incomplete observability situations. The generalized formulation yields effective results as it has been implemented on various test systems. Zero injection and nonsynchronous measurements are the two fundamental factors that affect the observability of power systems. The numerical observability of a system has been fully addressed in [12] using the binary semi-definite programming model, whilst considering the inequality constraints. The proposed approach in this paper is applicable to AC and DC systems and it converges to lesser PMU numbers compared to other pre-existing techniques. Similarly, the zero injection buses and conventional measurements' existence have been considered in [13] along with single branch and single PMU outage, using an integer linear programming model. The OPP problem can also be solved with the objective of bad data detection during state estimation as in [14]. The main idea in [14] is that by adding a few extra PMUs in strategic locations bad data can be detected in critical measurements. With the increasing risk of False Data Injection Attacks (FDIA) in PMU-based state estimation systems, article [15] presents a data filter to avoid incorrect solutions based on faulty measurements. The situational awareness for dynamic state estimation is improved using Extended Kalman Filter (EKF) technique to enhance the quality of unknown input data to PMUs [16]. Receiving, processing and storing PMU data is an incumbency that the Phasor Data Concentrator (PDC) is responsible for. In [17] the delay of PMU streams are managed by PDCs in active distribution power systems. Moreover, in [18] a framework based on PMU data-compression is presented to detect the accurate time and place of an event based on predefined rules. The uncertainty associated with variegated PMUs in active distribution grids and its effect on system's state estimation is described in [19]. Furthermore, a two-step algorithm based on prelocation and correction is introduced in [20] to solve the uncertain operation mode or to present a series device model in a system equipped with PMUs.

The post-fault actions in systems that are equipped with PMUs are also a research domain in measurement systems. Article [21] exploits decision trees to present a voltage analysis framework in post-contingency situations using real-time data of PMUs. Also, [22-23] presented an adaptive prediction method to forecast the transient instability of a system and help it to maintain its stability using PMU data.

B. Contributions & Paper Organization

This paper presents a broad taxonomy domain of contributions that can be summarized as follows:

Simultaneous Voltage and Phase Measurement: In this paper, both the voltage and the phasor that are measured by μPMUs are taken heed. Considering the phasor angle is vital since the power factor of the events' equivalent circuit is affected by that and as microgrids (MG) are sensitive to such changes, accurate measurements are required.

Minimum Exploitation of μPMUs: The proposed solution framework presents a method that requires only two μPMUs along the main feeder for figuring out the source and location of every event. That is, by installing one μPMU at the beginning and one at the end of the line we can guarantee a sound visibility of the system.

Deploying IoT in μPMUs' Communication: In systems where advanced measuring devices i.e. μPMUs are exploited, using a high-tech communication infrastructure is inevitable. Therefore, in this paper the IoT-based communication of μPMUs is considered to foster a secure and high-speed data transfer foundation.

Presenting a Stochastic Framework for Modeling Uncertain Parameters: In this paper, the Two-Point Estimate Method (TPEM) is used to model the load uncertain values. The presented stochastic framework matches the event detection solution methodology and it does not increase the computational burden nor the execution time of the simulations.

The rest of the paper is presented as follows. The problem formulation, event allocation procedures and the objectives are presented in section III. The TPEM stochastic framework is exemplified in section IV. The IoT integration on power system is introduced in section V. The solution methodology and its application is described in section VI. The simulation results and case studies are analyzed in VII. Finally, the concluding remarks are presented in section VIII.

III. Problem Formulation

In this section different stages of the proposed data-driven event detection using μPMUs' data are discussed to familiarize the audience with the problem of finding the source and location of an event. The presented framework is consisted of four main stages:

Table I
Comparison of PMU and µPMU technologies [24]

Traditional PMUs	µPMUs
* Installed in transmission systems *±1% precision of total voltage error with ±0.1% voltage magnitude resolution *±1° % Angle measurement accuracy with ±0.1° % angle resolution *15 reading per second *Used in transmission network where: • Few transitions exist • Construction remains the same • There are few generators, all are large and stable. • A comprehensive model of this network exists	* Installed in distribution systems *±0.05% precision of total voltage error with ±0.0002% voltage magnitude resolution *±0.01% angle measurement accuracy with $\pm 0.002^{\circ}\%$ angle resolution *100/120 reading per second *Used in distribution network where: • Many transactions exist • The network is subject to reconfiguration • There are many small and unstable generators. • This system is poorly modeled and the transient behavior is subject to uncertainty.

Event detection: It is assumed that an event detection method has been applied to a MG, similar to what is expressed in [23]. Once it is verified that an event has occurred, it is required to find the approximate location of the event that is described in the next stage.

Finding the approximate event location: At this stage, detecting the accurate location of the event is not possible. However, the network operator can limit the location of the event to either the upstream of µPMU1, the downstream of µPMU2 or in-between them. Consider Fig.1 and Appendix I for understanding the calculations of equivalent circuits in this section. The occurrence of an event can be approximately detected by finding the real values of Z_{up} and Z_{down} as described in subsection II.B.

Applying stochastic forward and backward voltage calculations: At this stage the uncertainty in load at each bus is fed to a forward-backward voltage calculation algorithm. The results for each bus are calculated by successive use of Kirchhoff's Voltage Law (KVL). The stochastic framework is fully described in section III and the voltage calculations are described in subsection II.C.

Specify the faulty bus by data aggregation: After applying the previous steps, we have all the required data to detect the bus at which the event has occurred. Considering Appendix I, it is obvious that when an event occurs at a bus, a voltage source can be considered in the equivalent circuit and the KVL calculations will be missing a term and the successive changes in voltage will be miscalculated. Therefore, the bus at which the difference of forward and backward voltage changes is the minimum value is the one at which the event has occurred. This phenomenon is discussed in subsection II.D.

A. On the µPMUs

Small-scale power flow variations, higher levels of noise-influence, lower budget allocation and smaller data to network node ratio compared to transmission systems are among the challenges that need to be addressed in distribution systems. Therefore, in order to provide high-resolution data with real-time communication, µPMUs have paved their way into the distribution systems.

There exists a broad range of µPMUs' applications in distributions systems that can be categorized into two major groups: Diagnostic and Control. The diagnostic applications are basically concerned with the network's present or past conditions, while the control acquisitions are focused on the real-time status of the system [25]. The control applications include protective relaying, Volt-Var optimization and the coordination of MGs. The most important diagnostic applications are as follows:

Islanding detection: Despite the existence of anti-islanding protection on almost all the inverters, the dynamics of the network must be addressed in case a cluster of generation units or loads were separated from the network but had local connections.

Network configuration management: The main purpose is to find the actual state of system's composing units so that the system status can be verified precisely.

Detection of reverse power flow: Assuming the fact that the implemented protection and relaying on the distribution system is sensitive to the reverse power flows in the system, the µPMUs are able to differentiate the faulty and normal operational conditions as the reverse power flow is not an issue by itself.

State Estimation: In this paper, state estimation simply considers the fact that the phasor and voltage magnitude of all the nodes in the distribution system must be available or computed through the measured data of the µPMUs.

Fault Detection: The main goal is to detect the precise fault location by analyzing the measured data. The most common faulty scenarios include high-impedance faults, high frequency oscillations, capacitor bank switching and reactive power injection.

B. Approximate event detection procedure

Consider Fig.1 for comprehending the approximate event source location in the presented framework. Here, two µPMUs are installed on the system. The changes in voltage and current are indicated by ΔV and ΔI that can be calculated using post- and pre-fault measurements as (1) and (2), where the *fa* and *no* indices show the faulty and normal operation status of the system.

$$E(\Delta V_i) = E(V_{i,fa}) - E(V_{i,no}) \quad (1)$$

$$E(\Delta I_i) = E(I_{i,fa}) - E(I_{i,no}) \quad (2)$$

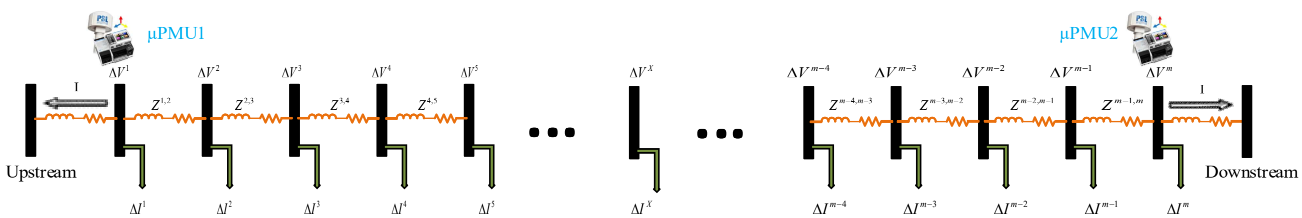

Fig.1. A simple distribution network, demonstrating the forward-backward approach by using two µPMUs at the first and the last feeders' buses

By calculating the $\Delta V / \Delta I$ value for the µPMUs that are installed in the upstream and the downstream of the network we will have:

$$Z_{up} = \frac{\Delta V_{up}}{\Delta I_{up}} \quad (3)$$

$$Z_{down} = \frac{\Delta V_{down}}{\Delta I_{down}} \quad (4)$$

Note that both the measured voltage and current have a magnitude and a phasor value. The real values of (3) and (4) are the tie breaker in finding the approximate event location [25]. If the $\mathrm{Re}\{Z_{up}\}$ is negative, then the event has occurred in the upstream of µPMU1 and if the $\mathrm{Re}\{Z_{down}\}$ is negative, an event has transpired in the downstream of µPMU2. Otherwise, the event is located between the µPMUs. Now, note that if the µPMUs are assumed to be located at the head feeder and the end feeder; therefore if $\mathrm{Re}\{Z_{up}\}$ is negative, then it is acknowledged that the main event is located outside the MG. Similarly, if $\mathrm{Re}\{Z_{down}\}$ is negative, it can be concluded that the event source is located at the terminal bus.

C. Forward-backward voltage calculations

The forward-backward voltage calculations are based on successive applications of KVLs on the networks' buses. Note that the load uncertain parameters are derived from the stochastic framework that is presented in section III. The forward bus voltage calculations are conducted based on (5):

$$\begin{aligned} &E(\Delta V_{m,f}) = \\ &E(\Delta V_{m-1,f}) + (E(\Delta I_{up}) + E(\Delta I_1) + \ldots + E(\Delta I_{m-1,f}))Z_{m-1,m} \end{aligned} \quad \forall m \in \Omega^{bus} \tag{5}$$

The backward voltage calculations are as described in (6):

$$\begin{aligned} &E(\Delta V_{1,b}) = \\ &E(\Delta V2_{,b}) + (E(\Delta I_{down}) + E(\Delta I_m) + \ldots + E(\Delta I_{2,f}))Z_{1,2} \end{aligned} \quad \forall m \in \Omega^{bus} \tag{6}$$

Here the main assumption is that the load impedances are constant. However, the general assumption can be taken into account as (7):

$$E(I_i) = E(I_{i,Z}) + E(I_{i,I}) + E(I_{i,P}) \tag{7}$$

where the indices Z, I and P indicate the constant values of impedance, current or power of the loads. (7) can also be reorganized as (8):

$$E(I_i) = Y_i E(V_i) + E(I_{i,I}) + \left(\frac{P_i}{E(V_i)}\right)^* \tag{8}$$

By substituting (8) into (2) we will have:

$$E(\Delta I_i) = Y_i E(\Delta V_i) + (P_i)^* \left(\frac{1}{E(V_{i,no}) + \Delta V_i} - \frac{1}{E(V_{i,no})}\right) \tag{9}$$

D. Objective

After calculating the forward and backward voltage differences in each bus, the final step is to locate the event precisely. As it is described in Appendix I, when an event occurs in a bus, this event can be modeled using an equivalent circuit that can be illustrated with a current source. Therefore, it can be interpreted that the faulty bus can be detected by finding the minimum value of the "difference of forward and backward voltage changes".

Thus, the abovementioned point can be found by calculating (10) and (11):

$$E(\phi_i) = \sum_{i=1}^{4} |\Delta V_{i,f} - \Delta V_{i,b}| \tag{10}$$

$$k = \arg\min(E(\phi_i)) \tag{11}$$

where k shows the number of the bus in which the event has occurred.

IV. Modeling Uncertainty in a Stochastic framework

In order to model the uncertain parameters' behavior, the TPEM is exploited in this paper. Similar to the Monte Carlo Simulation (MCS) method, TPEM uses deterministic techniques to solve probabilistic problems. However, the computational burden of TPEM is considerably lower. Moreover, since the TPEM doesn't require complete knowledge of the Probability Distribution Function (PDF) of all uncertain parameters, a smaller range of data and statistical moments (i.e. mean, variance, skewness and kurtosis) is required [26].

Thus, the aforementioned moments must be calculated for all uncertain parameters as the following:

1- Suppose that the uncertain parameter Q is related to y with the nonlinear function $y = f(Q)$ where $Q \in \Omega^{uncertain}$

2- Consider a probability function f_{qi} for each member of Q

3- Implement TPEM as described in (12)-(18) to substitute f_{qi} by mean, variance, skewness and kurtosis.

$$y = f(Q) = f(\mu_{q1}, \mu_{q2}, \ldots, q_{i,K}, \ldots, \mu_{qm}); \quad K = 1, 2 \tag{12}$$

$$q_{i,K} = \mu_{qi} + \xi_{i,K} . \sigma_{qi} \tag{13}$$

$$\xi_{i,K} = \frac{\psi_{i,3}}{2} + (-1)^{3-K} \sqrt{m - \left(\frac{\psi_{i,3}}{2}\right)^2} \tag{14}$$

$$\psi_{i,3} = \frac{E[(q_i - \mu_{qi})^3]}{(\sigma_{qi})^3} \tag{15}$$

$$\sigma = \sqrt{Var(y_i)} = \sqrt{E(y_i)^2 - [E(y_i)]^2} \tag{16}$$

$$E(y_{ij}) = \sum_{i=1}^{m} \sum_{K=1}^{2} (\omega_{i,k} \times y_{ij}(\mu_{q1}, \mu_{q2}, \ldots, q_{i,K}, \ldots, \mu_{qm})) \tag{17}$$

$$\omega_{i,K} = \frac{1}{2m} \tag{18}$$

where $q_{i,K}$ are the new points, produced by TPEM and its constituting elements can be derived from (13) and (14). The Standard Deviation (SD) values are calculated as per (16), where the weights of each point are assumed to be found via (18).

V. IoT INTEGRATION ON POWER SYSTEMS

With the increasing rate of miscellaneous devices that require to be networked and interconnected, as well as the corresponding big data that must be stored and processed, IoT and its subsequent technologies have paved their way into the operation of power systems. The IoT-networked devices have specific requirements i.e. low power consumption, durability and small form-factor; all of which can be attributed to the μPMUs. As it is illustrated in Fig.2, in a cloud-centric IoT framework the smart objects (μPMUs) measure the desired real-time parameters of the proposed power system and send the data to the cloud. The control signal will be formed in the cloud and it will be sent back to the power system operators. The IoT framework provides higher observability and controllability compared to traditional methods as it uses a low-latency communicational infrastructure which is not a case with traditional PMUs according to Table 1. IoT brings about rapid situational awareness in regards to fault detection and decision making. The highly visible system that has been brought about by the IoT framework has various potentials i.e. price and supply prediction, faster outage/ fault detection and restoration, anomaly detection, etc. [27]

Nevertheless, the large quantity of IoT objects and their data in smart grids lead to a troublesome system management for several reasons:

- The distance of cloud servers is pretty long from the main system that will impose communication delays.
- The constant measurements of real-time systems inflict an extensive load on the communication network, causing latency and inaccuracy.
- As third parties have access to the raw data in public clouds, cloud-centric IoT networks will be subject to security threats.

In order to cope with the deficiencies of cloud-based IoT systems, the Edge Computing (EC) technology is proposed. EC suggests that the measured data do not require to be transferred and the data can be processed at the edge of the IoT system close to where it has been collected. Not only does this technology reduce the data transmission volume, but it also reduces system latency [28]. The intelligence behind the EC is by analyzing the historical data and learning. This includes learning the load patterns, user preferences, locating sensitive nodes in the network, detecting congestion, voltage and current profile pattern in normal and faulty conditions, etc. The contributions regarding EC are further discussed in section V. In the communication infrastructure, the most important aspect is the data "send-process-receive" time. Now, if the main objective of using μPMUs is archiving or recording, then the "send-process-receive" time is not significant. However, implementing IoT enables the system operator to make more optimized choices based on real-time μPMU data analysis. For this purpose, optimal routing will be of great importance. In Fig.3, the uplink times of five different routes to scan the whole MG are presented. Knowing these times are important, as they guide the system operator to synchronize readings from different μPMUs in every route. It also helps the market operator to realize the data that must be neglected and the silent time for all the readings.

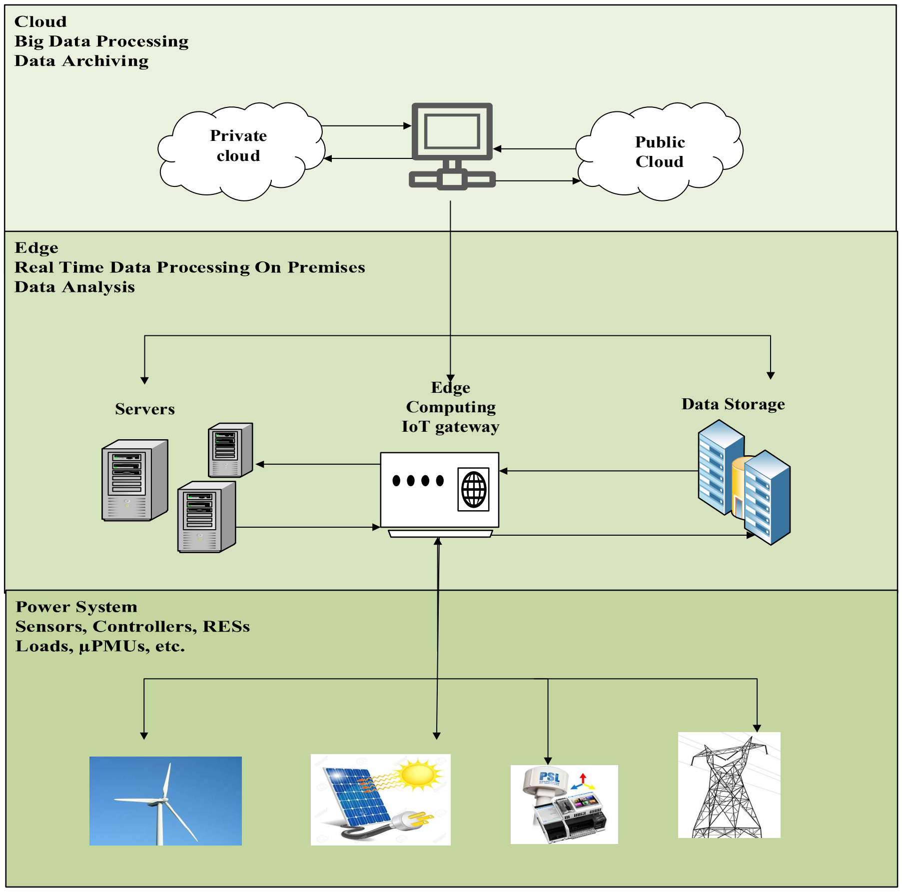

Fig.2. Cloud & Edge computing in IoT-based power system

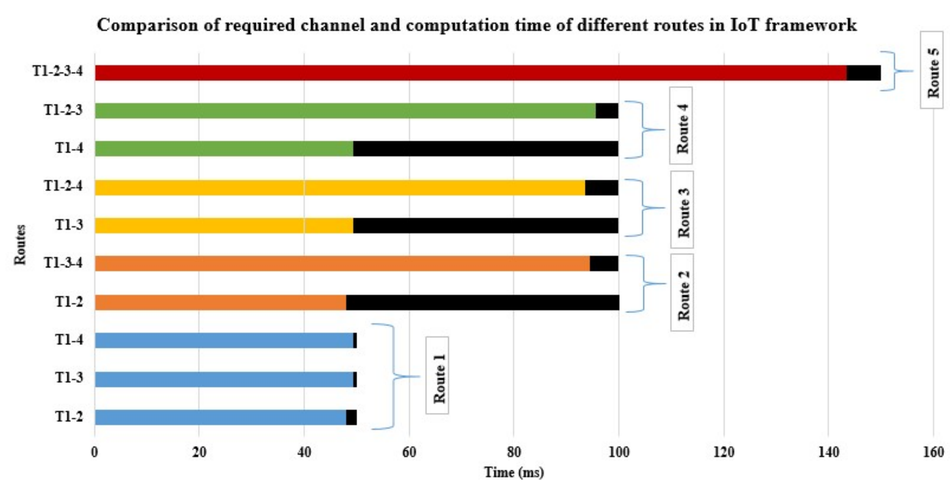

Fig.3. Comparison of required channel and computation times of different routes in IoT framework

Such analysis is mandatory to detect the optimal route for system's readings. Moreover, the data transfer capacity of the chosen IoT protocol must be considered. For instance in route 1, despite the fact that data transmission occurs 2 times faster compared to other routes, but the measurements occupy 3 channels. Since the communication regulations and IoT protocol capacity only offer a limited duty cycle in each channel, then the data need to be segregated among different channels and parallel computing will be a requirement. Also, in this figure the black bars show the time that the data from that specific sub-route must be neglected, since synchronous readings are required to be able to perform real-time analysis of µPMUs' data. The vertical lines are the readings frequency of the µPMU as illustrated in Table 1.

Considering the fact that the presented distribution MG has a relatively large dimension, it requires multiple channel and bandwidth access, high data transfer speed, minimized power consumption and maximized daily messages. These requirements can be addressed by IoT hub technologies. This technology allows the user to have bi-directional communications in cloud or edge environments.

VI. SIMULATION RESULTS

In order to validate the presented solution framework for finding the exact faulty bus location, we have taken 3 case studies and implemented them on the IEEE 85 bus test system [29], which is illustrated in Fig.4. Similar to [25], the present work has utilized the forward-backward approach for estimating the location of the faulty bus under three main case studies: capacitor bank switching, DER diversity or load switching and high impedance fault. To the best of our knowledge, this work is the first work using µPMUs for accurate fault allocation in the microgrids. Considering the high uncertainty sources, the present work has applied a stochastic framework based on Io-T to the problem formulation, in which the data transmission among µPMUs is performed via EC technology. Not only has the present work taken grid-connected scenario into consideration, but the islanded mode and the islanded mode with no RES availability in the microgrids have been studied. Each color shows a Forward-Backward method path. The first path contains the buses between µPMU1 to µPMU2 involving buses 1 to 16. The second one contains buses between µPMU1 to µPMU3 involving buses 1 to 8 and 17 to 31 and the last path is the buses between µPMU1 to µPMU4 means buses 1 to 9 and 32 to 41. As it is illustrated in Fig. 4, a 50 kW photovoltaic (PV) array is located at bus 3, two 100-kW wind turbines (WTs) are located at buses 29 and 34 and five 320-kW diesel generators (DGs) are located at buses 6,10,13,18 and 39. The presented system is studied under three main scenarios using an Intel core i5 computer with a 6 GHz RAM:

Scenario A: All units are available and the MG is connected to the main grid. The total load value is 2570.280 kW and the MG production is 1850 kW. **Scenario B:** The MG is in the islanded mode. The total production is less than the total load. Therefore, the system operator has to impose the system to load shedding based on the priority of each load. Many factors contribute to the priority of loads. One of the most important factors is the load's bus distance from the closest main bus. The lowest priority is for the loads that their buses are only connected to one of the main buses. The reason for such a decision is when an event occurs in these buses, the algorithm can easily locate the event. The next lowest priority is when two subsidiary buses are connected to a main bus and so on. The priority of the buses is as described in Table II. **Scenario C:** In the third scenario, the MG is still in the islanded mode and the geographical situation is such that the PV's and WTs' outputs are set to zero e.g. a still summer night. In the following, the first scenario is taken into consideration for three main case studies; that are capacitor bank switching, DER diversity and high impedance fault. Afterwards, scenario 2 and 3 are going to be compared under the three main case studies.

Table II: Load Priority List

Bus No.	Bus Connection	Load Priority
S5-1 to S5-6	Five subsidiary buses connected to a main bus	5 (highest)
S4-1 to S4-16	Four subsidiary buses connected to a main bus	4
S3-1 to S3-6	Three subsidiary buses connected to a main bus	3
S2-1 to S2-4	Two subsidiary buses connected to a main bus	2
S1-1 to S1-13	One subsidiary bus connected to a main bus	1 (lowest)

A. Scenario A: (Grid-connected mode), Case study I: Capacitor bank switching

As it is known, a part of active power is lost in the distribution system. In order to minimize these losses, capacitor banks are installed in MGs. Installation of capacitor banks will be pragmatic in: 1) power factor improvement; 2) voltage profile enhancement; 3) loss reduction.

Therefore, it is vital to know the precise location of injected active and reactive power. Moreover, reactive power control of the MG and knowing its injection status is of critical importance for network operator. In this paper, it is assumed that if an event occurs and the capacitor bank connects to or disconnects from the MG (generally speaking any variations in reactive power injection) can be detected using the data that are sent by µPMUs. In this way, if one of the capacitor banks is disconnected from one of the buses, the µPMU will detect the location of this event and by knowing this, the subsequences of such event can be suppressed. In this case study, it is assumed that a 600 kVAR capacitor bank is connected to bus 23 and an event occurs, causing the capacitor bank to be disconnected from this bus. Fig. 5 illustrates the φ value that is calculated by the presented solution framework. The figure points out that the φ value is minimized in bus 23 and the faulty bus is distinguished correctly.

B. Scenario A: (Grid-connected mode), Case study II: DER diversity or Load switching

DERs are electrical power sources or controllable loads that are connected directly/ indirectly to a local distribution system. PVs, energy storage units, small scale generators that consume liquefied petroleum gas, electric vehicles and controllable loads are among most well-known DERs. These resources produce power in lower scales than traditional generators. Technological advances, climate change policies and the increase in electric power consumption have led to an increment in DER utilization in North America. Fig.6 shows that more than 2000 MW of photovoltaic capacity is installed in Ontario [27]. With the importance of DERs determined, the second case is considering DER or load switching into account. In this case it is assumed that a DER power source with the capacity of 40kW+10 kVAR is switched in bus 10. Therefore, in this case the network operator realizes an event has occurred in this bus. Similar to the previous case, the algorithm has detected the faulty bus by determining the minimum φ value for bus 10. The results are illustrated in Fig. 7.

C. Scenario A: (Grid-connected mode), Case study III: High impedance fault

D. When a high impedance fault occurs, an electrified conductor impacts trees, buildings or other objects or it might fall on the contrary to low impedance faults that stream down large currents, the high impedance faults' current is low. Thus, detecting high impedance currents are not possible by utilizing traditional protective and relaying techniques and the overcurrent relays are unable to detect these faults. In this paper, it is presumed that a fault with a resistance value of 300Ω has occurred in bus 38. In this case study, voltage level and fault impedance is computed using the compensation theorem (see Appendix I). In this technique, the events in the MG are modeled with a current source that streams out a current that is proportional to the fault resistance. The values for this case study are presented in Fig.8. It is observed that the proposed solution methodology has detected the faulty bus precisely. *Scenario B: (Islanded mode), Case studies comparison*

As described before, in this scenario the system is operated in islanded mode, which means the MG is disconnected from the power grid. Therefore, the total load is greater than the total production and the extra load is shed as per Table II. The summation of low priority loads is 1742.04 kW. The total load is as described in the first scenario equal to 2570.280 kW and the MG production is 1850 kW. The part of load that has to be shed in this scenario is 720.28 kW, which is about 28% of the total load or about 41.3% of the low-priority loads.

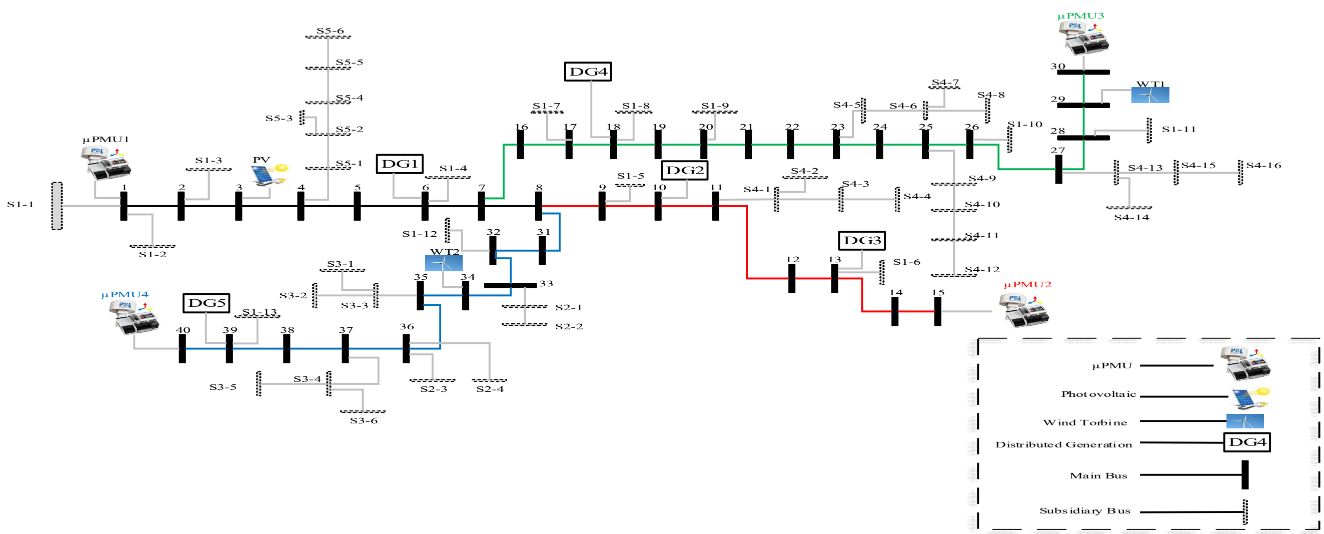

Fig.4. IEEE 85 bus test system observing with 4 μPMUs

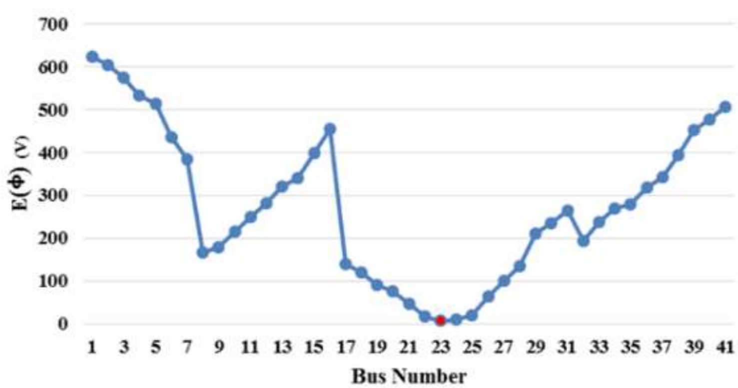

Fig. 5. Capacitor bank switching at bus 23

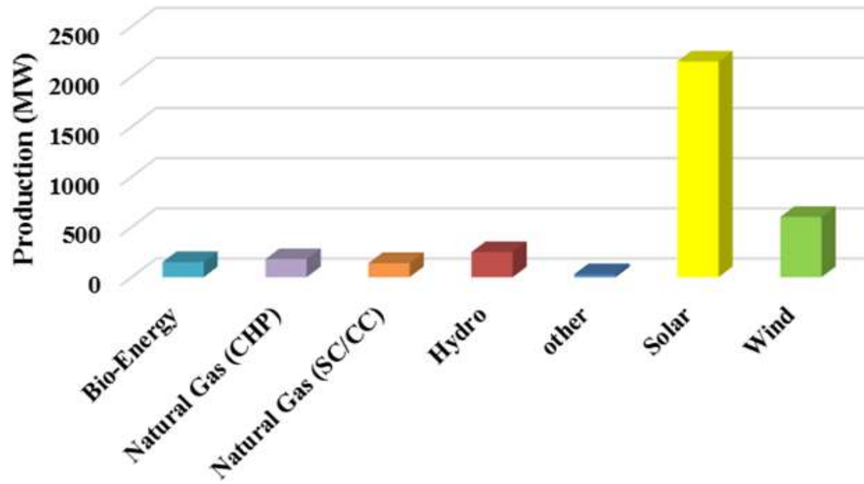

Fig.6. Distribution of energy resources in Ontario

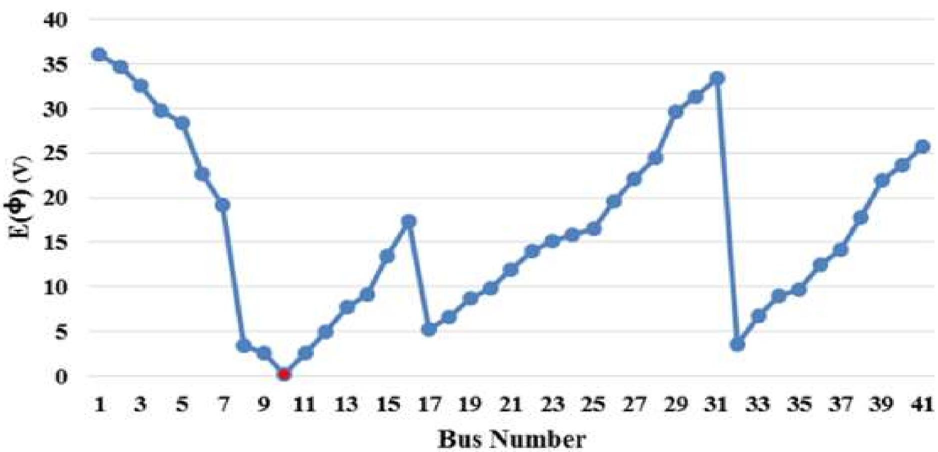

Fig.7. DER switching at bus 10

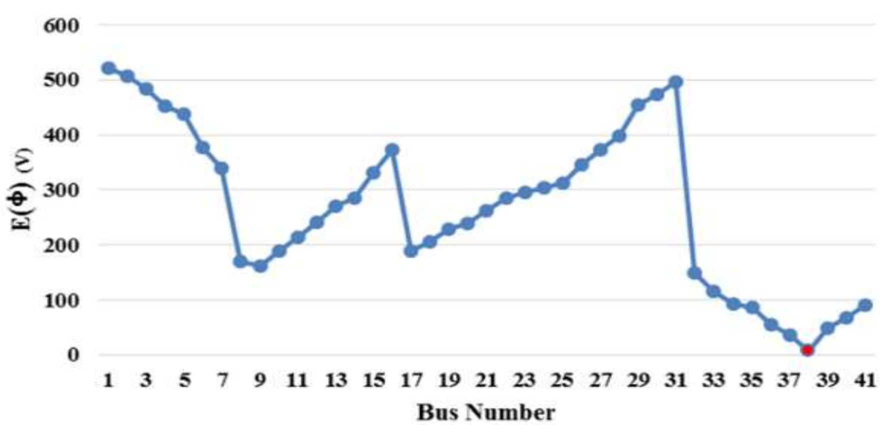

Fig.8. High impedance fault at bus 38

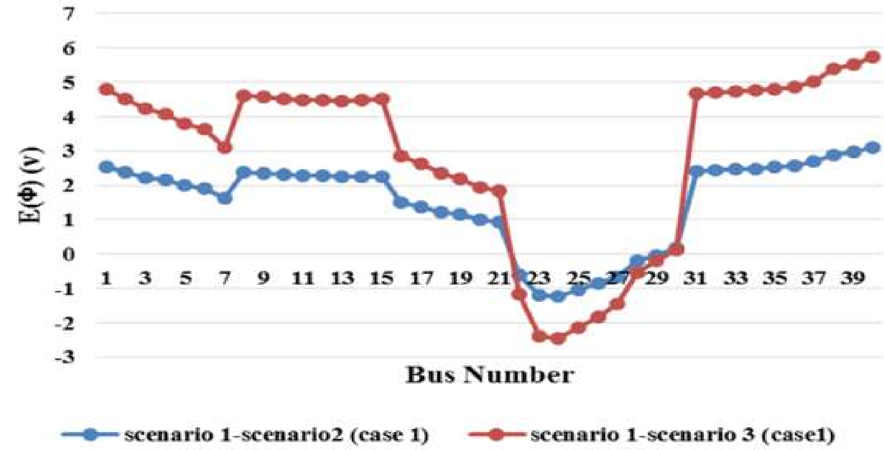

Fig.9. Voltage deviation of scenarios B&C in case study 1

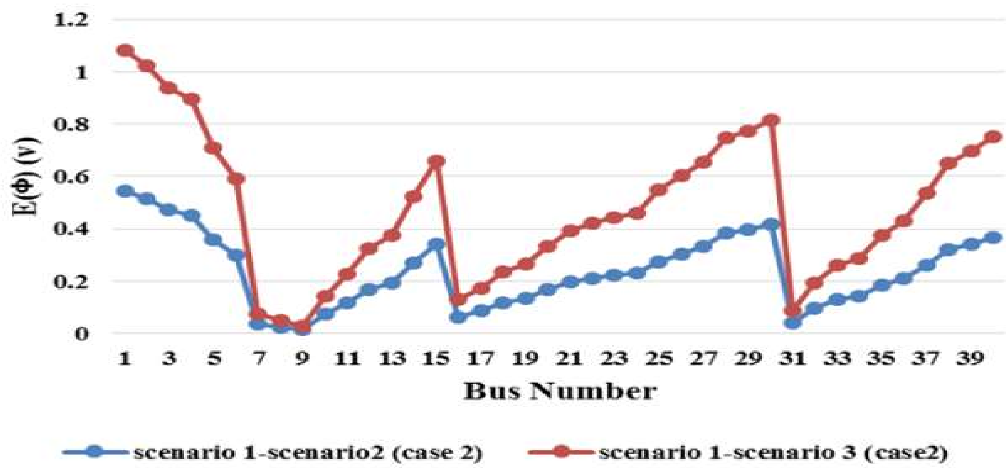

Fig.10. Voltage deviation of scenarios B&C in case study 2

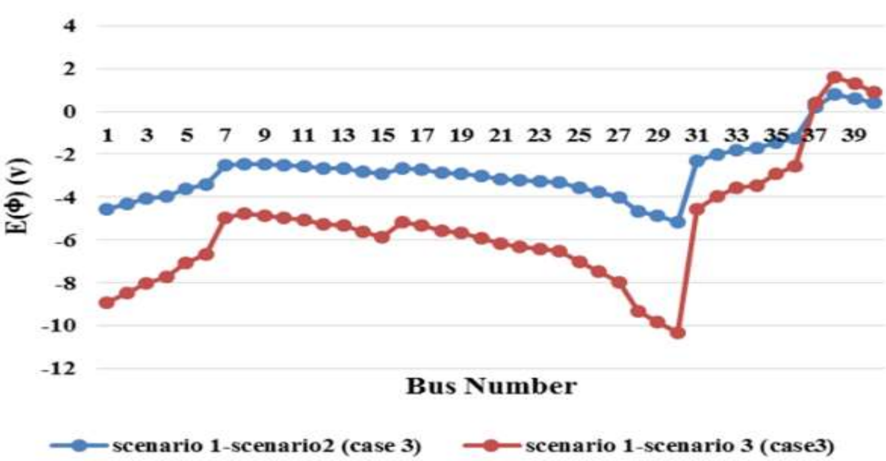

Fig.11. Voltage deviation of scenarios B&C in case study 3

E. Scenario C: (Islanded mode with no RES availability), Case studies comparison

In this scenario, the MG is operated in the islanded mode and the meteorological data is such that the output of PV and WT units are set to zero. In this case, the MG's production is lowered to 1600 kW and the rest must be provided by shedding loads. The shed loads is equal to 970.28 kW that is about 37.7% of the total loads or 55.7% of low-priority loads.

F. Discussion

Fig. 9 to Fig. 11 illustrate a better demonstration of the system behavior in scenarios B and C. In these figures the difference of φ values of these scenarios with scenario A (normal operation condition) in three case studies are shown. The figures clearly state that the third scenario had more impact on the MG, causing a higher φ deviation. That justifies the more load shedding proportions in scenario C compared to scenario B. Moreover, as discussed in section IV, the EC technology shows to be applicable in all scenarios and case studies. In Fig. 9 to Fig. 11, the comparison of the φ changing trend clearly marks the event location. These findings could be fed to a supervised machine learning algorithm. The algorithm stores these data and gets trained on that basis. Should an event occur in the MG, the EC technology matches the difference of φ values with the normal condition, finds the pattern that has the more similarity and detects the event location. The findings of this section are of vital importance since not only are the φ values applicable to find the location of an event, but the pattern that is formed from difference of φ values of every scenario with the normal operation condition can be used as a frame of reference in training the IoT-based framework.

VII. CONCLUSION

In this paper, a stochastic data-driven μPMU-based framework has been presented to detect the precise location of an event in a proposed MG. The presented solution methodology exploits a minimum number of two μPMUs to detect the exact event location using the compensation theorem and backward-forward voltage calculations. As the MG is sensitive to slight voltage/ current variations, the voltage phasor and magnitude measurements of the μPMUs have been used to increase the accuracy of the results. Furthermore, as the μPMUs are communicating using the IoT infrastructure, the data transfer and calculation complexity have decreased drastically. In order to evaluate the broadness of the presented framework, three case studies were taken into consideration under three main scenarios. Sound results were achieved under capacitor bank switching, DER switching and high impedance fault occurrence in the first scenario, where the MG was connected to the main grid. Analyzing the results of scenarios B and C, in which the MG operated in the islanded mode, justified the utilization of EC technology instead of cloud-based decision making. The results also showed that the patterns formed from φ deviations are applicable in training a supervised machine learning algorithm that will be further discussed in our future works.

VIII. APPENDIX I

The Compensation Theorem states that in every Linear Time Invariant (LTI) system, when the resistance of a branch is changed by ΔR, the current of that branch will change accordingly. This phenomenon can be modeled by assuming an independent voltage source $V_s = I(\Delta R)$ that is installed in series with $R+\Delta R$. Consider R_L is connected to a DC voltage source, whose Thevenin equivalent give V_0 as Thevenin voltage and R_{TH} as Thevenin resistance as described in Fig.12. Therefore, the current (I) can be calculated as in (19). Now assume that R_L changes by ΔR. Therefore, the new current I' is as in (20):

$$I = \frac{V_0}{R_{TH} + R_L} \tag{19}$$

$$I' = \frac{V_0}{R_{TH} + (R_L + \Delta R)} \tag{20}$$

The current changes can be calculated as in (21):

$$\Delta I = I' - I \tag{21}$$

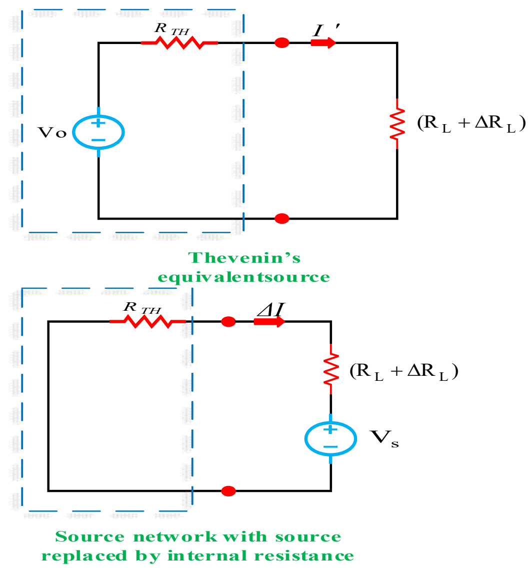

Fig. 12. Compensation Theorem implementation on Thevenin equivalent circuit

By substituting (19) and (20) in (21) it can be concluded that:

$$
\begin{aligned}
\Delta I &= \frac{V_0}{R_{TH} + (R_L + \Delta R)} - \frac{V_0}{R_{TH} + R_L} \\
&= \frac{V_0 (R_{TH} + R_L) - V_0 (R_{TH} + R_L + \Delta R)}{(R_{TH} + R_L)(R_{TH} + R_L + \Delta R)} \\
&= -[\frac{V_0}{R_{TH} + R_L}] \frac{\Delta R}{R_{TH} + R_L + \Delta R} \\
&= -\frac{I \Delta R}{R_{TH} + R_L + \Delta R} \\
&= -\frac{V_s}{R_{TH} + R_L + \Delta R}
\end{aligned}
\tag{22}
$$

REFERENCES

[1] Chunlin LiWeining ChenYoulong Luo, "Stochastic computation resource allocation for mobile edge computing powered by wireless energy transfer", Ad Hoc Networks, 21 May 2019, Volume 93.

[2] B. Pinte, M. Quinlan, and K. Reinhard, "Low voltage micro-phasor measurement unit," in 2015 IEEE Power and Energy Conference at Illinois (PECI), pp. 1–4, Feb. 2015.

[3] Bo ChaiZaiyue Yang, "Impacts of unreliable communication and modified regret matching based anti-jamming approach in smart microgrid", Ad Hoc Networks, November 2014, Volume 22, Pages 69-82.

[4] H. P. Das and A. K. Pradhan, "Development of a micro-phasor measurement unit for distribution system applications," in 2016 National Power Systems Conference (NPSC), pp. 1–5, Dec. 2016.

[5] Jacques Palicot, Christophe Moy, Rémi Bonnefoi, "Application of Hierarchical and Distributed Cognitive Architecture Management for the Smart Grid", Ad Hoc Networks1 May 2016, Volume 41, Pages 86-98.

[6] A. Eshraghi and R. Ghorbani, “Islanding detection and over voltage mitigation using controllable loads,” Sustain. Energy, Grids Networks, vol. 6, pp. 125–135, Jun. 2016.

[7] Y. Liu et al., “Wide-area-measurement system development at the distribution level: An FNET/GridEye Example,” IEEE Trans. Power Deliv., vol. 31, no. 2, pp. 721–731, Apr. 2016.

[8] A. Shahsavari, A. Sadeghi-Mobarakeh, E. Stewart, and H. Mohsenian-Rad, “Distribution grid reliability analysis considering regulation down load resources via micro-PMU data,” in 2016 IEEE International Conference on Smart Grid Communications (SmartGridComm), pp. 472–477, Nov. 2016.

[9] M. P. Vigliassi, J. A. D. Massignan, A. C. B. Delbem, and J. B. A. London, “Multi-objective evolutionary algorithm in tables for placement of SCADA and PMU considering the concept of Pareto Frontier,” Int. J. Electr. Power Energy Syst., vol. 106, no. 3, pp. 373–382, Mar. 2019.

[10] M. A. R. S. Cruz, H. R. O. Rocha, M. H. M. Paiva, M. E. V. Segatto, E. Camby, and G. Caporossi, “An algorithm for cost optimization of PMU and communication infrastructure in WAMS,” Int. J. Electr. Power Energy Syst., vol. 106, no. 3, pp. 96–104, Mar. 2019.

[11] B. Gou, “Generalized integer linear programming formulation for optimal PMU placement,” IEEE Trans. Power Syst., vol. 23, no. 3, pp. 1099–1104, Aug. 2008.

[12] G. N. Korres, N. M. Manousakis, T. C. Xygkis and J. Löfberg, "Optimal phasor measurement unit placement for numerical observability in the presence of conventional measurements using semi-definite programming," IET Generation, Transmission & Distribution, vol. 9, no. 15, pp. 2427 - 2436, Jul. 2015.

[13] K. G. Khajeh, E. Bashar, A. M. Rad, and G. B. Gharehpetian, “Integrated model considering effects of zero injection buses and conventional measurements on optimal PMU placement,” IEEE Trans. Smart Grid, vol. 8, no. 2, pp. 1006–1013, Mar. 2017.

[14] J. Chen and A. Abur, “Placement of PMUs to enable bad data detection in state estimation,” IEEE Trans. Power Syst., vol. 21, no. 4, pp. 1608–1615, Nov. 2006.

[15] S. Basumallik, R. Ma, and S. Eftekharnejad, “Packet-data anomaly detection in PMU-based state estimator using convolutional neural network,” Int. J. Electr. Power Energy Syst., vol. 107, no. 5, pp. 690–702, May 2019.

[16] E. Ghahremani and I. Kamwa, “Dynamic State Estimation in Power System by Applying the Extended Kalman Filter With Unknown Inputs to Phasor Measurements,” IEEE Trans. Power Syst., vol. 26, no. 4, pp. 2556–2566, Nov. 2011.

[17] P. Castello, C. Muscas, P. A. Pegoraro, and S. Sulis, “Active phasor data concentrator performing adaptive management of latency,” Sustain. Energy, Grids Networks, vol. 16, pp. 270–277, Dec. 2018.

[18] M. Cui, J. Wang, J. Tan, A. Florita, and Y. Zhang, “A novel event detection method using PMU data with high precision,” IEEE Trans. Power Syst., vol. 34, no. 1, pp. 454-466, Jan. 2019.

[19] J. Liu et al., “Trade-offs in PMU deployment for state estimation in active distribution grids,” IEEE Trans. Smart Grid, vol.3,

no.2, pp.915–924, 2012.

[20] C. S. Yu, C. W. Liu, S. L. Yu, and J. A. Jiang, “A new PMU-based fault location algorithm for series compensated lines,” IEEE Power Eng. Rev., vol. 21, no. 11, pp. 58–58, Jan. 2001.

[21] Ruisheng Diao et al., “Decision tree-based online voltage security assessment using PMU measurements,” IEEE Trans. Power Syst., vol. 24, no. 2, pp. 832–839, May 2009.

[22] H. Yang, W. Zhang, F. Shi, J. Xie, and W. Ju, “PMU-based model-free method for transient instability prediction and emergency generator-shedding control,” Int. J. Electr. Power Energy Syst., vol. 105, no. March 2018, pp. 381–393, Feb. 2019.

[23] Y. Zhou, R. Arghandeh, and C. J. Spanos, “Partial knowledge data-driven event detection for power distribution networks,” IEEE Trans. Smart Grid, vol. 9, no. 5, pp. 5152–5162, Sep. 2018.

[24] https://www.powerstandards.com/product/micropmu/highlights/

[25] M. Farajollahi, A. Shahsavari, E. Stewart, H. Mohsenian-Rad, “Locating the source of events in power distribution systems using micro-PMU data”, IEEE Trans. Power Systems, vol. 33, no. 6, pp. 6343-6354, Nov. 2018.

[26] J. M. Morales and J. Perez-Ruiz, “Point estimate schemes to solve the probabilistic power flow,” *IEEE Trans. Power Syst.*, vol. 22, no. 4, pp. 1594–1601, Nov. 2007.

[27] Z. Li, M. Shahidehpour, and X. Liu, “Cyber-secure decentralized energy management for IoT-enabled active distribution networks,” *J. Mod. Power Syst. Clean Energy*, vol. 6, no. 5, pp. 900–917, Sep. 2018.

[28] F. Samie, “Resource Management for Edge Computing in Internet of Things (IoT),” *PhD Thesis, Karlsruher Inst. Technol.*, 2018.

[29] D. Dinakara Prasad Reddy, V.C. Veera Reddy, and T., Gowri Manohar., “Optimal renewable resources placement in distribution networks by combined power loss index and whale optimization algorithms,” *J. Electr. Syst. Inf. Technol.*, vol. 5, no. 2, pp. 175–191, Sep. 2018.