State-of-the-Art in Synchrophasor Measurement Technology Applications in Distribution Networks and Microgrids

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ABSTRACT Although synchrophasor measurement technology (SMT) has become a somewhat mature and operational tool used in transmission-level power networks, its use in active distribution networks (ADNs) is still in very early stages. Due to distinct features (such as unbalanced operation, very low phase angle differences, greater harmonics pollution, and lower signal-to-noise ratios in distribution networks), transmission-level devices and applications may not be fully effective at the distribution level. Extensive research and development efforts are in progress to bring distribution-level phasor measurement units (DPMUs) to an operational stage in ADNs. This essential work is made even more urgent by changing ADNs that are widely integrating distributed energy resources and enabling demand-side entities as active network players, in some cases considering authorizing them for peer-to-peer energy trading. This paper focuses on SMT/DPMU applications in ADNs and microgrids. We specifically elaborate on how SMT/DPMUs are enabling 1) effective situational awareness, 2) enhanced protection and fault location functions, 3) novel control algorithms and augmented energy management applications, and 4) long-term baselining and analysis. Various barriers and challenges that come with rapid and broad deployment of SMT/DPMUs and their associated applications are also discussed.

INDEX TERMS Synchrophasor measurement technology (SMT), distribution-level phasor measurement unit (DPMU), active distribution networks (ADNs)

I. INTRODUCTION For decades, power systems have been monitored and operated using supervisory control and data acquisition (SCADA) systems that provide a quasi-static view of many, but not all, system state and control variables (for example, frequency, amplitude of bus voltages, line powers, generation and load quantities). State estimation has been a key building block of transmission energy management systems (EMS), trusted to estimate all state variables based on system-wide measurements received through SCADA. Since SCADA data are not precisely synchronized (variations in milliseconds to seconds), they are not homogenous in terms of time coordination, and state estimation might not converge with dependable outputs. SCADA data have also been too infrequent (measurements received by energy management system, EMS, every few seconds) to observe faster system dynamics, such as grid oscillations.

In the late 1980s and early 1990s, synchrophasor measurement technology (SMT) was first demonstrated and advanced devices named phasor measurement units (PMUs) were developed to address the need for monitoring system dynamics. PMUs along with other intelligent electronic devices (IEDs), local/regional phasor data concentrators (PDCs), and a broad range of analytical tools make up what are commonly referred to as wide-area monitoring, protection, and control (WAMPAC) systems (sometimes called wide-area measurement systems, WAMS). WAMPAC systems capture measurements (for example, frequency and voltage/current phasors), concentrate and filter the quantities at the regional or system control centers, and analyze the data. These measurements are then used to
support decision making across various monitoring, protection, control, and operation functions. A WAMPAC system may also be capable of transferring commands in a direction opposite the flow of measurement data, towards substations; PMU and IED output cards can directly implement commands received at the substation. WAMPAC technology has evolved in the last two decades (especially following the 2003 blackouts that affected various regions), to the point where WAMPAC systems are now partially operational in some power system control centers around the world. It is worth mentioning that WAMPAC is inherently more useful for applications demanding faster-response actions (such as protection, dynamic state monitoring, oscillation detection and control), while SCADA/EMS technology continues to perform near-term system operation functions (such as static state estimation, automatic generation control, economic dispatch, contingency analysis, and load forecasting). Reference [1] has speculated the broad range of WAMPAC applications. Figure 1 illustrates the maturity and readiness of these applications (ranging from the research and development (R&D) stage, through pilot implementation, and ending with operational deployment). Referring to this figure, it is evident that a majority of WAMPAC applications in bulk power generation and transmission systems have reached a pilot or operational phase, at least at some utilities. When properly implemented, these applications can lower the risk of generator instability, improve resilience of electricity infrastructure, accelerate service recovery, enhance power supply reliability, increase component utilization, optimize economic operation, and improve system planning.

Before smart grid initiatives, distribution networks received low levels of investment in measurement, monitoring, and control facilities (even though roughly more than 90% of end user power outages were linked to components in these passive distribution networks) [2]. Meanwhile, technical difficulties driven by the proliferation of distributed energy resources (DERs) have further revealed the weaknesses of passive distribution networks.

With the advent of smart grid concepts and technologies, legacy distribution networks are now becoming dynamic and complex networks with extensive integration of heterogenous and spatially-distributed electrical and IT components. Ideally, an active distribution network (ADN) should be able to host utility-owned or behind-the-meter DERs with allowance for reverse power flow, adapt to the ever-growing stochastic operation circumstances, maintain operational variables within acceptable ranges, and even occasionally disconnect from the main grid while continuing to operate as a microgrid (or a multitude of microgrids). This transformation requires advanced measurement, communication, computation, and control infrastructure implemented using efficient and reliable management and regulation strategies. In the wake of numerous WAMPAC success stories in generation and transmission systems, SMT is posed as a promising solution for monitoring, protection, control, and management of ADNs and microgrids. ADNs have unique features distinct from bulk power systems:

- ADNs are intrinsically unbalanced due to untransposed arrangements of conductors and asymmetrical utilization (caused by dominantly single-phase customers).
- Integrating renewable DERs intensifies an ADN’s variation/stochasticity and weakens the ability of prediction techniques and pseudo measurements to aid network operation.
- Owing to the short length and low impedance of branches, the nodes’ voltage phase angles are quite close to each other (usually less than 0.1° different between subsequent nodes). Accordingly, a regular PMU’s “standard-based” 1% total vector error (TVE) accuracy may not be sufficient.
- ADNs’ models and corresponding parameters are not as complete or up-to-date as those of generation and transmission assets.
- Reconfiguring an ADN or connecting/disconnecting a microgrid with the main grid can significantly change operation conditions and characteristics of the overall network.

For these reasons, WAMPAC applications used in existing bulk power systems may be less effective in ADNs. Consequently, the need for research and innovation in SMT advancement and application continues to grow.

This paper elaborates on the future applications envisioned for SMT in ADNs. We first focus on situational awareness and its elements, and then discuss protection schemes for the system and its components. Next, we consider control algorithms and management strategies, and finally we review the long-term advantages of using SMT in ADNs. SMT measurements and applications at distribution level may be complementary to those at transmission level.
This interaction is addressed in certain applications where it is very tangible. The paper concludes with an overview of an existing innovative microgrid, with discussion of its associated PMU use cases. Figure 2 shows the organization of this paper in more detail.

FIGURE 2. Organization and content of this paper

II. Situational Awareness

Situational awareness is the perception of environmental elements and events with respect to time or space, the comprehension of their meaning, and the projection of their future status [3]. Situational awareness is a fundamental prerequisite for effective decision-making across a broad range of conditions. In a setting like a distribution network with geographical dispersion, situational awareness involves deploying sensors (in a power engineering context, commonly referred to as measuring devices). A power system’s significance and the consequences of its interruptions determine how robust its situation awareness must be (geographical coverage, measurement accuracy, time resolution, and noise/contingency tolerance). With the advent of ADNs and microgrids, an accurate situational awareness system became crucial, particularly in the wake of customer participation in demand response plans, direct load control mechanisms, distributed energy resource (DER) integration, electric vehicle (EV) charging scheduling, and peer-to-peer energy trading. These progressive and leading-edge functionalities need a dependable, reliable, secure, and resilient ADN achievable using broad deployment of advanced sensors such as distribution-level PMUs (DPMUs).

Situational awareness for ADNs involves a number of elements including preliminary alarm setting on measured quantities, simple visualization dashboards, state estimation enhancement, and advanced data-mining analytics such as pattern recognition machines. This section discusses an extensive set of situational awareness tools for ADNs and microgrids that are emerging as DPMUs are deployed.

A. Topology Detection/Estimation

Detection of the exact distribution network topology (i.e., the status of all switches and circuit breakers in the network) is a prerequisite for all distribution management system functions including state estimation, demand side management, fault location and isolation, network reconfiguration, and DER control mechanisms [4]. Algorithms for topology detection can be categorized into two main classes. The first class applies state estimation mechanisms, using the power system’s circuit model. These methods estimate the status of switches given the quality of the match between the actual field measurements and the calculated states of the grid. DPMU phase-angle and high-accuracy measurements that enable state estimation (discussed in next subsection) are essential for this sort of analysis. The other major class of algorithms is data-driven (without using circuit models), based on data from DPMUs, smart meters, and/or conventional voltage and current measurement devices [5]. Time-series signature verification is a prominent method for topology detection in real time [4]. Time-series signature verification compares a voltage time series (collected by DPMUs), with a library of signatures computed \textit{a priori}, based on the possible network topology changes; the alternative with the best matching index would be the adopted choice. Time resolution and synchronization are crucial attributes of DPMU data for enabling data-driven topology processes.

A joint topology and impedance estimation solely from DPMU measurements has been proposed in [6]. The set of phasor measurements are used to estimate a Kron reduced network impedance or admittance model. Effective impedances between nodes are then calculated from the Kron reduced model. Finally, a complex recursive grouping technique has been developed to recover the network topology from the complex-valued effective impedance estimates. The proposed method is unsupervised (no user guidance or \textit{a priori} information about the network structure is needed), making it easier to apply and more resilient against human error.
B. State Estimation

State estimation is an optimization problem with the aim of minimizing estimation error in determining voltage magnitude and phase angle of all nodes of a given electric power network. Once the state estimation problem has converged to a unique solution, all other quantities of the circuit (including currents and powers) are computable, meaning the network may be called “observable”. State estimation has traditionally been a cornerstone for monitoring legacy power systems since it was the only means to attain system phase angles (for use as an indicator of system stability) from voltage/current magnitudes and active/reactive powers. In distribution networks and microgrids as well, state estimation is recognized as a core component of a distribution management system. The emergence of SMT has made the phase angle of complex quantities directly accessible in control centers, also bringing up the notion of state measurement. However, state estimation has not become obsolete as it yields the truest values for system state variables when measurements are prone to error (as is the case in real power systems). Note that this functionality needs some level of measurement redundancy, making the state estimation problem overdetermined. In this regard, zero-injection nodes (nodes lacking load or generation) are beneficial as they can be considered as perfect three-phase measurement of zero current injections [7]. Ideally, state estimation using DPMU phasor values involves a linear optimization problem whose solution is readily obtained with no need for iterative and computationally cumbersome (and time consuming) techniques [8],[9]. For this reason, state estimation for WAMPAC systems can be performed quickly and dependably, in contrast with conventional systems using nonlinear state estimation engines that take much longer to perform and lack guaranteed convergence.

Synchrophasor-based state estimation presents opportunities beyond the estimation of system state variables. In [10], linear synchrophasor-based state estimation was extended to a non-linear problem in order to estimate grounding resistances, neutral-to-earth voltages, and neutral currents. It was argued that existing multiphase state estimation models suppose earthing resistances are fixed and invariable parameters, which is not the case in the real world (where ground resistance strongly depends on time-varying moisture and temperature).

1) EARLY STAGES OF DPMU DIFFUSION IN ADNS

In the early stages of DPMU deployment in ADNs, the number of installed DPMU devices has been fairly low, providing only partial observability. Hence, it is barely feasible to have linear phasor-based state estimation operational. In this transitional stage, DPMU phasors can be combined with the dataset of conventional unsynchronized measurements and IED data in order to enhance both accuracy and convergence of nonlinear state estimation [11],[12],[13],[14]. This type of state estimation, referred to as hybrid-state-estimation (HSE), can partially take advantage of DPMU data, but is not yet executable quickly enough to monitor system dynamics. Pseudo measurements (forecasted values) are occasionally taken into account in HSE to support observability prerequisites or to promote redundancy level [7]. With the proliferation of smart meters, HSE might have access to their data; but it would be limited to the meter reading times (usually too infrequent and too late for HSE). HSE has also been devised for hybrid AC-DC distribution networks [15].

HSE can have two distinct structures, either simultaneous (single-stage) or sequential (two-stage) [1], as illustrated in Figure 3.

\[\text{Figure 3. HSE structures: (a) single-stage (b) two-stage}\]

In a single-stage structure, a selected set of synchrophasors is added as new measurements (likely with higher accuracy) to the nonlinear state estimation. Appropriate data must be selected meticulously from the DPMU data stream and voltage phase angle of one of the DPMUs is adopted as the reference angle of the state estimation expressions. In a sequential structure, nonlinear state estimation remains untouched but its output (which encompasses the node voltage phasors) is added to the linear state estimation, running over the DPMU data. Accuracy level of the outputs from the first stage of state estimation must be specified, as that information is needed in the second stage. Also, the outputs from the first stage state estimation should be phase angle shifted to match synchrophasor measurements. Any time resolution difference between the two paths reduces usefulness of DPMU data.

Linear state estimation can also be achieved with a limited
number of DPMUs using model order reduction techniques [16], [17]. These techniques involve reducing a large distribution network to a smaller one with similar electrical characteristics. The main backbone of the network, critical nodes and branches are untouched but subsidiary laterals and terminal nodes are removed (their bearings retained preferably by manipulating remaining attributes). In a real-world network, DPMUs should be placed strategically so that an analytical view of the network’s “reduced equivalent network” is fully observable and state estimation is executable. This enables a group of state variables (that correspond to the reduced network) to be measured/estimated with high accuracy at a fast rate. Next, state variables of the omitted sections of the original network are computed/estimated using conventional/IED measurements, smart meter data, or even pseudo measurements. This technique enables the most important state variables to be estimated accurately, reliably, and quickly, while variables with lower importance are calculated in a postprocessing phase. Figure 4 illustrates how to perform model-order-reduced state estimation for ADNs.

**FIGURE 4. State estimation for ADNs using model order reduction and a limited number of DPMUs**

The majority of state estimation techniques developed for distribution networks use exact modeling of the network (either holistic or reduced) and require sufficient measurements to ensure observability. These model-based techniques are vulnerable to errors in model parameters and require significant expansion and maturity of the measurement system, which takes time. Until then, data-driven techniques with a few installed DPMU devices, and even limited accuracy, can be very helpful [18], [19]. These techniques are drawing much interest in light of recent enthusiasm to expand the application of machine learning approaches.

2) STATE ESTIMATION ARCHITECTURES

State estimation algorithms designed for distribution networks can be categorized into three groups: centralized, decentralized, and distributed. Centralized algorithms involve gathering all measurements in the control center, aggregating all equations in a single but large-scale state estimation model, and solving the state estimation problem holistically [11],[20] or mathematically decomposed [21]. Unfortunately, centralized algorithms exchange a massive amount of data (require sufficient communication capacity) and involve tackling a high-dimensional optimization problem. Compared to positive-sequence state estimation used at a bulk transmission level, distribution network state estimation can be computationally more demanding since a three-phase representation is needed to fully capture performance during unbalanced operation. To make computations more manageable, after symmetrical component transformation, a large three-phase state estimation can be split into three (or two for three-wire distribution networks) smaller per-phase state estimation problems. It should be noted that in untransposed networks, the sequence circuits are not totally decoupled and could not be tackled independently. Nevertheless, in practice, since distribution network segments are very short, the network model is held symmetrical with fairly negligible errors. If even a small region is unobservable (due to either DPMU failures or communication system defects), centralized state estimation becomes unfeasible. This structure is not robust against communication link failures unless redundant measurements (or redundant communication routes) are provided, which is not likely in distribution networks.

Decentralized state estimation, occasionally referred to as hierarchical distributed state estimation, uses multiple local state estimations to solve smaller localized state estimation models; a single unit coordinates the solutions since the local problems are not totally independent [22]. Decentralized state estimation uses network partitioning to reduce the scale of the network while preserving estimation efficiency [23]. Geographical and topological criteria [24],[25], graph theory [26], clustering methods [27], and heuristic algorithms [28] have been proposed to achieve distribution network partitioning. On one hand, this strategy’s inner-region communication loads are localized; on the other hand, the coordinator need only transferring a limited volume of data (not raw measurements) to/from local SEs. Overall, the total measurement and data exchange burden is less. Also, this architecture is more robust against communication channel or measuring device outages; if happens, only local state estimation halts and other processes can proceed (albeit at a lower accuracy level).

Rather than using a central coordinator, distributed state estimation only requires local-area and low-bandwidth communications for coordination among adjacent subregions [23],[26],[29]. The ring structure is a communication topology well suited to this type of state estimation as it is quite robust against single communication link failure. Similar to the decentralized technique, network partitioning decisions play a critical role in distributed state estimation.
3) METROLOGICAL ASPECTS

Measurement error and redundancy affect state estimation performance. Rather than having a couple of degrees voltage phase difference across transmission lines, distribution network node states are very close to each other (the voltage phase difference at two consecutive nodes is typically less than 0.1°). These situations require not only more accurate DPMU devices [30], but also deployment of high-accuracy instrument transformers or sensors. These instrument transformers may have higher labor costs to deploy, which can increase the overall project cost. It is worth noting that a given network may use sensors/measurement transformers and DPMUs from different classes [7]. As state estimation output is directly influenced by measurements’ accuracy, it is crucial to clearly understand each measurement’s actual metrological calibration in order to fine tune the state estimation engine [31]. Since distribution networks are widespread with vast dimensions, they are unlikely to have many redundant measurements.

C. Stability Monitoring

For analysis and decision making about countermeasures, power system stability can be classified into different categories including frequency, voltage, and phase angle stabilities. Each category can be further classified depending on the time needed to apply preventive measures or corrective actions [32]. Distribution networks have very few synchronous generators, and they are closely coupled due to the limited geographical dispersion of the grid. Therefore, long-term stability studies of ADNs and microgrids mainly focus only on the voltage stability issue. However, short-term stability monitoring includes all frequency, voltage, and phase angle stabilities. Since these phenomena demand immediate protective actions, we cover them in Section III.

In addition to heavier loading, a distribution network’s voltage stability is hampered by the growing share of constant-power loads that are supplied by power-electronics converters. If voltage drops, a constant-power load increases current to offset the impact of lower voltage, and this reaction leads to further voltage drop. This adverse reciprocal process may continue until the system voltage totally collapses.

Voltage stability challenges are even more acute in ADNs that have more stochastic performance (due to DERs, demand-control technologies, and EV integrations), especially because they are regularly sited behind the meters (and out of a distribution system operator’s direct visibility). DERs are predominantly connected to the grid through inverters that transform DC to AC, and vice versa. In addition to several internal feedback loops of inverters to stabilize voltage, current, or power quantities, droop control logic is also implemented in most DERs (to emulate the stabilizing effect of rotational inertia in response to the grid frequency changes). Dynamics of these interconnected control loops, particularly during exogenous disturbances, can jeopardize the stability of the system. It should be emphasized that, if managed properly, inverter-based DERs offer greater flexibility and new control variables to tackle system anomalies.

Most research about voltage stability monitoring in distribution networks relies on offline studies, power flow results or simulated power-voltage curves. These methods can be ineffective in ADNs that inherently involve more volatile conditions and more variable configurations. Machine learning techniques, such as artificial neural networks (ANN) trained with offline data [33], are also less effective for ADNs. High-resolution phasor measurements associated with DPMUs at load buses can enable online voltage stability monitoring. Estimating a Thevenin Equivalent Circuit seen from the load buses, which can be materialized by DPMU phasor measurements, can help determine voltage stability curves and actual margins [34],[35],[36],[37]. Extending the conventional Thevenin Equivalent Circuit to an unbalanced three-phase version enables per-phase P-V curves to be estimated more accurately than single-phase models [38]. Clustering techniques running on real-time data from DPMUs may also enable earlier alarms about long-term voltage stability threats [39].

D. Disturbance/Anomaly Detection and Classification

Once a monitoring and control center is overwhelmed by data, visualizing and interpreting raw data streams is no longer practical. Therefore, it is essential to mine the data collected using analytic tools that can derive informative measurements and form automated reports [40]. Date-driven diagnostics have been used extensively to improve control algorithms, parameter estimation, and fault detection. In this sense, the SMT can also offer a toolkit for safeguarding ADNs [41],[42]. In this regard, the phase angle and high-resolution measurements of DPMU devices are more advantageous. In an ADN, anomalies and events can be caused by harsh weather conditions, low- or high-impedance faults, equipment degradation (e.g., partial discharge in a transformer), or physical/cyber-attacks. Widespread integration of DERs and implementation of microgrids can increase system vulnerability, as the system relies more heavily on data gathering and exchange platforms. Also, output power from DERs must be monitored closely because variations in renewable energy sources can cause it to fluctuate irregularly [43]. Detection of reverse power flow from the DER toward the grid is especially of importance in order to coordinate protection relays. In contrast to faults cleared urgently by protection systems, disturbance, abnormality, or disruptive events usually do not trigger immediate failures or damages. Still, if not detected and resolved, over time these events are a potential source of major failure. Early detection, localization and classification of these events/abnormalities can reduce expenses (maintenance and repair) and avoid future outages.
Predictive analytics tools can be effective in this regard. In addition to voltage and current phasors, DPMUs also estimate and transmit frequency and rate-of-change-of-frequency (RoCoF). Drastic variation in frequency or RoCoF signifies an active power imbalance, often originated by unintentional islanding or by generator/load connection/disconnection while in islanding operation mode [44]. Even in bulk power systems, fast and precise detection of uncontrolled islanding is crucial to enable timely actions that preserve the islands’ integrity and avert total blackouts. However, RoCoF measurement and applications have some distinct traits and differences in distribution and transmission levels. In comparison with high-voltage bulk power systems, distribution-level signals contain large amounts of noise which can drastically compromise RoCoF estimation, if not effectively filtered out. Islanded distribution systems or microgrids have natively lower inertia, which result in faster frequency dynamics and higher RoCoF variation. This feature urges quicker RoCoF calculation and broader RoCoF-oriented applications in order to retain stability of system frequency.

Since phase angles of node voltages are strongly correlated with frequency deviations, they can be used for event detection. If DPMUs are deployed, operators can perform forensic analysis of events or abnormal system conditions. Time-synchronization and high-resolution attributes of DPMU data are extremely important to this forensic analysis.

Fuzzy inference systems are promising to help identify and classify eventual electrical disturbances in ADNs [45]. A fuzzy inference system uses fuzzy set theory to map a system’s inputs (called “features” in classification problems) to its outputs (called “classes” in classification problems). To do so, the membership functions of linguistic variables are defined and if-then rules are extracted to map all credible combinations of input variables with one or more output variable. A set of if-then rules is then leveraged to explore possible scenarios for the output variables. The more inputs we have (i.e., comprehensive DPMU measurement sets including three-phase phasor voltages/currents along with frequency and RoCoF), the more inclusive rules can be defined to explicitly address envisioned credible scenarios. The defuzzification process eventually produces a specific value for each output variable. In this process, fuzzy sets and corresponding membership degrees result in a quantifiable crisp result. As it uses multiple rules for any situation, fuzzy logic theory is intrinsically robust against noise/errors in input variable measurements.

Machine learning techniques, in either form of supervised, unsupervised, or reinforcement learning (Figure 5), seem applicable for detection and classification of disturbances/abnormalities. These data-driven techniques are based on exploratory data analyses, involving computational statistics and data mining. Supervised learning uses labeled training data to perform function mapping between system inputs (DPMU data) and outputs (normal or abnormal status/types). Training performance would be satisfactory if training data covers enough scenarios to address normal and specific abnormal conditions. In real-world implementations, it can be challenging for training data to cover these scenarios without relying on simulation tools. ANN is a supervised learning technique that has been used widely to detect/classify events and abnormalities. In [46], an ANN algorithm composed of autoencoders and softmax classifiers is used to distinguish between two disruptive events (i.e., malfunctioned capacitor bank switching and malfunctioned regulator on-load tap changer switching).

Unsupervised learning uses datasets that are neither labeled nor classified. It looks for similarities and differences in the dataset and can cluster the data into distinct classes. Intuitively, unsupervised learning can also detect anomalous data that does not belong to an existing category. Reinforcement learning is applied if the decision-making environment is uncertain or complex. In order to reinforce its learning, the machine uses reward/penalty functions to guide decision making, without relying on labeled input/output pairs.

![Machine learning techniques and features](image)

**FIGURE 5.** Machine learning techniques and features

In addition to event detection and classification, event location is important to improve distribution network reliability. Circuit theory’s compensation theorem offers a fresh and effective approach to event location [47]. Based on this theorem [48], once an element changes in a circuit, an equivalent circuit can represent the amount of changes in nodal voltages and branch currents. In the equivalent circuit, we can replace the element that has changed with a current source that injects current at a level equal to the amount of change in the current going through the element; we should replace all sources with their internal impedances. The compensation theorem’s equivalent circuit uses DPMU voltage and current phasors to represent the event. Event analysis is much easier to perform on this equivalent circuit than on the original circuit. Note that this analysis would not occur without phase angle measurements from DPMU...
devices.

E. Cyber-Attack Detection

Cyber intrusion may seek to compromise measurement data to 1) reflect a fake abnormal condition and mislead the system operator to take hasty/costly incorrect actions, or 2) inhibit a system operator’s ability to detect a major event, resulting in higher costs and prolonged power outage. In power systems terminology, this type of attack is referred to as a false data injection attack (FDIA) [49],[50],[51],[52]. Deployment of a few DPMU devices in an ADN or microgrid enhances situational awareness and offers an unprecedented opportunity to detect compromised conventional measurements, even using simple comparative indices. Nonetheless, it is important to keep in mind that the DPMUs themselves can be exposed to malicious cyber-attacks [53] and should be protected with advanced intelligence.

In addition to FDIAAs, a DPMU cyber-attack might block the flow of data and hamper critical functions (such as state estimation) that rely on uninterrupted data streaming. Alternatively, the attack might spoof a GPS signal and alter the DPMU clock including pertinent data timestamps. As a result, voltage and current phase angles associated with a spoofed DPMU would not match with other devices, meaning that synchronization-critical applications would be compromised.

According to the literature, synchrophasor data analysis can pinpoint not only power system events but also anomalies in DPMUs themselves, typically at the expense of having some level of data redundancy [54],[55]. The state estimator’s bad data detection function can be used to immediately detect cyber-attacks on single or multiple DPMUs [56]. Differential synchrophasors are a novel effective approach to detect whether any DPMU has been compromised, and identify which one(s). Differential phasor refers to the difference in a complex quantity (in this case, voltage and current phasors) in pre- and post-event situations, i.e., before and after a power system disturbance and/or malicious DMPU attack [53].

F. Harmonic Distortion Monitoring and Tracing

If non-linear loads and electronic devices connected to distribution networks are injecting significant amounts of harmonics (of various orders) into the network, they can cause serious power quality challenges including overheating electric machines and causing malfunction of electronic devices such as protection relays. Non-linear loads connected to the distribution system result in harmonic currents. The flow of harmonic currents through system impedances in turn creates voltage harmonics. As a result, a harmonically polluted load connected to a given node may contaminate other nodes as well. The extent of signal harmonics, although naturally attenuating while travelling away from the harmonic injection source, might sometimes amplify due to resonances in the network’s elements. Harmonic propagation will depend on specific network topology and impedance characteristics [57].

Theoretically, DPMU signal processing algorithms working on discrete data samples of voltage and current can accurately estimate each signal’s harmonic content [58],[59],[60]. Although not outlined in the IEEE Std. C37.118.1, extended or combined IEDs can compute and report time-synchronized harmonic voltage and current phasors. By aggregating all this data, SMT can also perform harmonic monitoring of the system. Ideally this task can be implemented by harmonic state estimation, enabling us to mathematically quantify the level of harmonic pollution in the whole network, rather than just the nodes [61],[62]. Other optimization and analytical algorithms can also identify the main contributors to harmonics on the network and help understand how the harmonic pollution propagates over the network [63]. Harmonic monitoring and source detection algorithms can help system operators maintain power quality measures within permissible ranges and mitigate any violations. Once DPMU-enabled harmonic monitoring is operating, power quality assessments can be online and system wide, rather than relying on conventional local power quality metering.

III. Protection and Fault Location

A. Fault Identification

Traditionally, distribution networks have been operated with radial configuration encompassing unidirectional power flow and single-source fault current features. In these networks, short-circuit levels do not change drastically and overcurrent relays located at the beginning of the feeders are typically in charge of system protection. This scheme often fails to detect high impedance faults whose currents are within the operating current range. These faults, although they may not be serious threats for system operation, could cause bodily injury in the event of downed power conductors [64]. Single-phase loads and multi-point grounding strategy present challenges for high impedance fault detection, particularly at the substation level [65]. With the advent of DERs, these challenges become even more significant and complex, rendering many overcurrent protection scheme to be unfit and ineffective [66]. Having integrated DERs into the distribution network, power flow becomes bidirectional and faults are fed by DERs, in addition to the main grid. This situation is neither well known nor constant since DER connections (such as diesel generators or EVs) change dramatically over time and in different locations [55],[67].

ADN and microgrid protection can benefit from synchronized measurement technology in various ways. For example, adding the high impedance fault model to the state estimator model (and augmenting the state vector accordingly), enables state estimator algorithms to detect that a high impedance fault has occurred. In this context, it
makes sense to draw much more accurate results using a DPMU-based or enhanced state estimator approach [68],[69]. Interestingly, state estimators having near real-time functionality can be additionally leveraged to improve main or backup protection [70],[71],[72]. One approach is to consider different and augmented topologies with floating fault bus. A “more likely to be correct” solution would be chosen by comparing total residual value of state estimations [73]. A distributed dynamic state estimator incorporating dynamic models of components can also be fast enough to perform protection functions [74].

Apart from the state estimator approach, synchrophasor data can be used to detect short-circuit or high impedance faults through other sorts of analytical and data-driven techniques. Utilizing a discrete wavelet transform, the high-resolution waveform data provided by DPMU IEDs can be used to precisely identify high impedance arc faults [75]. Machine learning techniques are also prominent to address the challenging problem of high impedance fault detection [76],[77]. Wide-area phase angle criterion (based on DPMU measurements) offer a viable tool for building a microgrid protection system [78].

In order to protect ADNs, the research community has recently been investigating intelligent protection tools made possible by multi-agent systems (MAS) as an effective real-time platform [79],[80]. With a modular architecture, MAS agents can exchange data with each other (usually neighboring agents) to achieve a global goal while satisfying local objectives. Rather than relying solely on magnitudes of complex variables, MAS can lead to more effective applications and performance if the shared data are in the form of synchrophasors [81]. This domain matches well with the superior capabilities of intelligent systems and machine learning algorithms [82],[83],[84].

**B. Fault-Induced Delayed Voltage Recovery (FIDVR)**

FIDVR is an anomaly where the voltage magnitude of one or more network buses remains considerably depressed and uncontrolled for seconds or tens of seconds after a normal short-circuit fault clearing. The root cause of this defect is the stalling of AC motors, typically air conditioner compressors, initiated by the during-fault extra low voltage situation. It is worth noting that stalling of a motor is effectively a low-impedance short circuit with trivial active power but significant reactive power consumption. In FIDVR, the slow recovery of voltage level may bring about a pervasive outage or leave the system vulnerable to a widespread outage triggered by another event. Also, uncoordinated protection device operations can inadvertently extend the abnormal over/under voltage situation following the initial voltage collapse. Figure 6 shows the voltage profile of a typical FIDVR observation. The system’s original fault is rapidly cleared at $t_1$ but stalled motors prevent the voltage from recovering to its normal level. At $t_2$, the stalled motors are tripped out by thermal protection and the voltage rises but exceeds the normal level past $t_3$ due to sudden load reduction. Although the voltage control scheme operates at $t_4$, the motors starting at $t_5$ burden the network and voltage falls unfavorably.

![FIGURE 6. Voltage profile at an FIDVR event](image)

FIDVR is not a new phenomenon, but it became more of a concern once ADNs were equipped with monitoring devices and their power quality became more important. FIDVR, if detected promptly, can be corrected in various ways, including: rapidly interrupting stalled motors and starting them gradually at the normal voltage level, deploying under-voltage load shedding relays, or adding or relocating reactive power sources [85]. Voltage tracking and trending enabled by DPMU data can effectively detect FIDVR and rapidly initiate mitigating countermeasures [86].

**C. Auto-Reclosing**

In distribution networks, transient faults typically outnumber permanent faults. If successfully reclosed after the fault-originated interruption, transient faults clear themselves and let the network resume its normal operation. In this sense, auto-reclosers are extensively deployed in distribution networks to minimize interruption time and maximize reliability for the customer. Auto-reclosing is time sensitive and depends on the type of fault, well recognized as a technical challenge in the field of distribution protection. Reclosing on permanent faults or uncleared transient faults could impose further stress on the network, impair healthy components, or extend transient faults by re-feeding the fault current/flashover. Designing auto-reclosing schemes for ADNs hosting synchronous DG units is made tougher by stability requirements and out-of-step consideration of these units. DPMU data can help detect transient and permanent faults, and can boost the auto-recloser’s success rate [87],[88]. To do so, one approach is to compute and monitor variation in the total vector difference index (which is defined over two successive voltage phasor measurements in a moving window) [89]. This approach requires both voltage phasor measurement and high resolution DPMU data.

**D. Islanding and Resynchronization**
A microgrid is characterized by its capability to operate in an islanded mode, instigated either intentionally or unintentionally. In order to improve resiliency, the microgrid can become intentionally islanded if the utility grid fails or cannot meet a power quality criteria (e.g., extreme deviation in voltage or frequency) [90], [91]. Measurements from a DPMU located at the microgrid point of common coupling can be informative to detect these situations and to initiate the intentional islanding process [92], [93]. If islanding is unintentional, status information is required promptly (to switch the control and operation mode to the microgrid or to disconnect DERs if microgrid formation is not allowed by the grid codes). Frequency and voltage phase angle are the most relevant DPMU data for detection of islanding (since voltage magnitude and current phasors are mostly driven by local loading values). When DPMUs are installed at different locations, correlation analysis of their synchronized data can identify islanding [94].

DPMU measurements would also notify the microgrid controller when the main grid has reenergized or has come back to standard operating conditions. Once that happens, the microgrid can leave islanding mode and reconnects to the utility network for both economic and stability reasons. The reconnection command should only be executed in a synchronism condition, i.e., the breakers’ two sides having almost the same frequency, voltage amplitude and phase angle (to avoid damaging switching transients). This requirement applies to networked microgrids as well [95]. Synchronous islanded operation is an effective strategy to facilitate paralleling and to avoid damaging unsynchronized reclosures. In synchronous islanded operation, a microgrid continues to operate in the virtual synchronism with the main power or with another microgrid [96]. Obviously, this operation strategy depends highly on synchronized high-resolution voltage phasor and frequency measurements from DPMUs dispersed across the microgrids.

E. Fault Location

Rapid maintenance and restoration of the electricity supply calls for sufficiently accurate fault location algorithms. Historically, three classes of intelligent methods, impedance-based methods, and travelling wave techniques are devised for fault location on power networks. 1) The first class (the newest) is data driven and mainly relies on learning algorithms and regression techniques (such as support vector machines). As is the case for many data-driven approaches, preparation of a sufficiently investigated training dataset (labelled data) is a major challenge with this approach. 2) The second class uses voltage and current phasors at either or both ends of a faulty branch and estimates fault location accordingly. In this context, application of Tellegen’s theorem can facilitate the fault identification/location process. 3) Travelling wave techniques are mostly based on the time difference between fault currents observed at various locations. Their advantages are higher accuracy, faster detection, and robustness against flashover features; however, travelling wave techniques are often less affordable for distribution networks since they require extensive circuit studies or use of sensors with very wide frequency response. High-resolution and accurate DPMU synchrophasor data substantially enhances the performance of the first two classes of fault location algorithms mentioned above [97]-[98]. Fault location is made even more complex if inverter-coupled DGs that have a very limited fault current contribution (1.25 of rated current [99]) are integrated into ADNs. In this situation, DPMU data can still be very effective for fault location [100]. Typical fault location algorithms developed for ADNs are applicable in large-scale microgrids, but perhaps not necessary for small-scale microgrids.

IV. Grid Operation: Control and Energy Management

With increased penetration of DERs into ADNs (for example in a microgrid), it is critical to develop strategies to control and manage these active networks, and the elements within them. In order to proactively manage the power system, it is necessary to have transparent information about all devices on the grid (from power generation assets to devices operated by electricity consumers). Using automated controls and energy management, operational variables can be kept within acceptable ranges, and the power system supply and demand can be balanced in real-time. EMSs use performance metrics such as cost, carbon footprint, or reliability to optimize grid operation. Demand response controllers enable automatic peak load reduction and participation in energy markets (where allowed by local regulations) to generate additional revenue. In addition, storage assets can be automatically deployed to energize mission-critical loads [95].

The number of power electronics-interfaced resources hosted by ADNs (including PV units, battery storage units, electric vehicles, and speed-controlled motor loads) is rising sharply. From an operational point of view, these types of units offer much more flexible and faster control for both active power and reactive power absorption/generation. For example, an EV charger can readily provide capacitive or inductive reactive power support for the grid with continuous tuning. For better grid control and optimization, these resources should be integrated using novel control mechanisms rather than conventional strategies. In this sense, synchrophasor data offers enhanced stability and improved dynamic performance [101].

A. Control

Modern microgrid control strategies can make full use of DPMU data. Conventionally, frequency and voltage droop controls are used at the primary control level to adjust DER active and reactive output powers, often referred to as power sharing strategy. These mechanisms work based on the
variables’ deviation from nominal values. In order to eliminate the deviations, a centralized secondary control including a communication system should be in place. SMT can enhance the performance of these conventional techniques in various ways [102], [103]. It can enhance the dynamic performance for DERs (i.e., oscillation, overshoot, and frequency nadir), and can accelerate the realization of steady-state targets. Furthermore, on the basis of DPMU measurements, angle droop can effectively enable power sharing and improve stability. This technique, which has emerged due to the availability of the DPMU phase angle measurements, runs with no change in system frequency and less variation in voltage magnitudes [104].

Volt/Var control (VVC) is another distribution management system function whose performance is augmented using synchrophasor data from DPMUs located at compensator coupling points [105]. VVC is defined as the online coordination of reactive power resources (e.g., shunt capacitors) and transformers equipped with on-load tap changers (OLTCS), in order to achieve efficient feeder operation (while keeping voltage along the feeder within the acceptable limits). Conservation voltage reduction (CVR) is effectively an extension of VVC with capability to impact active power control to reduce energy consumption. CVR involves intentionally reducing the voltage level of demand-supplying nodes in order to manipulate their active power. As a substitute for optimization techniques, VVC and CVR can be implemented using voltage-to-power sensitivities (reflecting the relationship between voltage change and power fluctuation). The sensitivity coefficients are estimated using high-resolution voltage control records from the DPMUs [106], [107]. These factors (which are a fragment of the inversion of power flow Jacobian matrix) can derive the computationally efficient linearized power flow model around the operating point [108]. If properly taken into consideration, the sparsity of the Jacobian matrix could be beneficial for estimating sensitivity factors [109]. There are also other model-free techniques used in control engineering that can be effective alternatives to regulate voltage [110].

Another application to utilize DPMU data for optimal operation of ADNs and microgrids is dynamic line rating [113]. Since, generation of electricity is normally not near where it is consumed, electricity must be transmitted via a network of overhead lines and cables. A congested line or cable, whose current flow is constrained by its corresponding rating (typically thermal rating), would lead to underutilization of economic generation resources and other elements in the network. Although at design stages, line (or cable) rating is typically treated as a fixed value (calculated based on worst case conditions), the actual loadability depends on ambient conditions which vary over time, even on an hourly basis. As a result, components are utilized below thermal limits much of the time. This traditional practice, common due to a lack of real-time monitoring, squanders invested capital and limits the economic efficiency of market and system operations. Dynamic line rating uses either direct or indirect approaches to better utilize cable capacity. Direct approaches use temperature or other physical-attribute sensors attached to the component under question to report ongoing conditions and compute loadability margins. Indirect approaches can compute the conductor’s temperature as a function of its resistance value and current flowing through it (estimated by DPMU phasor measurements at both ends of the line or cable). Having access to high resolution DPMU data, machine learning techniques can be utilized to help optimize the system’s power flow.

V. Applications Beyond the Grid Operation

A. Component/Network Model Synthesis/Calibration

All monitoring, protection, operation, and control applications on ADNs entail sound and sufficiently comprehensive component and network models. Network line impedances are one of the most important parameters since they are essential for state estimation and power flow models as well as protection and fault location algorithms. A synchronized dataset from DPMU devices located across the ADNs is invaluable to help estimate impedance values [114]. Effectively, a “reverse conventional state estimation process” estimates unknown model parameters based on directly-measured state variables (rather than a conventional state estimator’s approach which estimates unknown state variables based on the model parameters). Typically, this application requires installation of DPMUs for high accuracy synchrophasor measurements at two ends of a branch, which may not be practical in most cases. Classifier machine-learning techniques could be promising for identifying distribution line parameters under insufficient synchrophasor measurements conditions [115]. Unsupervised machine learning can also address the specific problem of learning an ADN model (both topology and branch impedances) using only DPMU data, without any prior network information [6].

Transmission system operators often either do not need
detailed models of the distribution networks, or the models are not easily accessible. In addition, the proliferation of DERs and EV integration has made the network and the associated modeling more complex. Surprisingly, reduced order models of distribution networks often fulfill EMS package requirements adequately. To do so, steady-state models of unbalanced distribution networks or ADNs can be synthesized by leveraging time series measurements from DPMU devices. In this process, state estimation algorithms, the Kalman filter, or its augmented derivatives can be used for DPMU data cleansing [116], [117].

Characterization of DERs, especially those with power electronic interface, is needed for ADN protection, control, and stability design and studies. DER models may exist, but they often lack precise parameters. Measurements and recordings of DPMUs, particularly those sited at the DERs’ immediate nodes, can help a system expert tune up pertinent model parameters [118]. To do so, typically the DER in question is modeled using dynamic analysis software and the rest of the network is equivalenced to a controlled voltage source (Figure 7). The voltage magnitude and frequency of the delegate source can be set to resemble the DPMU recorded signals; the outgoing current (or active and reactive power injections to the grid) is compared with respective DPMU data. If mismatches are observed, the parameters are adjusted to sufficiently match the output with the real measurements. Due to the number of model parameters, sensitivity analysis is a vital preprocessing step to pinpoint the most influential parameters on various attributes of the output [119].

Given the small phase angle changes across a distribution feeder, it is ideal to compare the substation and customers’ voltage phase angles captured by DPMUs [120], [121]. A travelling utility staff member with a handheld PMU device needs only connect it to one outlet at each customer site and immediately identify the supply phase. For accurate identification, a transformers’ phase shifting (due to delta-wye arrangement) is a key parameter that must be taken into account. If phase shifting between the reference DPMU and the mobile one is unknown, a time-series correlation analysis of high-resolution DPMU measurements can disclose the connection phase but at the expense of capturing data for a long period of time [120]. Using a more analytical method, real DPMU measurements and smart meter data can jointly be imported to an optimization model (subject to network equations to figure out the connection phases) [122]. A customer’s final phase hosting combination will have measurements that are as consistent as possible with power flow constraints.

Keep in mind that phase identification is not a one-time task, rather phase allocations are likely to need periodic updates. For example, during the restoration process after a major event, the repair crew may intentionally or inadvertently connect an interrupted customer to a new phase which would require the phase identification process and balancing to be repeated.

C. Asset Management and Condition Monitoring

Power system components are expected to be running around-the-clock for decades. Tactics to monitor, care, and prolong the operation of power system equipment are valuable. By definition, power infrastructure asset management draws from practices/knowledge in engineering, management, and economics to maximize value (level of service) from the expenditure (power system assets and labor costs) [123]. Asset management takes place over the equipment’s entire life cycle including design, construction, commissioning, operation, maintenance, repair, modification, replacement, and

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**FIGURE 7.** Procedure for DER’s model calibration

**B. Phase Identification**

ADNs are often unbalanced as a result of hosting single-phase customers who are not evenly distributed among the three phases and do not consume electricity evenly. Add to that the proliferation of single-phase rooftop photovoltaic panels and EVs (by no means distributed uniformly), and the network can become critically unbalanced. Severely unbalanced operation deteriorates power quality, lowers the grid utilization factor, raises network losses, damages impacted assets, and ultimately increases electricity price. Phase balancing is a process for identifying customers’ connection phases and adding new customers (or relocating existing ones) in order to regain a balanced condition. Phase balancing can enhance a network’s hosting capacity; however, lack of information about hosting phases of single-phase customers and photovoltaic panels presents a serious challenge. Using phase identification, important hosting phase information can be obtained for customers and photovoltaic panels.

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decommissioning/disposal [124].

During operation and maintenance phases, condition monitoring systems are used for early identification of defects that might progress to interrupt service [125], [126]. Ongoing condition monitoring of utility equipment, particularly distribution transformers, can help not only avert device failures but also build a knowledge base for long-term decision making. High-resolution DPMU data can indirectly confirm equipment health diagnostics by looking for any irregular responses or behaviors. If irregularities are found, an inspection and maintenance crew can be dispatched to inspect the component and its operation [127].

D. Generation-Load Disaggregation

Without ready access to customer premises, generation from behind-the-meter DERs is not directly measurable. Net metering only captures the difference between customer local load and on-site generation; generation-load disaggregated values (invaluable for system security analysis) may not be available. For instance, in order to foresee loading levels during DER unavailability (or trivial generation), customers’ actual loads must be known. For wind or solar renewable DERs, the “disaggregation problem” can be addressed by analyzing the cross-correlation between pertinent DPMU and high-resolution wind or radiation data. This analysis can determine the portion of net metered data with a trajectory analogous to the corresponding environmental factor, the remainder an estimate of load value [128].

E. Load Characterization

Most, if not all, power system studies require valid static/dynamic load models. Inaccurate load models, which fail to truly represent load behavior, lead to erroneous/incorrect results, threatening security and stability of the system. Load modeling can be performed in either a microscopic or macroscopic fashion. Microscopically, modelling identifies load components and combines individual models into a major load model. Accuracy of this approach depends on having high-fidelity individual component models and depends on the composition of the load (which may have drastic variations). Macroscopic load characterization uses field measurements in ADNs and microgrids, preferably high-definition DPMU data. These types of techniques build and parametrize high-level models to understand how a particular load will respond given various options for load composition. The load model’s lookup table will then be accessible for future system studies [129].

As expected, DPMU measurement errors can compromise the results of load modelling if magnitudes of disturbance and error are comparable (particularly regarding the phase angle). Error analysis (including error source identification, characterization, and possibly compensation) is a rigorous but often necessary technical procedure to maintain a DPMU data repository that is invaluable for model synthesis and calibration [130].

Dependable load models are also required by transmission-level applications and studies. Bulk load modeling is usually conducted via a dataset of PMUs installed at transmission substations. These PMUs only read aggregated values of outgoing distribution feeders (at the high-voltage side of step-down transformers). Appending DPMU measurements to this process enhances data granularity, and ultimately leads to higher-fidelity models.

VI. Illinois Institute of Technology (IIT) Campus Microgrid

The IIT Campus Microgrid (Figure 8) located in Chicago is bounded by Michigan Avenue on the east, the Metra Rock Island train line on the west, 35th Street on the south, and 29th/30th Street on the north. The $14 million project, which was initially referred to as the “IIT Perfect Power System” and later as the IIT Campus Microgrid, was led by the Robert W. Galvin Center for Electricity Innovation. The on-site peak load of 12MW at the IIT Campus Microgrid, with an average value of 9MW, is supplied by a 9MW generation capacity made up of dispatchable units (combined-heat-power unit, diesel engines, and battery energy storage), and non-dispatchable units (PV panels and wind turbines). By using resources strategically, the IIT Campus Microgrid provides additional operational efficiency and flexibility for the distribution power system at IIT, while further enhancing campus reliability and resilience. The IIT Campus Microgrid is capable of islanding itself from the utility grid and restoring normal operation under emergency conditions [131].

Figure 8 displays the IIT Campus Microgrid with seven loops. Each loop consists of DERs and load entities. This loop-based topology enables the microgrid to adapt to changing grid conditions, and successfully respond to (and recover from) disruptions in extreme events [132]. From the very beginning, the IIT Campus Microgrid has been equipped with 12 PMUs for two purposes: 1) research and development activities revolving around the design and manufacturing distribution-level PMU (called smart PMU by that time), and 2) design and demonstration of brand new SMT applications for distribution systems and microgrids. PMU data has initially been utilized to monitor and record real/reactive power generation and consumption in real time, and provide the microgrid controller with the DER units’ instantaneous voltage and current phasors at a reporting rate of one signal per cycle [92]. Particularly in the islanded operation mode, high-accuracy and high-definition DPMU measurements (associated with building consumption, renewable resource generation, flywheel/battery storage and EV charging station status) are being exploited to quickly wipe out the generation-demand mismatches and stabilize grid frequency within an acceptable range. Data-driven event and anomaly detection is another application well
researched using IIT SMT data. As pointed out earlier, this application is highly dependent on the monitoring of high-resolution voltage magnitude, frequency and RoCoF.

PMU measurements, particularly those associated with building consumptions, are the main data source used for load characterization. Both static and dynamic load models were developed, which were crucial to ensuring reliable and secure operation of the IIT Campus Microgrid under islanding conditions [133].

As shown in Figure 8, one of the PMUs was installed at the north substation, which reports utility grid outages to the microgrid controller (so that the islanding process can be initiated if needed). Besides, the unintentional islanding detection was also studied. More critically, the PMU located at the main grid’s point of common coupling plays a critical role to facilitate the microgrid’s synchronization with the overall utility grid [92].

Last but not the least, regular baselining studies of microgrid performance and postmortem fault analysis are fully conducted using IIT Campus microgrid PMU measurements. More recently, field measurements from PMU devices became widely used in real-time hardware-in-the-loop simulations of the integration of the Bronzeville community and with IIT campus microgrids as a multi-microgrid cluster. Using these simulations, cluster capabilities are being verified under a variety of conditions before the physical connection takes place and before production-phase algorithms are deployed [134], [135], [136].

VII. Summary and Conclusion

Given how widely DERs are becoming integrated into distribution networks and how actively demand-response programs are being implemented, DPMUs can be deployed to support the monitoring, protection, control, management, and planning of the grid and its stakeholders. Synchronized and high-resolution DPMU phasor data, frequency, RoCoF, and other metrics can help take over or assist in a variety of tasks including anomaly detection, fault identification and location, grid operation and control, and asset modeling/management. Although challenging to collect, these data can play a critical role in enhancing power system reliability, resiliency, flexibility, and energy efficiency.

This paper aims to provide a comprehensive guide for researchers and practitioners interested in utilizing SMT/DPMU technology and applications for ADNs and microgrids protection, control, operation, and planning. We have provided a comprehensive review of the practices, latest learnings, and research trends for SMT/DPMU applications in ADNs and microgrids. We also discussed the forces leading to the advancement and adaptation of this technology to distribution-level systems. DPMUs can enhance topology detection and state estimation used to monitor the network. Conventional approaches for protection of networks and components have various weaknesses that can be improved using high-definition DPMU phasor data. With the direct access to grid-wide phase angle data, novel and more effective control algorithms are emerging. Model synthesis and calibration is now viable using DPMU apparatus integrated into the cyber layer of the power grid. We discuss the promise of data-driven techniques that utilize large repositories of data made possible by DPMUs, and explore the strengths and
Weaknesses of these techniques in comparison with model-based approaches. For each application, we looked at how and to what extent various DPMU measurement attributes (e.g., voltage phase angle, magnitude, frequency) are essential or beneficial. Table 1 summarizes these discussions in a graphical way.

**TABLE 1. Impact of DPMU measurement attributes on applications**

| Application Area               | Attributes          | Phase-Angles | Frequency and Rate | High-Resolution | Time-Synch. | Accuracy |
|-------------------------------|---------------------|--------------|-------------------|-----------------|-------------|----------|
| SE-based Topology Detection   |                     | Medium       | Low               | Low             | Low         | None     |
| Data-Driven Topology Process  |                     | Low          | Low               | Low             | Low         | None     |
| State Estimation and          |                     | Low          | Low               | Low             | Low         | None     |
| State Measurement             |                     | Low          | Low               | Low             | Low         | None     |
| Long-Term Stability Monitoring|                     | Low          | Low               | Low             | Low         | None     |
| Disturbance and Anomaly       |                     | Low          | Low               | Low             | Low         | None     |
| Detection                     |                     | Low          | Low               | Low             | Low         | None     |
| Cyber-Attack Detection        |                     | Low          | Low               | Low             | Low         | None     |
| Harmonic Distortion Monitoring|                     | Low          | Low               | Low             | Low         | None     |
| Fault Identification          |                     | Low          | Low               | Low             | Low         | None     |
| Fault-Induced Delayed Voltage |                     | Low          | Low               | Low             | Low         | None     |
| Recovery                      |                     | Low          | Low               | Low             | Low         | None     |
| Auto-Reclosing                |                     | Low          | Low               | Low             | Low         | None     |
| Islanding and Resynchronization|                   | Low          | Low               | Low             | Low         | None     |
| Fault Location                |                     | Low          | Low               | Low             | Low         | None     |
| Control                       |                     | Low          | Low               | Low             | Low         | None     |
| Energy Management             |                     | Low          | Low               | Low             | Low         | None     |
| Component/Network Model       |                     | Low          | Low               | Low             | Low         | None     |
| Synthesis                     |                     | Low          | Low               | Low             | Low         | None     |
| Phase Identification          |                     | Low          | Low               | Low             | Low         | None     |
| Asset Management/             |                     | Low          | Low               | Low             | Low         | None     |
| Condition Monitoring          |                     | Low          | Low               | Low             | Low         | None     |
| Generation-Load               |                     | Low          | Low               | Low             | Low         | None     |
| Disaggregation                |                     | Low          | Low               | Low             | Low         | None     |
| Load Characterization         |                     | Low          | Low               | Low             | Low         | None     |

**Color Legend:**
- **High**: Dark blue
- **Medium**: Light blue
- **Low**: Light green
- **None**: White

Widespread utility installation of DPMUs is moderated by the recency of this technology, lack of extensive research efforts and pilot demonstrations validating value, inadequate access to secure/fast communication media, financial limitations, and most importantly the massive volume of distribution networks. However, technical progress and a growing number of successful use cases would lead to recognition of SMT as a disruptive technology in the distribution level and broader deployment of DPMUs over the time. In particular, integration of DPMU functionality with other protection/measurement devices, such as relays, reclosers, PQ meters, and MV energy meters can reduce financial restraints.

The value of harnessing big databases for understandable, noticeable, and actionable knowledge is already recognized. Although this achievement is acknowledged in academia and R&D centers, power industry software vendors and service providers must employ data scientists to fully realize these exceptional benefits. Recruiting experts and employee training are also required to fully realize the advantages of DPMU technology.

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