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Article *in* Power Systems, IEEE Transactions on · January 2022

DOI: 10.1109/TPWRS.2022.3179488

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Stability and Dynamics of Active Distribution Networks (ADNs) with D-PMU Technology: A Review

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Abstract—**Massive integration of converter-interfaced distributed energy resources (CDERs) has resulted in many emerging stability issues and significantly complicated the dynamics of active distribution networks (ADNs). Large quantities of CDER systems with complex structures, time-varying parameters and 'black-box' controllers not only make the system modelling nearly an impossible task, but also considerably increase the dimension of dynamic models and thus the computational burden for the model-based stability analysis and control. Distribution-level phasor measurement unit (D-PMU) technology has a superior capability of monitoring, analyzing and controlling the real-time system dynamics. This paper provides a comprehensive overview on the state-of-the-art techniques of dynamics monitoring, analysis and control based on D-PMU technology in ADNs. A special emphasis is placed on the emerging instability incidents induced by CDERs. Although stability monitoring, analysis and control techniques based on PMU technology are well established in the transmission systems, substantial research efforts are required to extend these techniques to deal with the different dynamic characteristics of distribution systems. The application of big-data analytics in analyzing D-PMU data streams becomes prevalent, which can dig more information and thus provide more effective measures for stability analysis and control of ADNs.**

Index Terms— **Active distribution networks (ADNs), big-data analytics, converter-interfaced distributed energy resources (CDERs), distribution-level phasor measurement unit (D-PMU), stability analysis, stability control, stability monitoring.**

NOMENCLATURES

ADN	Active Distribution Network
ANN	Artificial Neural Network
API	Application Programming Interface
BTrDB	Berkeley Tree Database
CDER	Converter-interfaced Distributed Energy Resource
CNN	Convolutional Neural Network
COMTRADE	Common Format for Transient Data Exchange
DFT	Discrete Fourier Transform
DNN	Deep Neural Network
DSP	Digital Signal Processor
GPS	Global Positioning System
DISTIL	Design and Implementation of a Scalable Synchrophasor Data Processing System
D-PMU	Distribution-level Phasor Measurement Unit
DSO	Distribution System Operator
EV	Electric Vehicle
FIDVR	Fault Induced Delayed Voltage Recovery
GLM	Graph Laplacian Matrix
HDFS	Hadoop Distributed file system
LSTM	Long Short-Term Memory
LFO	Low Frequency Oscillation
LV	Low-Voltage
MPC	Model Predictive Control
MV	Medium-Voltage
OLTC	On-load Tap Changer
PCA	Principal Component Analysis
PLCC	Power Line Carrier Communication
PLL	Phase-Locked Loop
PNNL	Pacific Northwest National Laboratory
PPS	Pulse Per Second
PSDP	Power System Dynamic Performance
RES	Renewable Energy Source
RoCoF	Rate of Change of Frequency
SCADA	Supervisory Control and Data Acquisition
SG	Synchronous Generator
SL	Smart Load
SPD	Signal Produced by Disconnect
SQL	Structured Query Language
SSO	Sub/super-Synchronous Oscillation
SVM	Support Vector Machine
TSO	Transmission System Operator
TVE	Total Vector Error
UTC	Coordinated Universal Time
µPMU	Micro-Phasor Measurement Unit
VSI	Voltage Stability Indicator

I. INTRODUCTION

TO effectively achieve the Net Zero target, many countries and regions have proposed very ambitious plans in using clean energy and energy conservation technologies in their low and medium-voltage power networks. Massive integration of renewable energy sources (RESs, e.g., wind and solar) and wide utilization of smart loads (SLs, e.g., electric vehicles (EVs), heat pumps and smart appliances in the home) are thus supported and promoted by power industry worldwide. It can be certainly predicted that there will be a huge penetration of converter-interfaced distributed energy resources (CDERs) in the distribution networks, which has boosted the fast development of so-called 'active' distribution networks (ADNs) [1].

As a result, the dynamic environment of the distribution networks has been significantly changed and ADNs have encountered many new stability issues induced by: 1. the frequent interactions among different types of CDERs or between the CDERs and weak grids; and 2. the intermittence, uncontrollability and poor coordination of numerous CDERs. To accommodate these significant changes, two task forces of IEEE PES power system dynamic performance (PSDP) committee have proposed the updated frameworks of stability definition and classification for big-scale transmission systems and microgrids respectively and added new stability categories associated with CDERs accordingly [2][3]. However, the stability and dynamics issues of distribution systems have not been systematically summarized. In practice, it is actually vital for distribution system operators (DSOs) to acquire an in-depth understanding on the essential causes of the emerging instability issues and impact mechanisms of CDERs, and hence know how to respond in the real time. It is also important for them to be well equipped with the advanced monitoring, analysis and control techniques to effectively manage and mitigate these instability issues to prevent critical system accidents and enormous losses.

The phasor measurement unit (PMU) technology has been initially introduced to the power transmission grids to monitor critical nodes of the power grid. Subsequently, the same technology has been deployed in power distribution networks, and called 'distribution-level PMU (D-PMU).' However, the PMU technology developed for transmission grids cannot measure small phase angles in distribution networks. Consequently, the new PMU technology known as the 'D-PMU' or 'micro-PMU (μPMU)' has been developed with high resolution to be suitable for power distribution networks. The D-PMUs have a plenty of applications in power distribution feeders, which include state estimation [4], event detection and fault localization [5]-[7], power quality monitoring, and control of CDERs. Since power distribution networks are transforming to ADNs, the D-PMU technology can be actively deployed to monitor the dynamic performance and stability of ADNs.

This paper critically reviews the state-of-the-art techniques for the stability monitoring, analysis and control in ADNs based on D-PMU technology and provides a systematic summary on emerging dynamics and stability issues caused by the large-scale integration of CDERs in ADNs. The paper aims to facilitate DSOs in developing relevant grid codes and making operational decisions, and support researchers and manufacturers by highlighting potential opportunities. Current trends and future research directions for stability monitoring and control using D-PMU technology are also revealed and summarized. The paper has 8 sections in total. The introduction of the paper is given in Section I. Section II provides a general overview of D-PMU technology and data analytics frameworks. A comprehensive classification of emerging stability and dynamics issues in ADNs is presented in Section III. Section IV and V review the D-PMU-based dynamics monitoring & analysis and stability control in ADNs respectively. Real-world examples and applications of D-PMU networks and data analytics frameworks are introduced in Section VI. The future research directions in the aspects of stability monitoring, analysis and control using D-PMU data streams are discussed in Section VII considering the requirements of ADNs. Section VIII finally concludes the review paper.

II. A GENERAL OVERVIEW OF D-PMU TECHNOLOGY AND DATA ANALYTICS FRAMEWORKS

A. *Definition of Phasors, Synchrophasors, and Micro-Synchrophasors*

A phasor is a complex quantity defined with a magnitude and a phase angle of a sinusoidal waveform at a given instance of time. For example, the voltage in phasor form (exponential form) can be defined as follows

$$V = (V_m / \sqrt{2})e^{j\theta} \tag{1}$$

where V_m is the amplitude of the voltage waveform, and θ is the phase angle. Phasor can also be represented in rectangular form and polar form. The term 'synchrophasor' stems from the Standard IEC/IEEE 60255-118-1:2018 [8], which defines the 'synchrophasor' for a measured voltage waveform $v(t)$ as

$$v(t) = \left(\frac{V_m(t)}{\sqrt{2}}\right) e^{j(2\pi \int g(t)dt + \theta_0)} \tag{2}$$

where θ_0 is the initial phase angle and the $g(t)$ is the rate of change in phase angle. $g(t)$ is defined by [8]

$$g(t) = \frac{1}{2\pi}\left(\frac{d\left[\theta(t)\right]}{dt}\right) \tag{3}$$

If the frequency difference between the actual and nominal frequencies is a constant (Δf), then the phase angles of the sequence of phasors will change at a rate of $2\pi\Delta f$ $(1/f_0)$. The definition of a synchrophasor is also illustrated in Fig. 1.

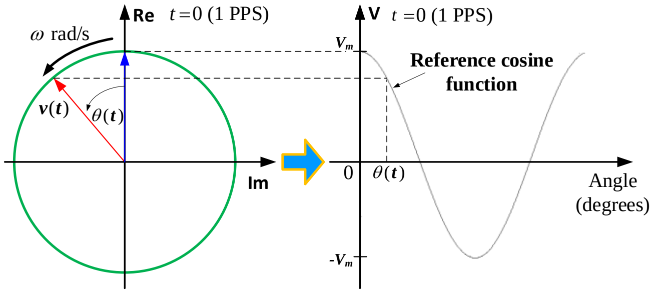

Fig. 1. Synchrophasor representation of a signal *v(t)*.

where ω denotes the nominal angular frequency of the system defined by 2π f_0, and $\theta(t)$ represents the instantaneous phase angle (i.e., a time varying quantity) relative to a cosine function at the nominal system frequency (f_0) synchronized to coordinated universal time (UTC) [8]. The reference cosine function has its maximum (i.e., V_m) at t = 0 (1 pulse per second (PPS)).

These reported angles then continuously increase with time until they reach 180° and wrap around to −180°. The synchrophasor is usually reported in angles between 180° and −180°. As synchrophasor measurements are captured based on a common time reference (i.e., UTC), they can be used for real-time monitoring of power systems; in particular, these measurements are directly comparable [8]. Synchrophasor measurements also capture waveform information, such as frequency, rate of change of frequency (RoCoF), local frequency swings, and oscillations. These parameters are usually extracted using additional algorithms after voltage/current phasor estimation [8][9]. Typically, the conventional synchrophasor measuring device (i.e., phasor measurement unit (PMU)) captures phase angles with a resolution of 0.02˚.

The term 'micro-synchrophasor' is often used when synchrophasor technology is deployed in power distribution networks with high-precision phasor measurement algorithms. The phasor measurement devices installed in the power distribution networks are often called 'micro-PMU (μPMU)' or 'distribution-level PMU (D-PMU).' Therefore, the primary difference between the conventional synchrophasor technology and the micro-synchrophasor technology is its high precision and resolution. For example, the micro-PMU has an angle resolution of 0.001˚ with an accuracy of ±0.003˚ [10][11]. Therefore, micro-synchrophasor technology is considered to be several times more accurate than the conventional synchrophasor technology.

B. D-PMU Technology

The low-voltage (LV) and medium-voltage (MV) networks have a low X/R ratio (<=1), and hence the angle difference between two nodes is relatively small compared with the transmission grids, which makes the micro-synchrophasor technology the ideal candidate for measuring small phase angles at high precision. The PMUs that employ the 'micro-synchrophasor' algorithm in distribution networks are called the D-PMUs or micro-PMUs. The typical architecture of a D-PMU is shown in Fig. 2.

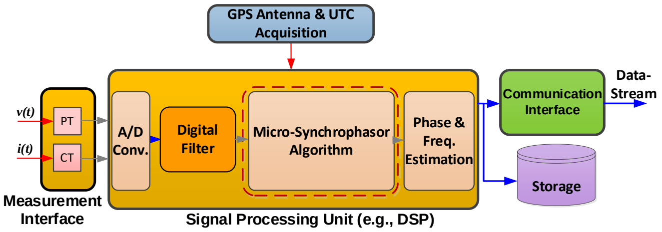

Fig. 2. The basic structure of the D-PMU.

The voltage and current signals acquired from the measurement probes are fed to the signal processing unit (e.g., digital signal processor (DSP)). At the DSP, analog signals are converted to digital form before fed-through a low-order digital filter to remove the harmonics in the waveform. In contrast, the conventional PMUs use hardware-based anti-aliasing filters, which may affect the accuracy, as small instability at the anti-aliasing filter capacitors would affect the accuracy of the measurements [12]. Therefore, commercial D-PMUs avoid having passive low-pass filters at the front end, and instead they use digital filters based on the advanced DSPs, which also help to achieve a small form factor for the D-PMU devices. After digital filtering, signals are fed to the synchrophasor estimation algorithm to capture the fundamental waveform (e.g., 50 Hz or 60 Hz) phasor. Subsequently, signals are processed further to estimate the other parameters, such as frequency and RoCoF. Then the phasor and the other captured parameters are time-stamped according to the GPS synchronized UTC timeframe, converted to the synchrophasor data format (i.e., Common Format for Transient Data Exchange (COMTRADE) [13]), and sent over to the distribution phasor data concentrator. Also, the data are stored in a local storage unit in case of a loss of the communication channel.

C. Capabilities of D-PMU Technology and Deployment within the Distribution network

The D-PMU technology is more advanced compared to the conventional PMU technology used in the power transmission grids. As mentioned, the micro-synchrophasor technology can measure phase angles and amplitudes as small as 0.001˚ and 2×10^{-4}% pu respectively, and hence the total vector error (TVE) can be maintained at or below ±0.01% (typical short-term TVE ≈ ± 0.002%) [10]. Under steady-state conditions, phasor, frequency and RoCoF data are streamed at two samples per cycle (i.e., 100 Hz for 50 Hz systems, or 120 Hz for 60 Hz systems) [11]. The D-PMUs continuously sample all input ac signals at 256 or 512 samples per cycle. These data are recorded within the instrument during power quality disturbances (e.g., Class A disturbances) [14]. Also, under large impulses, 4 million samples per second can be captured from the μPMU [12]. Therefore, these units can increase the waveform capturing rate under dynamic conditions.

The D-PMUs are typically deployed in MV and LV networks. Deploying the D-PMU at each node is economically and practically infeasible. Therefore, similar to the conventional PMUs installed in optimal locations of the power transmission grids, the micro-PMUs must also be installed in optimal locations of the power distribution networks for better observability. Research efforts have already been devoted to identify the most optimal locations for D-PMUs in the power distribution network [15]. The following factors should be considered when selecting optimal locations for D-PMUs in power distribution networks [15]-[18]:

1) Observability of topological structure (i.e., switching configurations) of the ADN,
2) Location of distributed energy resources (non-zero injection nodes),
3) Weak network nodes (e.g., node with high voltage sensitivity or low system strength),
4) Locations of voltage regulators and transformers,
5) Phase unbalance and phase configuration (i.e., number of phases)
6) Cost and budgetary constraints,
7) Required Measurement channels per node based on number of phases per node and phase observability.

Distribution networks have a comparatively complex architecture with switching configurations, and the power flow within the distribution networks is more complex than the transmission grids. Therefore, the observability of the topological structure is very important. Also, CDERs are connected to power distribution networks leading to bidirectional power flows and oscillatory stability issues in the network. Therefore, it is essential to monitor the CDER connected non-zero injection nodes in the distribution networks. Furthermore, long radial feeders would create weak network nodes, which would cause voltage stability issues in the network. Therefore, placement algorithms should ensure the observability of these weak network nodes in distribution feeder. Moreover, budgetary constraints and number of measurement nodes also play an imperative role in D-PMU placement as the distribution utilities typically require to minimize the capital and maintenance costs.

Typically, D-PMU placement optimization is defined as a minimization problem, where the objective can be formulated either based on the number of D-PMUs installed in the network or the total cost of D-PMUs [16]-[18]. The other factors, such as the observability, the total budget (when a minimization problem is defined around number of D-PMUs), weak network nodes and measurement channels can be treated as the constraints of the optimization problem.

D. Synchrophasor Big-Data Analytics Frameworks and Machine Learning Tools

D-PMU networks normally accumulate a large amount of data within a short-time period. For example, one D-PMU accumulates 500 MB per day [12], which means with 10 D-PMUs they would generate at least 5 GB of data within one day. Therefore, highly efficient data analytics algorithms are required for the offline and online processing of D-PMU data streams. In a typical synchrophasor architecture, the raw synchrophasor data streams are first stored in a database, which enables an easy access to synchrophasor data streams for further analysis. Subsequently, big-data analytic techniques are applied to the stored raw synchrophasor data to analyze and extract various information (e.g., patterns, features and anomalies). There is an increasing trend of using cloud-based distributed parallel processing architectures (e.g., The Berkeley Tree DataBase (BTrDB), Apache Hadoop) for storing synchrophasor data streams and applying big-data analytics and machine learning techniques as shown in Fig. 3 [19]. Furthermore, as these D-PMU networks generate a large amount of data, efficient data storing architectures are proposed (e.g., DISTIL) to extract the features and store only the difference between the primary and other data streams, and hence multiple redundancies can be achieved with such an advanced mechanism [20].

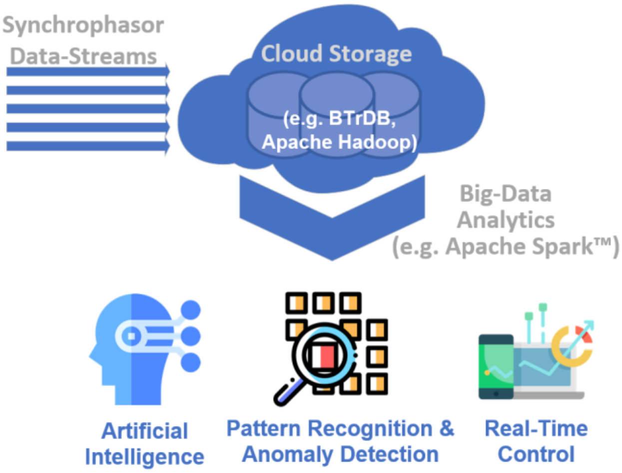

Fig. 3. Big-data analytics and machine learning architecture for synchrophasor data streams.

A number of pattern recognition approaches are applied to synchrophasor data streams to identify the patterns, features and anomalies of synchrophasor data streams. Time-series pattern recognition is the most widely used method to extract patterns and anomalies of synchrophasor data streams [21]. Autocorrelation analysis, wavelet decomposition analysis, principal component analysis (PCA) and deep learning approaches are some mathematical techniques that can be used for time-series pattern recognition in synchrophasor data streams [19]. The autocorrelation analysis can evaluate the strength of a pattern or relationship over the time, and hence the extracted pattern can be validated on a temporal basis. The wavelet decomposition analysis decomposes the synchrophasor data simultaneously while applying high and low-pass filters and identifying the dominant components. Therefore, it can extract the temporal patterns and anomalies of a synchrophasor signal. The PCA is mainly used to find spatial cross-dependencies across PMUs in the network. Therefore, PCA will assist to identify the similarities and differences between PMUs and enable to group the PMUs in the network. Furthermore, PCA can also be applied for anomaly detection in synchrophasor data streams. In terms of the deep learning approaches, long short-term memory (LSTM)-based deep neural network (DNN) and convolutional neural network (CNN) are used for detecting low frequency oscillations [22], abnormal events, and temporal events from synchrophasor data streams.

The University of California, Berkeley is one of the pioneer institutions which developed a data analysis architecture for D-PMU networks [11][23]. They have developed a cloud-based data storing and processing architecture for a network of D-PMUs. In this architecture, D-PMUs send the data streams via the internet protocol to a cloud-based database server, and the database is designed on the extremely efficient Berkeley Tree Database (BTrDB) as shown in Fig. 4. This architecture efficiently stores the multi-time-series synchrophasor data streams without requiring phasor data concentrators. Along with this database system, a big-data processing system has also been built with the capability of processing a large set of data in the real time, which is called DISTIL (Design and Implementation of a Scalable Synchrophasor Data Processing System) [20].

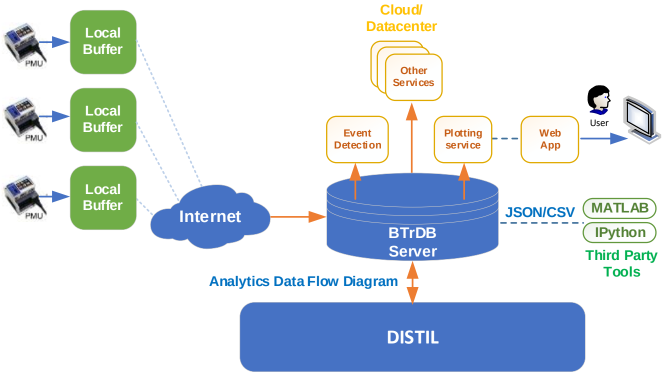

Fig. 4. D-PMU data analysis architecture developed by University of California, Berkeley [23].

The Pacific Northwest National Laboratory (PNNL) uses the Hadoop Distributed file system (HDFS) to store synchrophasor data streams and then use the Spark for big-data analysis and machine learning. The Spark offers high-speed parallel processing capability with its powerful memory architecture. The Python is used as an intermediate programming tool to extract data from the HDFS and prepare Spark data frames to use in the Spark Structured Query Language (SQL) application programming interface (API) [19] for developing big-data analytics techniques. The PNNL D-PMU data analytics framework is shown in Fig. 5.

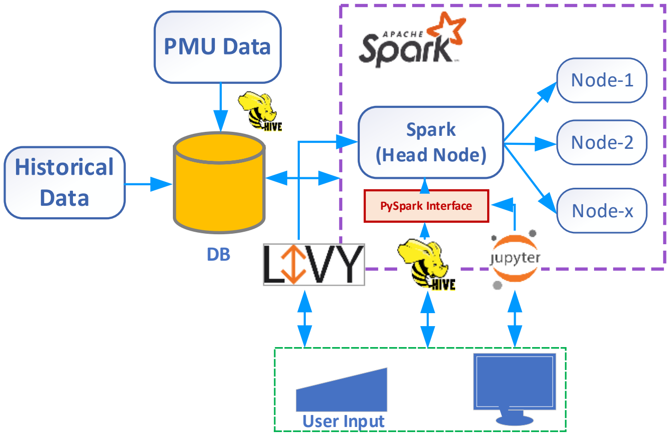

Fig. 5. The PNNL D-PMU data analytics framework [19].

Once the synchrophasor data streams are stored and processed in a database, they can be used to identify and assess the stability issues and control the equipment of ADNs, which will be reviewed in the following sections.

III. CLASSIFICATION OF EMERGING STABILITY AND DYNAMICS ISSUES IN ACTIVE DISTRIBUTION NETWORKS [2] [3]

The conventional distribution networks are considered to be passive as they consume power only and power flows are in a single direction from upstream generation source to the downstream consumer. However, with the proliferation of CDERs, such as wind and solar energy sources, battery energy storage systems, and converter-interfaced smart loads (e.g., EVs), passive distribution networks have been transformed into ADNs with bidirectional power flows. These changes have resulted in various instability and dynamics challenges in distribution networks [24] and some issues have also affected the power transmission grids [25]-[27].

Although the two task forces of IEEE PES PSDP committee have recently proposed the updated frameworks of stability definition and classification of power networks and microgrid respectively to accommodate the new instability issues associated with above-mentioned CDERs [2][3], their main focuses are either on big-scale interconnected transmission grids or small-scale local microgrids. Therefore, in this paper, the major emerging stability and dynamics threats in medium-scale and MV ADNs potentially causing major network disruptions are systematically classified with their essential mechanisms discussed in the following subsections.

A. Unintentional Islanding [28]

Unintentional islanding is mostly triggered by unexpected system faults and accidental human/protection malfunctions. Unintentional islanding normally has two different forms: 1) unintentional islanding of individual distributed energy resources, and 2) unintentional islanding of an entire distribution feeder or a part of it. In each case, it would lead to power interruptions or partial blackouts. The distributed energy resources could disconnect from the network due to the large voltage rise caused by the reverse power flow in the distribution feeder [29]. This would result in rapid voltage variations in the feeder, and ultimately due to the rapid changes in the power flow direction, directional protection schemes installed at the medium distribution feeders can operate leading to unintentional islanding of the distribution feeder.

B. Oscillations [30]

The oscillations observed in ADNs normally have two origins: 1) propagation of oscillations from the upstream (e.g., oscillations caused by generator trip-off events and transmission line trip events from the transmission grids [30]), and 2) oscillations induced by small-scale CDERs installed in ADNs (e.g., oscillations caused by the control interactions of CDERs [31][32]). The review and classification efforts in the paper are mainly devoted to the endogenous oscillations for ADNs.

The nature and dynamic performance of ADNs are considered to be very different from those of the transmission grids, which results in different oscillation problems and classifications. In contrast to the bulk transmission grids, the size of the ADNs is comparatively smaller and there is no conventional power plant in ADNs. As a result, no conventional oscillation problems have been observed, such as low frequency oscillation (LFO) and sub/super-synchronous oscillation (SSO), which are mainly associated with either big-capacity synchronous generators (SGs) or their shaft. Instead, due to an increasing number of CDERs including RESs and SLs integrated to the ADNs, more frequency and voltage oscillations have been seen caused by the unbalanced sharing of active and reactive power among different CDERs. Moreover, the interactions among different system controllers (e.g., generator and converter controllers) and distribution network dynamics are also the major components of the oscillations in ADNs. Since different system controllers have very different time constants, and the ADNs are operated with a higher resistance to reactance ratio and thus fast network dynamics, the frequency of oscillation problems in ADNs can range from several Hz to several kHz.

Therefore, the classification of oscillation problems in ADNs can be illustrated by Fig. 6 below.

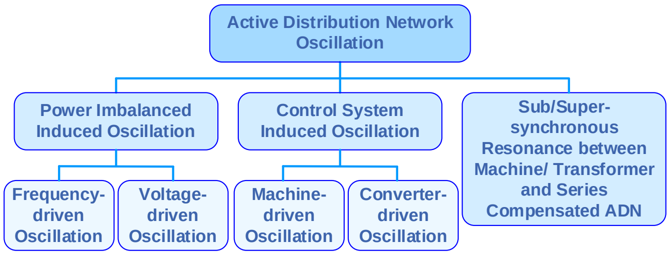

Fig. 6. Classification diagram of oscillations in active distribution network.

As demonstrated in Fig. 6, the oscillation problems in ADNs can be mainly classified into three categories based on their different causes and mechanisms as follows.

1) Power imbalance induced oscillation

This type of oscillation takes place when there is a poor sharing of active or reactive power among different CDERs (e.g., RESs and SLs) and hence it is named as power imbalance induced oscillation [33]. In particular, the poor coordination among multiple frequency controllers of CDERs and thus their inappropriate active power sharing would trigger small-perturbation stability issues resulting in undamped frequency oscillations in the span of a few seconds to a few minutes. This is the first type of power imbalance induced oscillation, i.e., frequency-driven oscillation. On the other hand, the poor coordination among reactive power and voltage (QV) droop of multiple CDERs and therefore small differences in voltage magnitude at CDERs would yield high circulating reactive power flows and hence result in large voltage oscillations. This is the second type of power imbalance induced oscillation, i.e., voltage-driven oscillation [34].

2) Control system induced oscillation

This type of oscillation may rise due to inadequate control schemes or poor tuning of one or more pieces of CDER controllers, which pertains to components like electric machines, converter control loops, filters and phase-locked loops (PLLs) etc. This category of oscillation can be further subcategorized into machine-driven oscillation and converter-driven oscillation. The former oscillation is associated with poor tuning of machine exciters and governors. The latter oscillation involves the slow interactions among outer loop dynamics of CDER converter controllers (i.e., comparatively 'lower' frequency oscillation in the range from a few Hz to tens of Hz) and fast interactions among inner loop dynamics of CDER converter controllers and fast network dynamics (sometimes also called harmonic frequency oscillation or harmonic resonance in the range from hundreds of Hz to several kHz).

3) Sub/Super-synchronous Resonance between Machine/Transformer and Series Compensated ADN

The sub/super-synchronous resonance as another type of oscillation has not been reported as frequently as the previous two types of oscillation in ADNs and mainly refers to the electrical resonance between the machine associated with CDER and series compensation embedded in ADNs [35]-[38]. The essential cause of this self-excitation resonance is owing to the net negative resistance as the inherent negative resistance of the machine rotor exceeds the positive resistance of the circuit at or near the resonance frequencies. Another sub/super-synchronous resonance which could potentially occurs in ADNs is the ferro-resonance between the magnetizing reactance associated with a transformer and series capacitance in ADNs.

C. *Voltage Instability [39]*

Voltage stability issues in ADNs can potentially result from: 1) rapid voltage decrease in the distribution feeder due to heavy loads and unintentional islanding of CDERs under heavy load scenarios [39][40]; 2) the fluctuating power output of CDERs, e.g., ramping PV power due to changing cloud cover [41][42] and intermittent wind power due to changing wind speed [43].

Considering these instability risks, some stability studies have been conducted on the steady-state voltage stability [44]-[46] and the post-fault transient voltage stability [47]. Reference [44] proposes a voltage stability index to identify the stability margin of ADNs. Reference [45] analyzes the voltage stability of ADNs by identifying the worst node in the system. Usually, the network nodes with a high sensitivity of voltage are more prone to voltage instability/collapse. And the network nodes located at the end of the distribution feeder are more prone to large voltage variations, which can become a major problem for the customers at the end of the feeder. The Bifurcation theory is applied to investigate the impact of filter reactor and reactive power load on the voltage stability of ADNs in [46]. The impact of different ADN control strategies on the post-fault voltage is explored in [47].

On this basis, different CDERs have been utilized to improve the voltage stability of ADNs such as converter-interfaced distributed generation [48] and energy storage system [49]. The sizing and placement of distributed generation has been discussed to support voltage stability in [50] and [51]. Various optimization and coordination strategies of CDERs have been developed for the voltage and Var control of ADNs [52]-[54]. A network reconfiguration technique is also proposed for the enhancement of voltage stability of ADNs in [55].

D. *Frequency Instability*

For an isolated ADN or an ADN after the unintentional islanding, frequency instability can be a critical challenge. The intermittent and stochastic characteristics of the renewable power generations and smart loads can cause big and sustained power fluctuations. However, since there is no conventional bulk power plant in ADNs, there is a lack of system inertia and generation reserve to handle these power fluctuations. As a result, the steady-state frequency operational limits can be frequently violated, activating under-frequency and over-frequency schemes. In addition, a sudden change in power due to system faults might lead to a fast decay/rise of frequency and hence a big value of RoCoF. In this case, the Frequency Nadir/Vertex would easily go beyond a certain threshold in a very short period, and then the automatic load shedding/generation tripping scheme would be triggered even causing a system blackout [56]. To date, some research efforts have been devoted to solving the frequency instability of ADNs such as the design of decentralized active demand response system [57] and distributed energy storage unit [58].

IV. D-PMU-BASED DYNAMICS MONITORING AND ANALYSIS METHODS

A. *Unintentional Islanding Detection and Analysis*

The unintentional islanded networks may experience severe unstable frequency and even blackouts. Compared with conventional methods such as power line carrier communication (PLCC), signal produced by disconnect (SPD), and supervisory control and data acquisition (SCADA)-based methods [28], the detection methods of unintentional islanding based on the high-quality and rapid-rate data of D-PMUs can produce accurate results and achieve small or even zero non-detection zones, which does not require to deploy the relevant transmitters or receivers [59].

The synchronized phasor measurements from D-PMUs including frequency and voltage can be directly compared between the main grids and potential islanded networks [60]. Unintentional islanding can be detected when their differences exceed certain thresholds [59]. Similar to the application of PMU in transmission grid islanding detection, measurement features including RoCoF and rate of change of angle differences extracted from D-PMUs can also be employed to detect the unintentional islanding [61]. Since the signal processing techniques can be appropriately programmed by the built-in microprocessor of D-PMUs, the above-mentioned applications do not require any additional hardware unit [62]. If properly deployed and configurated, D-PMUs can even directly monitor the open/closed status of circuit breakers and thus the islanding conditions [63]-[65].

To deal with the conflicts among multiple islanding detection indicators from D-PMUs, principal component analysis (PCA) and artificial neural network (ANN) classifiers are used to obtain the consistent results in [66] and [67]. The islanding detection method proposed in [68] can effectively tackle the cyberattack issues considering that the operation of D-PMUs hugely relies on the communication network for data transmission and hence is very vulnerable to cyberattack.

B. Oscillation Monitoring and Analysis

Traditionally the oscillations at distribution level have not been investigated much as opposed to those at transmission level. However, with the emerging oscillation issues in ADNs, more research efforts have been devoted in this field recently. The oscillation events occurring across the distribution feeders are observed remotely by the available D-PMUs and thus their impacts can be analyzed [69]. A novel data-driven technique is introduced to extract and analyze events such as distribution-level oscillations from the extremely large collection of raw D-PMU data in [70]. A multi-class support vector machine (SVM) classifier is trained and tested over 15 days of real-world data including 1.2 billion measurement points and 10,700 events from two D-PMUs on a distribution feeder in Riverside, CA, USA.

Some synchrophasor technology-based oscillation detection and source localization techniques employed in the transmission grids can be also transferred and applied to the real-time monitoring and analysis of oscillations in ADNs [71][72]. The common goal is always to enhance the visibility and situational awareness of the abnormal dynamics, which can extend both above and below the substation. The effective oscillation detection and prompt actions taken to restore the network stability can largely contribute to the security and reliability of both transmission and distribution networks [72][73]. Synchrophasor technology-enabled energy flow analysis initially proposed for transmission grids is another effective tool for detection and source localization of various power oscillations in the system [74][75]. The equivalence and consistency between energy flow analysis, modal analysis and damping torque analysis have been strictly proved. Therefore, the dissipation rate of oscillation energy can be used as an important index to monitor and assess the damping performance of the interested oscillation modes in ADNs.

Apart from the dominant oscillation problems in ADNs, the low frequency oscillation mainly concerned by transmission system operator (TSO) can also propagate into distribution networks through substations. It is reported that low frequency oscillations occurring in transmission grids can be accurately monitored by D-PMUs deployed at the distribution level. A series of work [76][77] indicates that the low frequency oscillation events excited by various disturbances in Western Interconnection of the North American power system are detected by using monitoring data from a frequency monitoring network consisting of D-PMUs at the end-user voltage level (120 V). Similarly, the work in [30] monitors and analyzes the low frequency oscillations based on the measurements of D-PMUs deployed in 120 V distribution networks in Texas. The detection of low frequency oscillation with D-PMUs at the distribution level is an effective supplement to the oscillation monitoring at transmission level. Moreover, once the oscillations are detected, distribution networks can also damp oscillations with available resources to mitigate their potential damages [78].

C. Voltage Instability Detection and Analysis

Massive integration of the renewable CDERs and frequent switching of the networks have posed a critical challenge to voltage instability detection and analysis in ADNs. The real-time wide-area measurements of D-PMUs can effectively capture all these changes in ADNs and enable a wide range of voltage stability assessment methods. For distribution networks with a radial topology, a voltage stability indicator (VSI) is proposed and accessed for each individual bus by forward sweeping from substation to the downstream buses with the assistance of D-PMU measurements in [39][40]. An offline trained and periodically updated decision tree-based VSI assessment model is proposed in [79], which conducts voltage stability analysis utilizing the past representative and forecasted system operation conditions. Some assessment methods initially developed to tackle transmission grid voltage instability can be also applied to ADNs. Based on Thevenin equivalent theory, the coupled single-port method [80][81] and linear index method [82] can achieve a high assessment accuracy by using real-time wide-area measurements. The effect of measurement uncertainties and quality on the accuracy of Thevenin equivalent impedance-based methods is discussed in [83] and [84]. A 3-phase long-term VSI is proposed in [85] by extending Thevenin equivalent to unbalanced 3-phase circuits so as to deal with the unbalanced operation of lines and loads in ADNs. Then a convex optimization formulation to estimate the 3-phase Thevenin equivalent naturally using unbalanced D-PMU measurements is proposed to calculate the proposed VSI in an online model-free manner, which is validated to be effective in identifying the regions causing long term voltage instability in a wide range of scenarios.

Some operational events that would potentially lead to abnormal voltage conditions and risk of instability can also be detected and monitored by D-PMU measurements. A generalized Graph Laplacian Matrix (GLM) method to visualize different voltage events in a real test feeder is proposed in [86]. In [87], a detailed data-driven experimental analysis on how different voltage-level networks are affected by capacitor bank switching events is conducted in ADNs. Measurements from two feeder-level and load-level D-PMUs are used to detect the capacitor bank switching events and analyze their dynamic effects, which eliminates the need of separate sensors mounted on the switched capacitor banks. A measurement data-driven framework is proposed to distinguish two disruptive events, i.e., malfunctioned capacitor bank switching and malfunctioned regulator on-load tap changer (OLTC) switching from two normal operating events, i.e., the abrupt load change and reconfiguration in distribution networks, which are closely related voltage stability [88]. The event classification is formulated using a neural network-based algorithm, i.e., autoencoders along with softmax classifiers. The fault induced delayed voltage recovery (FIDVR) is another operational event which might bring about the voltage instability [89][90]. Following a fault clearance, the voltage may remain considerably low for a relatively long period due to the motor stalling etc. in ADNs. D-PMUs can track the entire procedure of an FIDVR event in the real time, and support FIDVR detection and mitigation measures. A data-driven probabilistic detector using wide-area high-resolution D-PMU measurements is proposed in [91] to detect FIDVR events following disturbances and assess their severities. Fast detections enabled by D-PMUs can help gain more time to deploy relevant control actions for mitigating the FIDVR events and reducing voltage instability risk.

Different from transmission lines, the X/R ratio of distribution feeders is comparatively lower, which has resulted in the nonnegligible coupling between the voltage variations and the active power injections, and reduced the effectiveness of reactive power compensation-based voltage regulation [92]. On the other hand, the intermittent and uncertain nature of renewable CDERs due to the stochastic solar irradiance and wind speed can cause considerable fluctuations in active power injection and hence the bus voltage [93]-[95]. D-PMUs, by sampling voltage waveforms with high frequency and reporting voltage phasors with fine resolution, are able to record rapid voltage fluctuations and then send them to detection modules. The detections can be conducted either inside D-PMUs by embedded algorithms or outside D-PMUs by external processors [96]. The traditional algorithm is to calculate root mean square values of voltage samplings within a certain time window. Voltage sags/swells are detected when the root mean square value is lower/higher than the preset thresholds [97]. Moreover, a kernel PCA and a partially Support Vector Machine (pSVM) are employed in [98] for voltage sag detection based on data index and reconstruction error. It should be also noted that the voltage fluctuations may sometimes inversely affect the performance of D-PMU phasor estimations [99].

D. Frequency Instability Detection and Analysis

Frequency deviation and its associated rate are the two most important indices that can indicate frequency stability and reflect system generation-load balance conditions. Thus, the frequency instability detection and analysis mainly focus on these two factors. The D-PMUs can provide a direct measurement on the frequency and RoCoF as byproducts of phasor estimation via post processing, and some D-PMUs are also equipped with the under/over frequency detection functions. Compared with existing frequency detection and analysis devices, network configured D-PMUs can provide synchronized frequency monitoring at multiple locations with a higher accuracy. The distribution-level measurements normally contain more harmonics and noises than those at the transmission level, so that more dedicated frequency and RoCoF estimation algorithms inside D-PMUs are developed for a better estimation accuracy [100]. The performance of different algorithms in estimating frequency and RoCoF is compared in [101]. The window function that sets sample weights and the window length indicating sample coverages are two main parameters highly affecting the estimation accuracy of the algorithms like Discrete Fourier transform (DFT) [102]. Considering the unbalanced operation of ADNs, D-PMU data from all three-phases are preferred for more robust estimations, although a frequency estimation would normally be available from a single-phase measurement [103]-[105]. It should be noted that single displayed frequency estimate usually refers to the average of estimated values of available phases, or the frequency of the positive sequence component when all three phase measurements are available.

With the intermittent nature of renewable power generation, system inertia becomes demanding resource to support system frequency response. A non-invasive method is proposed in [106] to assess the system inertia distribution based on the transient frequency measurements from D-PMUs. A robust algorithm to calculate the RoCoF and determine starting point of the power system frequency event is presented in [107]. Upon the detection of the frequency event, power mismatch between generation and load demand is estimated at the early stage of the event. Practical issues including the measurement reporting rate and estimation time are also discussed. A SVM-based method is proposed in [108], which leverages D-PMU measurements to predict and monitor frequency stability in the system restoration process. A data-driven method utilizing the data from D-PMUs is proposed to classify the frequency events observed in ADN feeders [109]. The proposed method mainly has three functions enabled by three developed techniques respectively. The Granger causality technique can detect if the frequency event propagates from the transmission grids to the main feeders of the ADNs. The trained sparse coding dictionary technique can determine the spectral frequency of abnormal events and thus reveal the physical causes of the frequency events. The moving z-score-based event-pair detector technique can identify whether the frequency event is falsely induced by instantaneous frequency estimation algorithms.

V. D-PMU-BASED STABILITY CONTROL METHODS

Distributed energy resources are the primary generating units in ADNs compared to SG-dominated conventional power systems. Intermittency and uncertainty associated with these distributed generators specially renewables cause the generated power in ADNs to vary drastically. Reference [110] proposes a novel control strategy using time series data provided by PMUs for early detection of such irregularities and control of RESs in ADNs. If not done so, ADNs can experience voltage and frequency-driven oscillations as highlighted in Section III. However, controlling the voltage and frequency of ADNs is more challenging than that in conventional power systems. For example, the typical control actions such as the use of an on-load tap changer or a capacitor bank may not control the voltage properly in ADNs. Rather, the distributed control with proper communication and coordination among different CDERs can initiate satisfactory preventive control actions in ADNs.

The aforementioned objective can be achieved in a greater accuracy with the help of high-resolution time-synchronized measurements through D-PMUs installed in ADNs. However, the literature on using D-PMU data for different control actions in ADNs is not rich compared with other applications highlighted in previous sections. For example, the three review papers [65], [111], [11] on D-PMU applications have not explicitly discussed about the controller design techniques for the stability enhancement of ADNs. Nevertheless, considerable amounts of previous work are available for voltage/frequency control and power management in MV ADNs using local measurements. Model Predictive Control (MPC)-based voltage control strategies [112][113], agent-based generation and demand coordination [114], droop-based control strategies [33] to improve transient performance of islanded ADNs are few examples of different controllers for ADNs using local measurements available via SCADA or some other means. These controllers may perform better by using high-resolution D-PMU measurements.

The time-synchronized D-PMU data provide greater visualizations of ADNs. Thus, D-PMUs can play a major role when designing robust controllers in MV ADNs where multiple CDERs are connected as clusters. In such situations, the contributing CDERs for different controller design requirements may be physically apart. The distributed MPC algorithm [115], augmented voltage-to-power sensitivity estimation method [116][117], two-level local and MPC-centralized control method [118], and multi-agent system control method [119] demonstrate that the D-PMU data can be effectively used to regulate the voltage in the real-time operation of ADNs. Furthermore, [120] proposes an Extreme Seeking algorithm to island a portion of ADNs while simultaneously providing the voltage regulation. The reactive power injection of EV chargers may also be a good controllable variable under their presence in ADNs. The hierarchical control scheme in [121] is proposed by coordinating the above-mentioned variable for voltage regulation in highly unbalanced distribution networks. Reference [120] and [121] show that the paralleled operation of individual controllers as well as hierarchical control between local and centralized controllers with the help of D-PMU data can effectively accelerate the control process.

Frequency control of ADNs in the islanded mode is also a challenging task. This is due to the fact that different CDERs in ADNs need to properly coordinate and adjust their output power in order to maintain the dynamic balance between the generation and the load. The availability of D-PMU data allows the implementation of secondary frequency control actions with proper communication among different CDERs in the islanded ADNs. Reference [122] proposes a new time-variable secondary frequency control for droop-controlled islanded systems. This algorithm uses both power and frequency variations with the help of D-PMUs to speed up the frequency correction. Furthermore, the ability of thermostatically controlled loads and energy storage systems in rapidly changing their operating conditions can positively contribute to the frequency regulation process of these systems. This feature has been utilized in designing a novel D-PMU measurement-based frequency controller in [123]. A novel distributed control architecture is proposed in [124] for CDERs, which can control voltage and frequency as required. This architecture first utilizes synchrophasor data provided by D-PMUs installed in CDERs to predict the steady-state behavior of the system subsequent to disturbances. It is revealed that this distributed controller based on a concept of corrective parcel and stabilizing parcel can effectively improves damping and mitigates overshoot of oscillations while speeding up the recovery of the expected steady-state conditions. The three-layer hierarchical control logic proposed in [125] uses cloud-based IoT infrastructure for voltage and frequency control of ADNs with CDERs. This architecture requires the D-PMU data to be communicated to the cloud for control and islanding detection purposes, thereby achieving the stability within 2 s of islanding.

In addition to the voltage and frequency control requirements in ADNs, there also exist oscillatory stability issues due to interactions among power electronic converters in ADNs as highlighted in Section III. However, the use of D-PMU data for such oscillatory instability mitigation is not rich yet [124]. The time-synchronized measurements of D-PMUs can be effectively used in robust damping controller design to handle such situations in ADNs. In addition to that, the D-PMU data can be also used for control of LV distribution networks such as active power control among PV inverters as shown in [126].

VI. Recommendations for Future Research

Considering the potential of the D-PMU technology and the challenges of emerging stability and control issues in ADNs as reviewed above, the following research areas are considered to be promising and hence recommended for future studies.

1) Due to the high-resolution nature of the D-PMU technology, it can be utilized for high-speed detection of complicated stability issues and ‘faster’ dynamics problems emanating from potential faults in ADNs. Hence, systematic real-time dynamics monitoring and stability analysis techniques by using the D-PMU technology can be further developed considering unique dynamic features of ADNs.

2) ADNs can operate as self-sustained autonomous entities without depending on the main power grids. However, to facilitate such an autonomous operation, control systems (e.g., voltage and frequency control) require highly precise phasor measurements, mainly for providing the synchronization references for CDERs. The D-PMU technology is capable of providing high-precision measurements, such as phase angles and frequency for the synchronization of CDERs. Therefore, further research can be conducted on the autonomous operation of ADNs employing a D-PMU network.

3) The deployment strategies of D-PMUs in ADNs can be developed in the system planning stage to improve the technical and economic performance of stability monitoring, analysis and control. The optimal deployment locations and numbers of D-PMUs should be investigated especially considering the frequent switching feature of ADNs.

4) Compared with the PMUs employed in the transmission grids, the volume of D-PMU data in ADNs is much larger, which provides great opportunities as well as critical challenges for the data analytics. Powerful big-data analytics techniques should be developed to efficiently process the data and reliably deal with the data quality and security issues, so that the performance of D-PMU-based stability monitoring, analysis and control can be ensured. Moreover, the data communication and information sharing strategies among multiple D-PMUs in ADNs would be another important factor in affecting the performance and thus requires further research.

5) Compared with the traditional oscillations in the transmission grids, the emerging wideband oscillations mainly induced by the integration of CDERs in ADNs are more complex in nature and have received immense attentions.

Robust monitoring and data analytics enabled by D-PMU technology can be used to extract the in-depth physical features and thus reveal the essential causes of these oscillations. Relevant control strategies can be also developed and applied with the support of D-PMU technology.

VII. CONCLUSIONS

As summarized in Table I, the paper presents a comprehensive review on the emerging stability and dynamics issues in ADNs and the state-of-the-art D-PMU measurement-based methods to tackle these issues for the stable operation of ADNs. Quite a few relevant techniques are developed by the existing literature to monitor, analyze and control different types of instability incidents observed and reported in ADNs, including the unintentional islanding, oscillation, voltage instability and frequency instability. Compared with conventional instability problems of the transmission grids, the mechanisms of the emerging dynamics issues in ADNs as affected by massive integration of CDERs and the distinctive natures of networks are less understood and have not been fully explored by either academia or industry. The unavailability of accurate and reliable system modelling is one of the major factors to hinder the above-mentioned tasks. Alternatively, micro-synchrophasor technology can be adopted as a real-time operational tool to precisely identify and characterize these dynamics incidents and enable the big-data analytics to effectively analyze and mitigate these instability issues. Future research efforts are needed and thus recommended to further advance various enabling methods and techniques in this area.

TABLE I

A SUMMARY OF REVIEWED REFERENCES

References	Contributions
[1]-[3][24]-[58]	ADN basics and its emerging stability & dynamics issues
[4]-[7]	General applications of D-PMU/PMU technology
[8]-[23]	D-PMU/PMU technology basics, deployment, data analytics and real implementation
[59]-[109]	D-PMU-based dynamics monitoring and analysis
[110]-[126]	D-PMU-based stability control

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