Distribution Synchrophasors

By Hamed Mohsenian-Rad, Emma Stewart, and Ed Cortez

IN THE EVOLUTION OF ADVANCED SENSING TECHnologies, transmission systems have led distribution. The visibility and diagnostics of the transmission grid have been transformed over the past decade with the systematic deployment of phasor measurement units (PMUs). Similar and even more advanced new information sources are now becoming available at the distribution grid, using distribution-level PMUs, also called *micro-PMUs* (*μPMUs*). μPMUs provide voltage and current measurements at higher resolution and precision to facilitate a level of visibility into the distribution grid that is currently not achievable. However, mere data availability in itself will not lead to enhanced situational awareness and operational intelligence. Data must be paired with useful analytics to translate these data to actionable information. In this article, we explore some of the opportunities to leverage μPMU data, combined with data-driven analytics, to help electrical distribution system planners and operators to get out in front of problems as they evolve.

The data generated by μPMUs are a prominent example of big data in power systems. Each μPMU generates 124,416,600 readings per day. Therefore, μPMUs installed on a handful of utility distribution feeders can generate terabytes of data on daily basis. Because μPMUs stream their measurements continuously, the data must be collected, cleansed, and processed, all in real time.

The collected μPMU data must then be dissected into descriptive, predictive, and prescriptive analytics. While descriptive analytics focuses on what happened in the past, predictive analytics aims at what may happen in the future. Both are stepping stones toward prescriptive analytics—optimizing the future with informed decisions. Here, we consider case studies in both descriptive and predictive analytics and provide a sampling of the benefits derived from μPMU data.

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Pairing Big Data with Analytics to Create Actionable Information

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What Is μPMU, and Why Is It Needed?

Some of the characteristics of the distribution grid that cause difficulties for conventional sensing and measurement technologies include randomness of customer behavior, high nodal volume, lack of useful metadata, and the number of unknowns such as grid topology, controls, and behavior of behind-the-meter resources. The electric utility industry has recently taken important steps toward improving distribution network visibility to address some of these challenges, through the integration of smart meters. Even though smart meters give a 15-min interval time-series data set containing valuable information on customer behavior, they do not provide the transient information of voltage and current behavior useful for possible diagnosis of incipient failures. This and other shortcomings can now be addressed by using μPMUs.

While μPMUs can support or contribute to some of the applications of transmission-level PMUs, such as synchronized locational measurement of fundamental frequency or identification of interarea oscillations, it is, instead, the time series (i.e., the sequence of synchronized phase angle and magnitude measurements on three phases) that provides the greatest benefit to the distribution system.

A typical μPMU is connected to single- or three-phase distribution circuits to continuously measure global positioning system time-referenced magnitudes and phase angles of voltage and current at two readings/cycle, or 120 readings/s. This is 108,000 times faster than the reporting rate of a typical smart meter, which provides one reading every 15 min. Each of these data sets is useful for a specific purpose—but using the data in their most "fit for purpose" role can be challenging. In sensing and measurement for the distribution grid, no one-fits-all approach exists; an all-of-the-above mentality is needed, but this remains a research challenge. Since 2015, several μPMU devices have been installed at pilot test sites in the state of California, including multiple 12.47-kV test feeders in the city of Riverside.

Example 1

Consider the distribution feeder in Figure 1, where two sensor locations are marked—one at the secondary of a 69-kV/12.47-kV transformer at the feeder head and another one at the secondary of a 12.47-kV/480-V transformer at a commercial building. The measurements at sensor 1 are

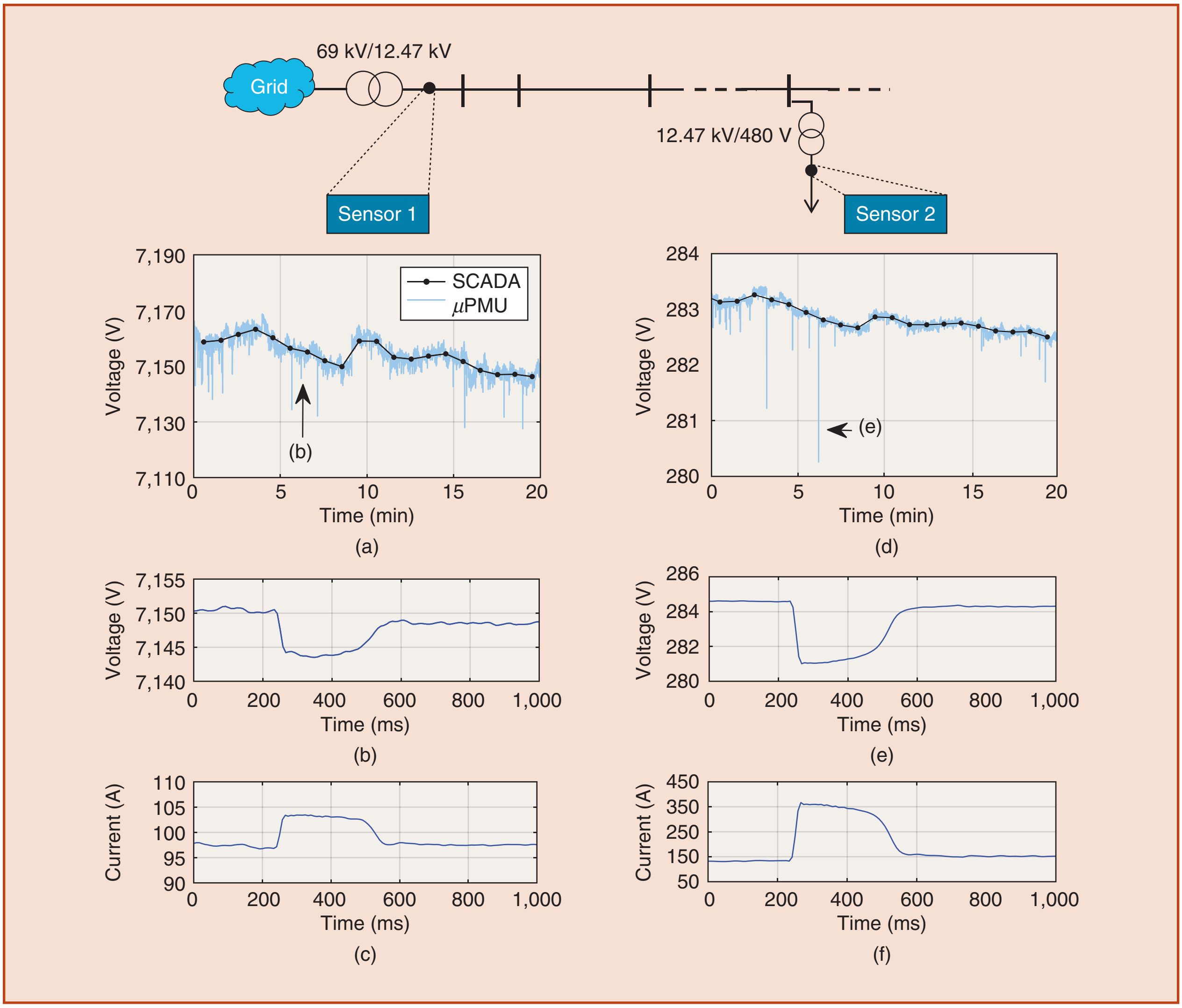

figure 1. An example of μPMU readings compared to a standard SCADA or meter reading: (a) SCADA and μPMU measurements at sensor location 1, (b) the voltage magnitude measurement by μPMU at sensor location 1 after zooming in, (c) the current magnitude measurement by μPMU at sensor location 1 after zooming in, (d) SCADA and μPMU measurements at sensor location 2, (e) the voltage magnitude measurement by μPMU at sensor location 2 after zooming in, and (f) the current magnitude measurement by μPMU at sensor location 2 after zooming in.

shown in Figure 1(a)–(c). The measurements at sensor 2 are shown in Figure 1(d)–(f). Only one phase is shown here. The black curves with dotted markers in Figure 1(a) and (d) show the measurements made by standard supervisory control and data acquisition (SCADA) meters reporting one root mean square (rms) value per minute. The blue curves show the measurements made by μPMUs that report 7,200 magnitude values/min.

The measurements made by μPMUs provide much more detail about voltage fluctuations. For instance, they reveal several momentary voltage sags, as shown in Figure 1(a) and (d). Two synchronized voltage sags around the sixth minute are of particular interest and marked with arrows in both figures. They are zoomed in on and magnified in Figure 1(b) and (e), respectively. These voltage sags last about 200 ms. The corresponding changes in current are shown in Figure 1(c) and (e), respectively. In this example, the voltage sag is load induced, as opposed to grid induced, because it is caused by turning on a large load at the location of sensor 2. The load's surge current momentarily takes down voltage. The impact is not only seen at the load location but can also be traced all the way up to the feeder head at the substation. In this example, the high temporal resolution as well as the time synchronization of the μPMU measurements is the key to identifying the root cause of the voltage sags.

Descriptive Analytics

Most efforts to analyze μPMU data have previously focused on diagnostics, where an event or a fault and possibly its root causes are explained after the fact. A human expert is often inserted into the loop, sometimes conducting the diagnosis with a power flow model. In this section, we discuss two such use cases utilizing the μPMU data collected from Riverside, California.

Example 2

Figure 2 depicts the synchronized voltage transients during an animal-caused short-circuit fault event. The fault occurred on a lateral not too far from the substation, affecting mostly one phase. Only the affected phase is shown in this figure.

Voltage phasors are measured by three μPMUs at three locations. μPMU 1 is installed toward the end of a lateral (not the faulted lateral) on the faulted feeder. The short-circuit fault momentarily brings the voltage down to zero at the location of μPMU 1, causing a brief interruption, as shown in Figure 2(a). μPMU 2 is the point of common coupling of the faulted feeder at the substation. The short-circuit fault creates a severe voltage sag at this location, as shown in Figure 2(b). Finally, μPMU 3, installed on another feeder several miles away from the faulted feeder, records a considerable voltage sag, as shown in Figure 2(c), albeit much less severe than what μPMU 2 has captured.

This type of synchronized distribution grid voltage data can be used to calibrate the coordination of the distribution system protection devices. But, more importantly, these data could enable a quick deployment of field crews to the particular fault location, with an indication of what may have been damaged based on the observed fault characteristics.

Example 3

The high reporting frequency of μPMUs allows them to capture hundreds of voltage events every day. Some of these events have root causes at the transmission level, which may not be of much interest to distribution operators. Therefore, it is necessary to distinguish transmission-induced events from distribution-induced ones. The latter can then be used in various distribution-level diagnostics. We can make such a distinction by comparing synchronized voltage measurements at neighboring distribution feeders.

An example is shown in Figure 3, where four voltage events are marked. Event 1 appears in feeder 2 but not in feeder 1, so it is induced by the loads and equipment on feeder 2. Events 2 and 4 appear in feeder 1 but not in feeder 2, so they are induced by the loads and equipment on feeder 1. Event 3, which is the most severe voltage transient event in this example, appears in both feeders. Therefore, it is most likely caused by issues at a higher voltage level, such as the transmission or subtransmission systems.

Data from μPMUs have also been used recently for other descriptive analytics, such as evaluating photovoltaic site performance; determining voltage controller behavior, topology, as well as for phase detection; and performing resource

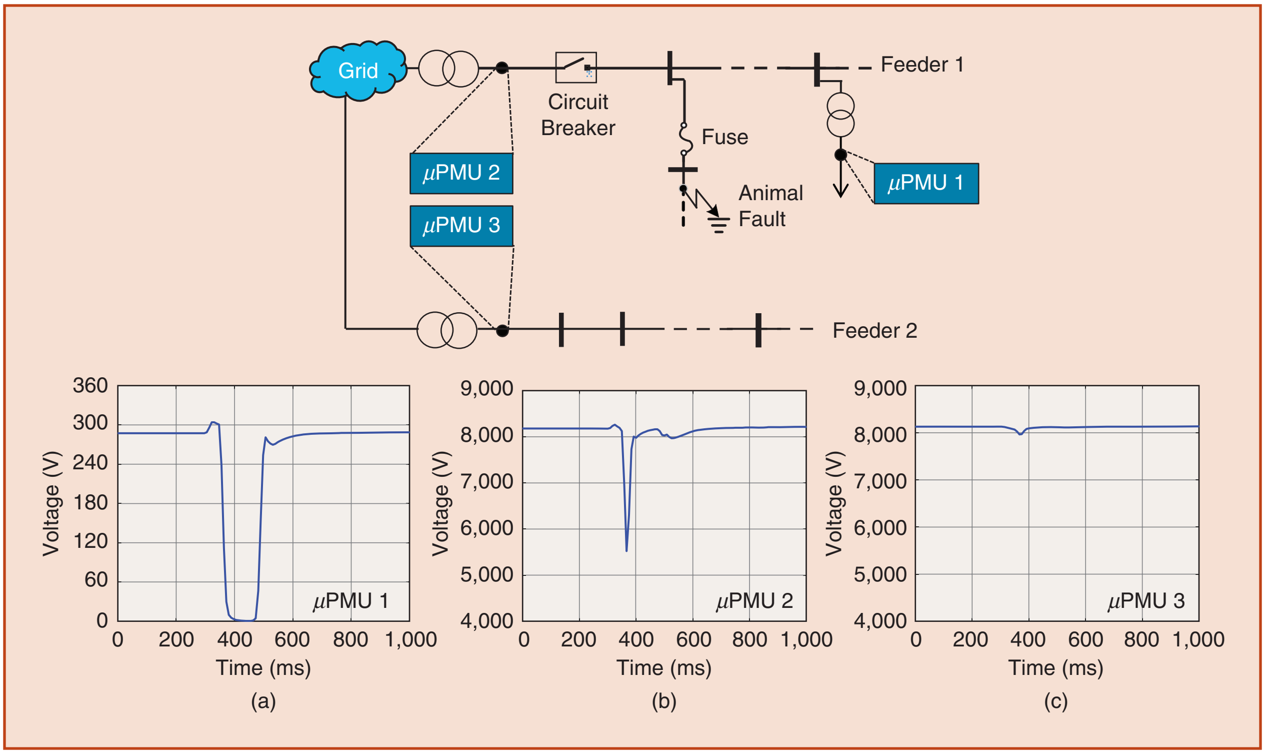

figure 2. The impact of an animal-caused short-circuit fault recorded at three geographical locations. (a) The short-circuit fault momentarily brings the voltage down to zero at the location of μPMU 1, causing a brief interruption. (b) The short-circuit fault also creates a severe voltage sag at μPMU 2. (c) μPMU 3 records a considerable voltage sag on another feeder, although much less severe than what μPMU 2 captured.

> µPMUs provide voltage and current measurements at higher resolution and precision to facilitate a level of visibility into the distribution grid that is currently not achievable.

selection for electricity market participation on the demand side. While the suite of applications is growing, the requirements for analytics around data quality, communication, and computational power continue to be major challenges for industry and academia.

Predictive Analytics

Descriptive analytics is tremendously useful for managing the existing distribution grid. The input of high-fidelity data, such as µPMU data, is an important leap forward. On the other hand, grid modernization has made a significant push toward predictive and prescriptive analytics.

Solar power forecasting, for example, has long been hindered by a lack of measurements at the distribution grid level and, more often than not, relies on either direct sensing of the generator or a forecasting approach that may use weather sensors and capacity estimates per feeder. Similar, and arguably more challenging, forecasting needs now arise at the millisecond scale and transient level, e.g., with respect to the operation of solar panel inverters, transformers, and capacitor banks. µPMUs and related data-driven techniques can help greatly in such applications.

In this section, we discuss two predictive analytics examples based on real-world µPMU data. Both examples are related to the monitoring and maintenance of grid equipment and assets. This is motivated by the fact that a typical distribution feeder may have thousands of devices, such as transformers, capacitor banks, fuses, relays, and switches. It is too cost-inefficient to install a dedicated asset-monitoring sensor on each device. Interestingly, it *is* possible to monitor a large number of grid assets using the synchronized and high-resolution measurements collected by a few µPMUs and distinguish between different types of equipment failures. The collected data can lead to the identification of anomalies not yet significant enough to cause a fault or customer interruption but, if not addressed, likely to cause failures in the near future.

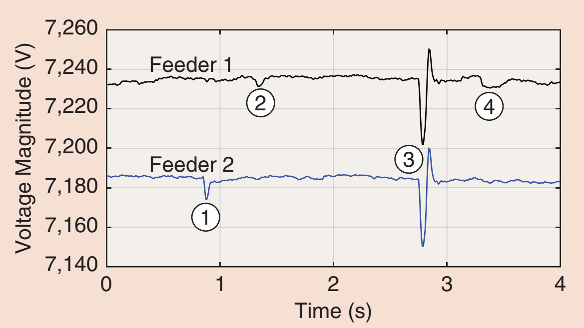

figure 3. Four voltage transient events marked on synchronized voltage measurements at two feeders.

Example 4

A distribution feeder includes a three-phase switched capacitor bank rated at 900 kvar. The capacitor bank is switched on and off by a vacuum switch. The timing of the switching is controlled by a volt-var controller. A transient limiting inductors device is installed in series with each phase of the switched-capacitor bank to limit transient currents during switching events or faults. The capacitor bank is installed a few miles away from the substation on a lateral.

However, its operation can be observed remotely using a µPMU installed at the feeder head at the substation. A switch-off event of the capacitor bank is captured and shown in Figure 4. First, using the voltage magnitude measurements, one can confirm that switching off the capacitor results in a permanent drop in voltage, as one would expect and as shown in Figure 4(a). Importantly, there is also a severe current overshoot on phase A and a severe current undershoot on phase C during such a capacitor bank switch-off event, as shown in Figure 4(b). We can conclude that the capacitor bank is switched off at zero crossing of phase B.

Repeated current synchrophasor measurements on multiple days show a very similar switching-off signature. The overshoot and undershoot on phases A and C last for about 200 ms (a relatively long time). It appears that the capacitor bank is not initially de-energized on phases A and C at the time of switching until several cycles later, as shown by the current phase angle measurements in Figure 4(c). This may indicate some hardware or control malfunction, while the large magnitude and the long duration of the current overshoot and undershoot could be a power quality concern for customers. This type of event analysis allows proactive crew dispatch for repair or replacement with minimal customer interruption.

Example 5

A distribution substation transformer has an incipient failure not yet detected. µPMUs are installed in nonoptimal locations, i.e., with no primary intention to monitor the operation of the transformer. During a typical on-load tap changer (OLTC) action (commonly utilized for voltage regulation across the United

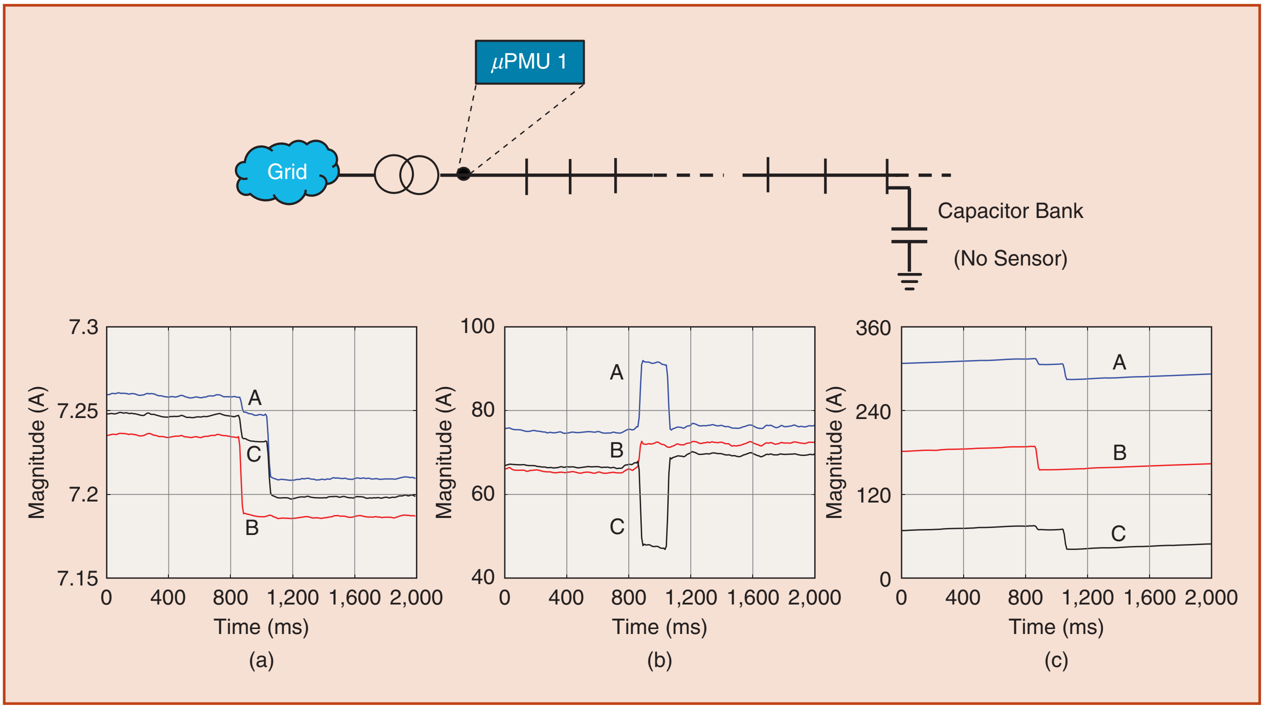

figure 4. A switching-off event of a switched capacitor bank remotely observed by a µPMU. (a) Switching off the capacitor results in a permanent drop in voltage. (b) A severe current overshoot on phase A and a severe current undershoot on phase C occur during the capacitor bank switch-off event. (c) The capacitor bank is apparently not initially de-energized on phases A and C at the time of switching until several cycles later.

States), the effective turns ratio of the transformer is changed; this is accomplished with a mechanical movement of a spring-loaded contact, often in an oil-filled environment. Common methods for sensing the failure of such a component include dissolved gas analysis and oil-level measurements. These methods often require taking the device offline for complete testing.

In this real-world example, precise synchronized voltage measurements from µPMUs were also examined to determine any anomalous behavior related to the tap changes. Anomalies were, in fact, detected on the primary side of the transformer in the form of synchronized voltage rise and sag during a tap change, as seen in Figure 5, despite the lack of additional prior indications by other sensors on the field. This could be related to the abnormal behavior of the resistor or reactor bridge within the OLTC (used to limit the circulating current during the mechanical change) or to an oil leak causing arcing within the device. Interestingly, neither the oil sensor nor the smart meters had detected the presence of an anomaly. When the field crew visited the transformer location after the µPMU data analysis, it was determined that a repair was necessary. Following the repair, the anomaly disappeared. With continued oil leakage and in the absence of µPMU data analysis, there would have been a catastrophic transformer failure and customer interruption.

A Note on Examples 3 and 4

It is worth emphasizing that neither the capacitor bank anomalies in Example 3 nor the transformer anomalies in Example 4 were identified by other existing sensors on the utility grid. Both sets of anomalies were in the form of transient events that were visible only to the sensors with high sampling rates at milliseconds, such as µPMUs. Although the real-life µPMUs that provided the measurements to perform the analyses in Examples 3 and 4 were not initially intended for the analyses in either example, they were able to provide highly insightful measurements to detect incipient failures.

The application of incipient failure detection, coupled with close to real-time communication, will allow early corrective

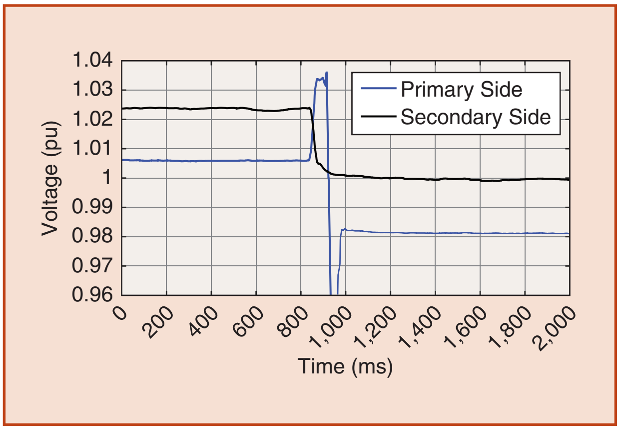

figure 5. The tap-change event of an OLTC observed by two µPMUs.

> Since 2015, several µPMU devices have been installed at pilot test sites in the state of California, including multiple 12.47-kV test feeders in the city of Riverside.

actions. For instance, in Example 4, the action to reduce transformer load was taken quickly, without major operator or field crew intervention, and the transformer was then flagged for repair. Such proactive approaches help prevent consumer interruptions, enable utilities to repair rather than run to failure, and minimize field crew dispatch time.

Unlocking the Power of Big Data

From Examples 1–5, it is clear that there is an enormous amount of information to extract from even a small number of µPMUs, as long as one can zoom in on, detect, and scrutinize each event within its millisecond time scale. In particular, one can expand the core ideas presented by these examples to remotely monitor hundreds of pieces of grid equipment, assets, distributed energy resources, inverters, and loads on each feeder, thus building the key to true situational awareness in power distribution systems.

However, the main challenge is to go beyond manual methods based on the intuition and heuristics of human experts, such as those described in Examples 1–5. Instead, it is crucial to develop the machine intelligence needed to automate and scale up the analytics on billions of µPMU measurements and terabytes of data on a daily basis and in real time. In this section, we make the case that big data analytics (BDA) is the key to addressing the challenges in working with µPMU measurements and so turn the data into actionable insights in a scalable fashion.

BDA is the process of examining big data to uncover hidden patterns, unknown correlations, customer preferences, population behaviors, incipient failures, operation irregularities, and other useful data-driven intelligence. In power systems, the findings from BDA may lead to relieving threats; preventing, predicting, or responding more quickly to faults; improved efficiency; new revenue opportunities; and better customer service.

Significant technical advances have recently been made within the area of BDA in the form of new predictive and forecasting techniques; data mining and machine learning tools to enhance classification, regression, clustering, and dimension reduction; artificial intelligence to enable cognitive simulation, expert systems, and perception; statistical analysis; and advanced data visualization. As computational power grows and is potentially distributed out to the grid edge, the analytics field will expand and enable the modernized power distribution grid to develop.

The first, and most important, BDA application in the context of this article is diagnosis and prognosis based on µPMU data in an automated fashion using machine intelligence—as opposed to case by case or even manually, as is currently the norm in this field. For instance, recall from Example 3 that filtering out the voltage transient events caused at the transmission level is a critical task that must be performed continuously to allow a focus on events that may indicate any potential anomaly in terms of grid equipment and customer loads on the distribution feeder of interest. Therefore, the visual classification approach discussed in the "Descriptive Analytics" section has limited use in a real-world application. Fortunately, one can use proper

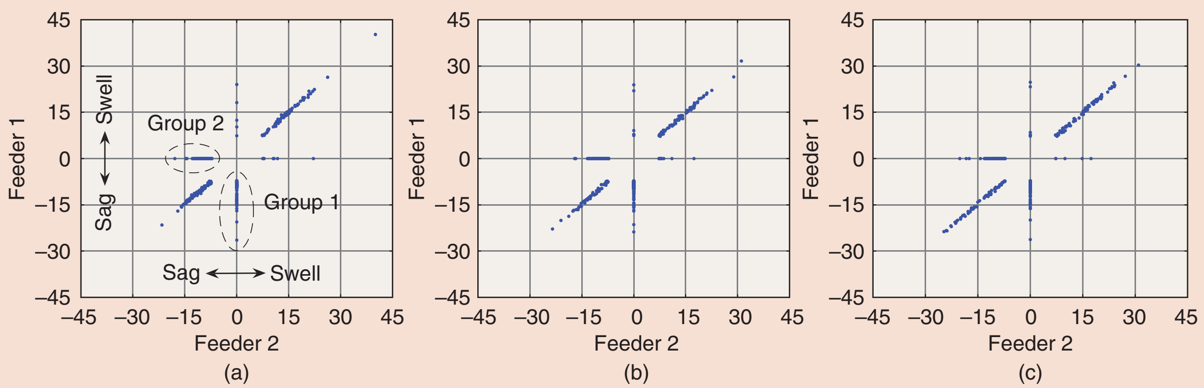

figure 6. A statistical analysis of synchronized transient voltage events on two neighboring feeders: (a) phase A, (b) phase b, and (c) phase C.

> The application of incipient failure detection, coupled with close to real-time communication, will allow early corrective actions.

statistical analysis tools to conduct such classification, in large part, automatically.

As shown in Figure 6, all transient voltage events above 0.1% rated magnitude during one day are cross-correlated using synchronized voltage measurements on three phases of two neighboring feeders. Each point indicates an event that was detected on at least one feeder. The location on the *y*-axis indicates the transient voltage change detected on feeder 1, while the location on the *x*-axis indicates the change detected on feeder 2. The events are either voltage sags or voltage swells. In Figure 6, and on each phase, the diagonal points indicate those voltage transient events initiated at the *transmission* level. They comprise roughly one-third of all major voltage transient events that appear on these two distribution feeders. They are *not* of primary interest to distribution engineers.

The events distribution engineers care about are, rather, the two groups of points that fall inside the two dashed ellipsoids marked in Figure 6. Note that the ellipsoids are marked on only phase A to avoid crowding the figure; however, similar ellipsoids can be also identified for phases B and C. "Group 1" indicates the major transient voltage sags caused by the equipment and/or loads on feeder 1. "Group 2" indicates the major transient voltage sags caused by the equipment and/or loads on feeder 2. The events in Group 1 comprise 65%, 71%, and 70% of all major voltage transient events on phases A, B, and C of feeder 1, respectively. The events in Group 2 comprise 60%, 65%, and 64% of all major voltage transient events on phases A, B, and C of feeder 2, respectively. The two feeders have equal ratings. Extended statistical and data mining analysis, along with the use of techniques such as pattern recognition, could be used to identify the root causes of the differences between the two feeders as well as whether a site visit or repair is necessary. Essentially, this is an input-to-risk-based maintenance schedule, with a greater number of anomalies located on the distribution system leading to a greater potential for an outage.

Data-driven techniques based on μPMU measurements can sometimes turn traditionally challenging problems of power distribution systems into somewhat trivial tasks. One such example is phase identification, which is the problem of identifying the correct phase connection for each single-, two-, or three-phase load. Traditionally, phase identification is performed by analyzing the correlations across voltage rms values. However, phase identification can also be accomplished using a simple data-driven analysis of phase angle measurements.

An example is given in Figure 7. Here, we plot the probability distribution, in the form of a discrete histogram, of the relative phase angle difference between the voltage phasor at a single-phase load and the voltage phasor at each phase of the substation. The distribution is formed close to 0°, 240°, and 120° for phases A, B, and C, respectively. Clearly, the load is connected to phase A. This is also a technique that could enhance the ability to use smart-meter data. With the meter's phase identified, more focused control can be developed at a granular level. This technique can be applied throughout the distribution system and will become significantly important

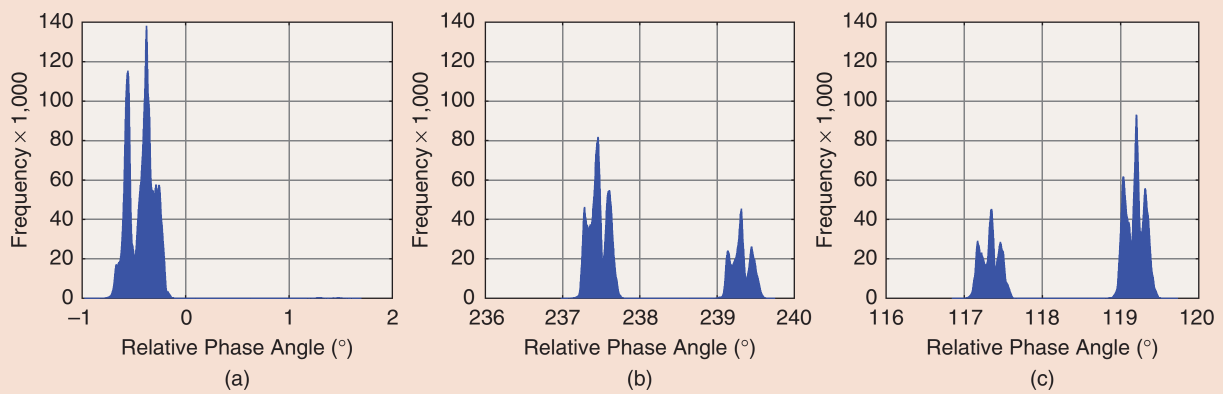

figure 7. The relative phase angle difference distribution between a single-phase load and each of the three phases at the substation: (a) phase A, (b) phase B, and (c) phase C.

Proactive approaches help prevent consumer interruptions, enable utilities to repair rather than run to failure, and minimize field crew dispatch time.

as the balance of the distribution system becomes more variable with behind-the-meter generation.

Traditional power system analysis is typically based on modeling physical systems. In contrast, BDA approaches are much more data driven. For example, in the previously discussed phase identification problem, we do not need to know the topology of the feeder. However, we might benefit from a hybrid of data- and model-based approaches. In that case, there is a need for technical tradeoffs between the details of the models and the dimension of the data.

The applications of BDA go far beyond the previously described case studies. In fact, most of the recently developed BDA tools and techniques are discovery- and exploration-oriented. In other words, they do not require us to predetermine what, exactly, we expect to look for or see in the data. In this regard, instead of building systems that manipulate the μPMU data to reach certain foreseen objectives (such as phase identification or equipment fault detection), the BDA paradigm seeks to enable and facilitate different possible (yet still unknown) objectives to be pursued. There is also a great potential to develop methodologies that can extract actionable insights from the aggregation and disaggregation of the data from other sources in addition to μPMUs, such as smart meters, transmission-level PMUs, power quality sensors, and grid metadata.

As we enter this new frontier in visibility and controllability for the electric distribution system, with customers and customer-side resources becoming heavily engaged in their own supply, it is easy to say that a highly accurate, high-fidelity distribution-level synchrophasor measurement is a hammer looking for a nail. The case studies illustrated here are common grid health and visibility problems, which have had little application for scalable solutions in recent years. Each of these issues was detected by one sensor or a pair of sensors on a distribution feeder with a limited set of deployments in a research environment and very limited application of advanced BDA techniques.

There are numerous BDA techniques being developed outside of the field of power engineering that can be adapted. For example, in genetics, BDA is used to search for the correlation of genetic mutation to cancer diagnoses. In social science, BDA can help identify target audiences for products and services. With further enhancement of these techniques and development of new areas of research such as hybrid data-driven and power flow model approaches, we can enable an unprecedented level of visibility and true operational excellence for a modernized grid.

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For Further Reading

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