Data Analytics and Knowledge Discovery in Microgrid Systems

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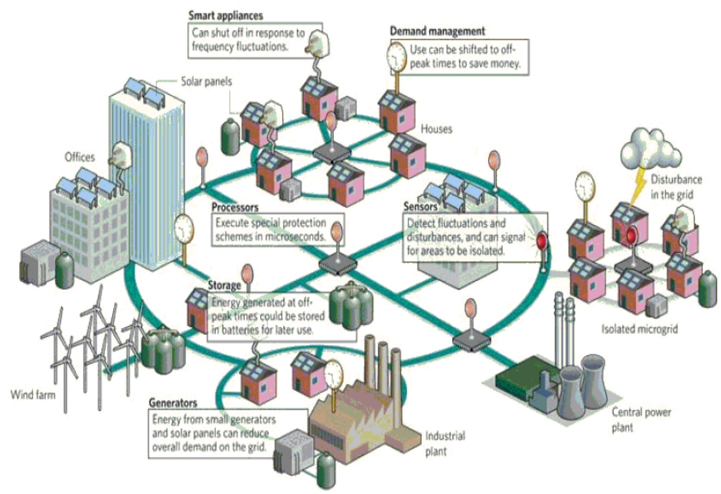
Introduction: Energy microgrids are a key building block of future smart grids. Microgrids integrate modular energy sources, such as solar, wind, thermal generators, fuel cells, etc., with energy storage devices and both critical and non-critical loads to form low-voltage distribution systems. By definition, a microgrid is a group of interconnected loads, energy storage and generation systems within clearly defined boundaries that act as a single controllable entity with respect to the grid. A microgrid can operate in both grid-connected mode (to support the local distribution system)or operate in islanded mode(to protect users from grid instability). In this context, local generation systems also called distributed energy resources (DER) support local thermal and electrical demand while ensuring reliability and power quality with lower emission footprint. Maintaining this profile relies on the flexibility of advanced power electronics that control the interface between micro generation and storage sources and their surrounding AC system.



While microgrids can be a source of renewable and reliable energy for utility distribution systems, significant challenges exist in stable operation and meeting economic goals of the microgrid owners. Any instability in the microgrid and/or faulty islanding can trigger failure of the surrounding distribution systems. As an example, relay misoperations and equipment failures are the two highest priorities in avoiding large scale outages. Approximately, 65% of misoperations are caused by incorrect settings/login/design errors, relay malfunctions, and communication failures [1]. Monitoring microgrid-utility interaction at the point of common coupling (PCC) with the utility is of utmost important to detect anomalies and trigger appropriate protection mechanisms at the distribution substation [2].

Currently installation and operation of microgrids is cost prohibitive due to expensive energy storage systems and advanced device interfaces that are needed to interact with other distributed energy resources and demand. Due to lack of state estimation mechanisms, management of energy storage and other distributed generation systems also requires extensive and exhaustive data aggregation coupled with complex control procedures. One of the expected advantages of microgrids is having a higher availability compared to the current electrical grid due to local isolated generation and storage. But lack of robust knowledge discovery techniques makes storage life estimation or prediction of failure of local generation a challenge. In addition, high variability and intermittency of power generated from renewable energy sources poses significant challenges for the stability of the distribution systems. Advanced knowledge discovery techniques and data analytics are needed to improve the reliability of the microgrids while increasing the contribution of renewable energy sources to the utility distribution system.

Broadly speaking, analytics approaches have direct impact in two aspects: reducing the CAPEX (capital expenditures, i.e., investment on expensive system monitoring and controls hardware or software, and infrastructure-level instrumentation) and reducing the OPEX (operational expenditures, i.e., managing to extend life/reliability while meeting optimal efficiency/cost/emission goals).

Background: Due to the tremendous increase in size of data gathered from varied devices, such as phasor measurements units (PMUs), relays, smart meters, and Plug-in Hybrid Electric Vehicles (PHEV), data analytics today plays a significant role in decision making processes, to control and automate such processes, and in general to avoid failure and instability. The role of data mining and machine learning in realizing various smart functionalities in the power grid is studied in [3]. In [4], Ranganathan and Nygard present a decision tree model to support system operators in making effective decisions in smart grids. Fault protection and recovery is an area that has received attention as well [5]. In [6], data analytics is used to identify anomalous performances for short term and long term planning for asset replacement. Visual analytic approaches are explored in [7, 8]. Finally, Simmhan et al. in [9] present a software architecture prototype to support demand response optimization in USC campus microgrid. All these approaches aim to provide better scientific understanding and insight about the system.

Our work in this space: We are committed to the use of knowledge discovery techniques to optimize the design and management of all aspects of microgrid operations. Our ongoing work in this space spans a spectrum of topics as described next. The common thread in all of the below topics is a careful integration of the "cyber" and the "physical" aspects as detailed. It should be noted that these are meant to be representative and are by no means exhaustive.

Charging station placement for EVs (Cyber: EV characteristics + Physical: Human mobility patterns): Greater penetration of electrical vehicles (EVs) requires effective algorithms for placement of charging and storage infrastructure. Issues to be taken into account include [10]: prediction of EV charging needs based on owners' activities, prediction of EV charging demands and available charge of EV batteries in multiple locations, design of distributed mechanisms that manage the movements of EVs to different charging stations, and optimizing the charging cycles of EVs to satisfy users' requirements, while maximizing vehicle-to-grid profits. We have developed a novel urban computing approach [11, 12] to optimize charging station placement and storage unit design. We use network models of urban environments that painstakingly detail individuals, their activities on a typical day, along with demographic attributes. Over such network models, we superimpose behavioral models that capture EV adoption, use, and charging patterns. Data mining and optimization algorithms help identify best locations of charging stations. Furthermore, we evaluate the network before and after the deployment of charging stations, to recommend the installation of appropriate storage units to overcome the extra load imposed on the network by the charging stations [13]. Thus, we assume that each charging station uses storage to offset the impact of charging on the grid. Other strategies such as upgrading transmission lines or vehicle-to-grid (V2G) are not appropriate or not well developed yet. Thus, well-designed and optimized charging/storage infrastructure placement can help ensure lasting EV adoption and usage.

Battery management systems (Cyber: Control strategies + Physical: Battery characteristics): Batteries play an important role in modern sustainable energy systems. Due to their limited life time and costs, having a deep understanding of how batteries operate in working situations is crucial to design advanced control mechanism for them. Battery performance and life time is highly dependent on how it is used and also on environmental working conditions. We have developed an integrated data-driven framework to study the behavior of battery systems in a grid, using data mining techniques. This framework provides an integrated solution that considers different internal and external parameters of a battery in the context of its circuit. Operating characteristics of batteries can be understood by defining the states of our system and characterizing state transition diagrams. Such results are valuable for storage administrators to provide guidance about the performance and optimization of systems. Building on such results, we harness the available data taken from measurement units to estimate the remaining life of the battery in terms of efficiency and capacity (using regression methods). Furthermore, the pattern of battery usage is uncovered, resulting in a more accurate estimation of battery efficiency. The ultimate goal is to use these results to develop more intelligent control strategies and improve the efficiency of whole energy storage system.

Outlier detection (Cyber: Device controls + Physical: sensor networks): In microgrid operation, outliers are conditions in datasets most likely caused by malfunctions in sensors, devices, or data transmission. While early detection of outliers is necessary to build a proper control strategy and in root cause diagnostics, forecasting their occurrence can aid in more precise and real-time decisions. Currently, human experts play an important role in monitoring the behavior of devices on the smart grid. Automated intelligent decision making for controlling devices, e.g., avoiding voltage drops, foster the need for more efficient and faster algorithms. Novel data-driven approaches are required for online outlier detection in microgrids when several devices are operating in unison. In our work, considering the underlying microgrid infrastructure, we are developing a unified framework that considers all parts of microgrid as an integrated system. Analyzing data gathered from multiple devices results in more precise knowledge rather than considering each of them as independent subsystems.

State space modeling (Cyber: Discrete space models + Physical: Continuous-time models): More broadly, because first principles models of interactions between cyber and physical components are not readily available, automated data mining techniques for state space modeling become crucial. A key research issue is to seamlessly summarize the plethora of observables and transitions in practical systems with a few states whose representations can yield both qualitative insight into functional behavior and quantitative insight about how to "drive" a system into desirable portions of the state space. Our prior work in this space has shown to be useful for diverse domains such as systems biology [14] to physical plant diagnostics [15] and we are exploring applications to microgrid management.

There are numerous other avenues for data mining research at the intersection of "Cyber" and "Physical", e.g., the use of analytics to aid in modeling interactions between the power grid and climate systems [16]. In closing, while data mining and knowledge discovery techniques have been used in specific contexts of microgrid operation, their potential remains largely untapped. An integrated approach exploring their use at all levels of the microgrid "stack" can yield significant benefits toward CAPEX and OPEX objectives.

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