Learning ORDER: Learning for Operationalizing Data into Energy Management

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Research area: Smart Grids [SmG]

Executive summary

Future electric power distribution grids will be supplied to a large extent by distributed energy resources (DERs), such as PV panels and battery energy storage, and more active demand-side participation. New means of customer engagement will also provide new data sources that system operators can potentially leverage for more economical and reliable grid operations. Therefore, system operators are likely to thwart conventional control practices in favor of proactive operations that *operationalizes* grid data by leveraging customer data to harness DER flexibility. This will require ethical data utilization practices.

This transition, however, is hindered by legal, economic, and technical barriers to access data and DER control interfaces. Like electricity several decades ago, customer data becomes a commodity, and the assumption that the system operators access and utilize all customer data for free will not hold in the future. Customer grid data is also multifaceted and contains more information than usually assumed: residential consumption exposes household activities, and industrial consumption exposes sensitive information about production processes. Naively sharing customer data thus entails significant privacy risks. Finally, even with the full access to data, system operators may still lack fast computational and communication means to produce and broadcast control actions in real-time, thus failing to extract the maximum utility from data.

Motivated by these barriers, the goal of this project is to develop data- and learning-based grid operating models that address economic, privacy, and inclusion challenges of energy data management of the future. We do not postulate that all data is available in real-time and that the system operators can utilize it instantly. Instead, the major processes of data curation and utilization are moved offline to learn the optimal DER control. Then at the real-time (online) stage, the learned policies are invoked to address such operational problems as real-time optimal power flow, demand response and transmission-distribution coordination.

First, this project will develop the marketplace for acquiring grid customer datasets to be used in learning optimal grid operations. This marketplace will perform economic and operational evaluations of customer datasets based on their contribution to learning accuracy. It will then clear data transactions between the system operator and customers while featuring fundamental market properties, such as incentive compatibility. For example, residential customers will be incentivized to exchange their electric vehicle charging profiles for a cheaper and uninterruptible power supply.

Next, since the learning of optimal operational policies requires highly granular datasets, this project will develop privacy-preserving algorithms to safely release such datasets, while giving formal guarantees to data owners (e.g., customers) that the sensitive features contained in their datasets will not be exposed. This entails the application of differential privacy methods – the gold standard of algorithmic privacy – that add noise to original information to mask certain data properties. Starting with the applications of standard noise-adding algorithms, this project will then develop extensions to guarantee high dataset fidelity and to minimize the noise to improve the learning accuracy without sacrificing privacy guarantees.

Finally, to alleviate and overcome computational and communication barriers, this project will develop new learning algorithms to train operational policies to use only a subset of contextual information available in real-time, such as state and weather measurements. As this information does not describe grid conditions with 100% accuracy, the algorithms will be designed to internalize feasibility and optimality criteria. To certify the performance of these algorithms, this project will develop tight bounds, which will give formal guarantees to system operators that the adoption of the learning-based grid management will not steer system operations beyond security margins and the optimality loss (if any) will not exceed a prescribed threshold.