

## Advanced Data Analytics for Power Systems

Experts in data analytics and power engineering present techniques addressing the needs of modern power systems, covering theory and applications related to power system reliability, efficiency, and security. With topics spanning large-scale and distributed optimization, statistical learning, big data analytics, graph theory, and game theory, this is an essential resource for graduate students and researchers in academia and industry with backgrounds in power systems engineering, applied mathematics, and computer science.

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“There are only a few industries that generate an equally large amount of data with a comparable variety, and societal importance. Data analytics is thus rightfully at the heart of modern power systems operations and planning. Focusing on applications in power systems, this book gives an excellent account of recent developments and of the broad range of algorithms and tools in the area of data analytics, as well as of the applications of these tools for solving challenging problems from a novel angle. Covering a wide range of fundamental problems, from state estimation to load scheduling and anomaly detection, the book is not only an excellent source of inspiration, but can also serve as an extensive reference for the gamut of operational problems faced in the power industry.”

György Dán, KTH Royal Institute of Technology

# Advanced Data Analytics for Power Systems

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## Preface

The existing power grids, being recognized as one of the most significant engineering accomplishments, work exceptionally well for the purposes they have been designed to achieve. Enabled by advances in sensing, computation, and communications, power grids are rapidly growing in scale, inter-connectivity, and complexity. Major paradigm shifts in power grids include departing producer-controlled structures and transforming to more decentralized and consumer-interactive ones, being more distributed in electricity generation, enhancing the coupling between the physical and cyber layers, and operating in more variable and stochastic conditions. Driven by these emerging needs, power grids are anticipated to be complex and smart networked platforms in which massive volumes of high-dimensional and complex data are routinely generated and processed for various monitoring, control, inferential, and dispatch purposes.

There has been growing recent interest in developing data analysis tools for designing or evaluating various operations and functions in power systems. Due to the complex nature of power systems, often the existing theories and methodologies cannot be directly borrowed, and there is a critical need for concurrently advancing the theories that are driven by the needs for analyzing various aspects of power systems. This has led to new research domains that lie at the intersection of applied mathematics and engineering. The research in these domains is often conducted by researchers who have expertise in developing theoretical foundations in data analytics, and at the same time are domain experts in power systems analysis. Some of these domains include large-scale and distributed optimization, statistical learning, high-dimensional signal processing, high-dimensional probability theory, and game theory.

Analyzing large-scale and complex data constitutes a pivotal role in the operations of modern power systems. The primary purpose of this book is to prepare a collection of the data analytics tools that prominent researchers have identified as the key tools that have critical roles in various aspects of power systems' reliability, efficiency, and security. Different chapters discuss the state of the art in different and complementary theoretical tools with in-depth discussions on their applications in power systems.

The focus of this book is at the interface of data analytics and modern power systems. While there is extensive literature on power systems, that on *modern* systems is rather limited. Furthermore, there is an explosive amount of literature being developed on data analytics by different scientific communities. Most of these techniques are being applied to various technological domains (including power systems) as they are being developed.

There is a growing need for having a coherent collection of topics that can serve as a main reference for researchers in power systems analysis.

This book brings together experts in both data analytics and power systems domains. The shared purpose in all the contributed chapters is maintaining a balance between introducing and discussing foundational and theoretical tools, as well as their applications to the engineering-level power system problems. These chapters, categorically, fall under the following six broad topics.

**Part I: Statistical Learning:** The first part introduces cutting-edge learning techniques and their applications to power systems operations. It covers topics on topology learning, system forecasting and market operations, deep learning, and real-time monitoring.

**Part II: Data-Driven Anomaly Detection:** The second part is focused on statistical inference techniques and their applications to agile and reliable detection of anomalous events in power systems. This part includes topics on change-point detection theory, active (control) sensing, random matrix theory, and graph-theoretic modeling of grid resilience.

**Part III: Data Quality, Integrity, and Privacy:** The third part covers challenges pertinent to data reliability. This part includes topics on data integrity attacks and counter-measures, information-theoretic analysis of cyber attacks, and data-dimension reduction methodologies for enhancing data quality and privacy.

**Part IV: Signal Processing:** The fourth part discusses modern signal processing techniques and their applications to power system analysis. Specifically, it covers topics on graph signal processing, Fourier analysis of power system data, and compressive sensing.

**Part V: Large-Scale Optimization:** The fifth part encompasses topics on large-scale power flow optimization when facing system uncertainties, distributed power flow optimization, load management, storage planning and optimization, and optimization techniques involved in integrating renewable resources and electric vehicles.

**Part VI: Game Theory:** Finally, the sixth part focuses on the interactions of the different decision makers that are involved in the generation, transport, distribution, and consumption of energy using tools from game theory, mean fields, and prospect theory. This part includes the analysis of energy-storage, large populations of electrical vehicles, consumer behavior, and distributed power scheduling.

This book is designed to be primarily used as a reference by graduate students, academic researchers, and industrial researchers with backgrounds in electrical engineering, power systems engineering, computer science, and applied mathematics. While the primary emphasis is on the theoretical foundations, all the chapters address specific challenges in designing, operating, protecting, and controlling power systems.