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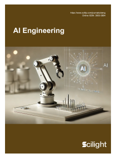

Perspective

AI and ML Methods for Enhancing Power System Operations

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Abstract: With the growing scale and complexity of modern power grids, recent advances in computing technologies, together with the availability of plenty of heterogeneous data, open the door for applying state-of-the-art machine learning approaches to solve critical power system operation and control problems. This Perspective discusses major data-driven machine learning methods and their potential applicability in integrating with physical model-driven approaches to reshape operational practices across modern power systems, followed by the introduction of five contributed articles in the Inaugural Issue of "AI and ML Methods for Enhancing Power System Operations".

Keywords: power system optimal operation and control; model-driven; data-driven

In the past decades, the operation and control decision-making of power systems primarily relied on physical models and numerical calculations. However, with the growing scale and complexity of modern power grids, it becomes more difficult to accurately model the physical power system and to efficiently solve the corresponding optimal operation and control problems. To this end, the recent advances in computing technologies and the availability of plenty of heterogeneous data in power systems open the door for applying state-of-the-art machine learning (ML) approaches to solve critical power system operation and control problems.

Compared to traditional approaches that rely solely on physical models and numerical calculations, the ML approaches stand out for their ability to analyze data, to discover hidden data patterns, trends, and associations, and to yield useful knowledge and insights for fast yet efficient decision-making. In the context of modern power systems, which have grown significantly in scale and complexity, ML approaches can leverage available data to uncover valuable insights into the underlying physical power grid. These insights can assist operators in understanding and revealing the relationship between system parameters and related decision-making, enabling more efficient and accurate solutions to optimal operation and control problems.

ML approaches exploit data gathered from observations or experiments on a system to build models for prescribing the system's behavior, or to derive decision rules to interact with the system. ML approaches can be classified into three basic categories:

(i) **Unsupervised ML methods** can learn a function that uncovers hidden patterns in the unlabeled, unclassified, or uncategorized training data using techniques such as clustering algorithms, association learning models, and anomaly detection approaches. The learned function can then be applied to associate the future sample dataset with the identified patterns. Clustering algorithms discover potential similarity in a dataset and group them with the same feature; association learning models identify key attributes by inquiring about essential features of a data sample correlated with other features; anomaly detection approaches explore false data by scanning for outliers in a dataset or noticing abnormal patterns or actions. The use of clustering analysis to generate intelligent power system operation scenarios under typhoon conditions [1] is an example of unsupervised ML method applications.

(ii) **Supervised ML methods** can learn a mapping function based on the labeled training datasets to compute approximations of outputs as a function of inputs. The learned function can then be used to predict class labels and decisions for future instances. Popular supervised ML methods include decision trees, neural networks, support vector machines, linear regression, nearest neighbor, etc. The use of a graph convolutional neural network with a long-short-term memory (LSTM) to identify the location of the oscillation sources in power transmission grids [2], the application of a multi-scale attention-based convolutional neural network framework to detect surface flaws in photovoltaic (PV) panels [3], the implementation of an LSTM neural network to predict warm-start points of power system operation problems [4], and the adoption of deep neural network models to predict building electricity loads [5] are examples of supervised ML method applications.

(iii) **Reinforcement learning methods** aim at deriving an approximation of an optimal decision strategy to maximize the system performance, in which the agent(s) interact with the environment by performing actions and gaining rewards (i.e., reinforcement signal). Methods such as Q-learning, State-Action-Reward-State-Action, and deep Q network belong to this category. Reinforcement learning has been widely used in various power system applications, including optimal power flow, stability and frequency control, renewable and DER coordination, microgrid and storage management, demand response optimization, and protection and restoration strategies. Nevertheless, as highlighted in [4], purely reinforcement learning methods, similar to other ML approaches, cannot fully ensure critical power system security constraints, necessitating post-processing or correction actions.

Existing operation and control decision-making processes of power systems can be divided into model-driven and data-driven ML methods. Model-driven methods make full use of the physical model structure to design decision-making strategies, which mathematically belong to non-deterministic polynomial-time hard (NP-hard) problems. Data-driven ML methods, on the other hand, could enhance the computational performance of power system operation and control decision-making processes and augment their modeling capabilities with important and more complex physical and operational constraints. Indeed, although efficient relaxation and decomposition approaches have been explored for decades to solve such NP-hard problems, the computational performance remains a significant practical concern, as these problems need to be solved multiple times on a daily basis with very short market-clearing windows. To this end, data-driven ML methods, effectively extracting information from previously solved instances, could be applied to improve the performance of such similar instances in the future. Moreover, certain important and more complicated physical and/or operational constraints in operation and control decision-making processes of power systems could be hard to formulate mathematically, such as those involving autonomous smart grid technologies and flexible consumer behaviors/preferences. To this end, ML methods could be valuable in deriving proper approximations of these complicated relationships for operation and control decision-making models.

Despite the increasing interest and rapid expansions in applying ML techniques to address technical challenges in the power system field, significant opportunities and hurdles remain in adapting ML methodologies for operation and control problems. A key challenge is the need for large datasets, while solution accuracy often suffers from convergence gaps. To this end, a promising direction is to combine the advantages of model-driven and data-driven ML methods to form a physics-informed data-driven ML framework. Such a framework has the potential to lower the data demands while significantly improving computational efficiency. As a result, an effective combination of physical model-driven and data-driven ML approaches is expected to yield more efficient solutions for strengthening the secure and economic operation and control of power systems.

The Inaugural Issue centers on the theme of "AI and ML Methods for Enhancing Power System Operations" and highlights how data-driven approaches are reshaping operational practices across modern power systems. The five contributed articles collectively illustrate the breadth of current ML applications in power systems, ranging from the simulation of power system operation scenarios under extreme weather conditions [1] and the optimal solution of operation problems [4], to the identification of power system oscillation locations [2]. In addition, they demonstrate how ML techniques can facilitate the effective integration of emerging technologies and assets into power system operations, including photovoltaic generation [3] and building electrification [5].

Intelligent Scenario Generation for Weekly and Daily Power System Operations Under Typhoon Conditions [1] presents a framework for generating power system operation scenarios under extreme weather conditions, such as typhoons, to evaluate system stability and quantify operational risks under such complex meteorological conditions. It combines autoregressive integrated moving average forecasting, Monte Carlo simulation, numerical integration, and clustering analysis to generate representative scenarios that capture the spatiotemporal impacts of wind stress on variability in renewable generation and load as well as on random failures of the transmission infrastructure.

On Wide-Band Oscillation Localization in Power Transmission Grids: Explainability and Improvement [2] investigates an interpretable data-driven ML framework for the transmission network broadband oscillation positioning to quickly and accurately position the oscillation source in renewable energy-penetrated power grids.

The proposed approach leverages transmission network measurement sampling data and integrates a graph convolutional neural network with an LSTM, providing an interpretable framework to improve the wideband oscillation localization and support stable power grid operations.

Dynamic Attention and Context-Aware Feature Fusion for Multi-Scale Solar Panel Defect Detection [3] presents a multi-scale attention-based convolutional neural network framework for accurately detecting surface flaws in PV panels, aiming to maintain energy efficiency and reduce repair costs of PV panels. Considering the diverse nature of PV panel surface defects in terms of size, shape, and visibility, the proposed framework composes a multi-scale feature extraction module, a dynamic attention module, and a context-aware fusion module to capture defects across scales, emphasize relevant regions, and integrate semantic information effectively under visually complex conditions.

An LSTM-Driven Efficient Solution Algorithm of Economic Dispatch with Integral Constraints for Energy-Intensive Enterprise Microgrids [4] proposes a data-driven solution algorithm to effectively solve the computationally intractable economic dispatch problem with integral constraints, describing energy balance of device-specific continuous-time operational dynamics, to support the optimal operation of energy-intensive microgrids. An LSTM neural network is trained to predict a warm-start point that satisfies all inequality constraints for accelerating the computational performance with enhanced solution quality.

Building Electricity Load Forecasting Considering Climate Change Impacts: A Multi-Factor Deep Learning Approach [5] speaks to improving building load forecasting by effectively accounting for the differences between indoor and outdoor climate conditions, which play a critical role in influencing energy consumption patterns in buildings. Deep neural network models, enhanced with building-adjusted internal temperature index, exhibit strong performance and yield superior electricity load predictions that are crucial for efficient power system operation and planning, especially in urban environments where building energy dynamics play a significant role.

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X.C.: conceptualization, investigation, writing—original draft preparation; L.W.: conceptualization, supervision, writing—original draft preparation, reviewing and editing. All authors have read and agreed to the published version of the manuscript.

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This Perspective does not involve any raw data.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

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