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HIGHLIGHTS

- Five data-driven use cases in active distribution networks are summarized.
- Data-driven algorithms are categorized into four groups.
- Comprehensive datasets and standardized testing systems are emphasized.
- Primary challenges and opportunities that data-driven methods face are discussed.

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ABSTRACT

This paper reviews the burgeoning field of data-driven algorithms and their application in solving increasingly complex decision-making, optimization, and control problems within active distribution networks. By summarizing a wide array of use cases, including network reconfiguration and restoration, crew dispatch, Volt-Var control, dispatch of distributed energy resources, and optimal power flow, we underscore the versatility and potential of data-driven approaches to improve active distribution system operations. The categorization of these algorithms into four main groups-mathematical optimization, end-to-end learning, learning-assisted optimization, and physics-informed learning-provides a structured overview of the current state of research in this domain. Additionally, we delve into enhanced algorithmic strategies such as non-centralized methods, robust and stochastic methods, and online learning, which represent significant advancements in addressing the unique challenges of active distribution systems. The discussion extends to the critical role of datasets and test systems in fostering an open and collaborative research environment, essential for the validation and benchmarking of novel data-driven solutions. In conclusion, we outline the primary challenges that must be navigated to bridge the gap between theoretical research and practical implementation, alongside the opportunities that lie ahead. These insights aim to pave the way for the development of more resilient, efficient, and adaptive active distribution networks, leveraging the full spectrum of data-driven algorithmic innovations.

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1. Introduction

Distribution networks are undergoing two significant transformations. The first transformation involves the shift from the single, grid-sourced distribution system for power supply to a system characterized by bidirectional energy flow. This change is driven by the rapid integration of various distributed energy resources (DERs). The widespread adoption of behind-the-meter renewable energy sources (RES) such as rooftop solar photovoltaic systems, introduces new forms of uncertainty and variability that challenge the traditional operations paradigm developed by distribution utilities. Furthermore, the distributed nature of RES dramatically increases the complexity of power flow and voltage characteristics across distribution networks. On the load side, the trend towards electrification of heating and transportation further increases this complexity as the increasing peak loads may quickly outweigh capacity constraints [1].

The second transformation encompasses the digital transition. This shift introduces new measurement, communication, and control devices, enriching operational methods and enhancing visibility for monitoring and managing distribution networks. Key technologies such as advanced metering infrastructure (AMI), micro-synchrophasors, power electronic devices (PEDs), soft open points, soft power bridges, and distribution automation devices are emerging as valuable assets in the distribution grid. These technologies are integral both to the network and to customer premises, offering advanced capabilities for communication and control. The digital connectivity and programmability of these devices enable a rich set of new functions, allowing utilities to more effectively manage the distribution grid and address the challenges mentioned earlier by actively and precisely controlling energy flows. At the same time, these advancements raise important questions concerning privacy, security, safety, and reliability in the operation of distribution systems.

Together, these two transformations signify a pivotal shift from *distribution network operations* to *distribution system operations*. A distribution system operator (DSO) not only expands its capabilities in managing networks but also ensures the overall functionality of the broader active distribution system. This is achieved by integrating the operation of the network with DERs, adopting practices reminiscent of those at the transmission level, and including local electricity market operations. Such advancements fundamentally alter the operational dynamics of electric utilities and the roles of local communities. With distributed control becoming increasingly feasible and widespread, microgrids and local energy communities are gaining the capacity to operate with enhanced autonomy. This evolution allows for reconfigurable distribution networks that can function with a reduced dependency on the centrally operated utility grid.

While these transformations are well under way in many countries around the world, academic communities have proposed new methods, techniques, and frameworks that facilitate innovative services for DSOs. These advancements leverage the data, computation, communication, and control capabilities afforded by the digital transition. With the increased popularity of artificial intelligence (AI) and data-driven optimization methods, there are high hopes that such new functionality may help bridge the gap towards the increased requirements imposed on DSOs due to the DERs and digital transition. A rapidly growing body of literature applies data-driven optimization and AI to distribution networks, including applications such as network reconfiguration and restoration, crew dispatch, Volt-VAR control (VVC), grid services provision, and optimal power flow (OPF). This paper provides a critical review of data-driven optimization, control, and decision-making in these application areas within distribution networks, identifies possibilities to improve and enable DSOs, highlights current theory-practice gaps, and lists open research questions. Note that this paper is dedicated to focusing on short-term control, optimization, and decision-making in active power distribution networks. Long-term expansion planning lies beyond its scope. For thorough reviews of active distribution network expansion planning, we refer readers to established review articles [2–4].

The motivation for this paper arises from clear limitations observed in existing literature reviews on data-driven methods within active distribution networks. Previous reviews have often adopted a narrow focus, typically addressing specific applications or isolated methodological approaches, thereby lacking a comprehensive integration of diverse machine learning methodologies. For example, reviews by Abdelkader et al. [5] and Allahmoradi et al. [6] primarily focus on Volt/VAR optimization, whereas Bertozzi et al. [7] emphasize grid stability control. Mohd Azmi et al. [8] address a variety of challenges within active distribution networks, with a strong emphasis on information and communication technologies (ICTs). Tightiz and Yoo [9] explore data-driven microgrid management systems but focus specifically on microgrid-level issues rather than providing a comprehensive view of distribution networks. Radhoush et al. [10] and Ibrahim et al. [11] emphasize end-to-end machine learning strategies. Similarly, Barja-Martinez et al. [12] offer insights into artificial intelligence applications, but mainly within the scope of big data services, not fully capturing broader methodological integrations. Compared to existing data-driven literature reviews of power systems, our paper stands out by offering comprehensive summaries from both use cases and algorithmic perspectives. Moreover, we provide an insightful review of open-source datasets and testing systems, which are crucial for the validation of data-driven control, optimization, and decision-making algorithms and solutions. By synthesizing a broad spectrum of methodologies and pinpointing critical technical gaps, our paper not only refreshes the current knowledge base regarding data-driven approaches but also charts explicit pathways for future research and realizing data-driven distribution networks.

The remainder of this paper is organized as follows. Section 2 reviews the motivation for data-driven control, optimization, and decision-making. Section 3 reviews applications for data-driven optimization in distribution networks. Section 4 summarizes existing data-driven control algorithms. Section 5 introduces relevant datasets and testing systems. Section 6 discusses the challenges and opportunities. Section 7 provides the concluding remarks.

2. Motivation for data-driven solutions in active distribution networks

Utilities have widely developed and implemented model-based algorithms for control, optimization, and decision-making within active distribution networks. Despite their extensive development and deployment over decades, these algorithms encounter two primary limitations. First, model-based algorithms may not satisfy the need for real-time decision-making due to the growing complexity, variability, unobservability, and uncertainty of the distribution system. Most decision-making problems in distribution networks can be formulated as mixed integer programming (MIP) problems or nonlinear programming (NLP) problems. The complexity of solving such problems escalates rapidly as the problem size increases. Second, the distribution network physical models underpinning these algorithms are often unreliable. The majority of model-based optimization algorithms are built based on the distribution network's topology, parameters, and customer data in the geographic information system (GIS) and customer management system [13]. However, maintaining accurate, complete, and current information about the distribution network, especially as its complexity grows, can be a labor-intensive task.

In response to the demands of real-time decision-making and the challenges posed by insufficient model information, recent years have seen a significant surge in data-driven approaches aimed at addressing decision-making problems within active distribution systems. Besides, the development of 'learning to optimize' algorithms [14] represents a notable advancement in solving optimization problems. These algorithms have been specifically designed to enhance the performance

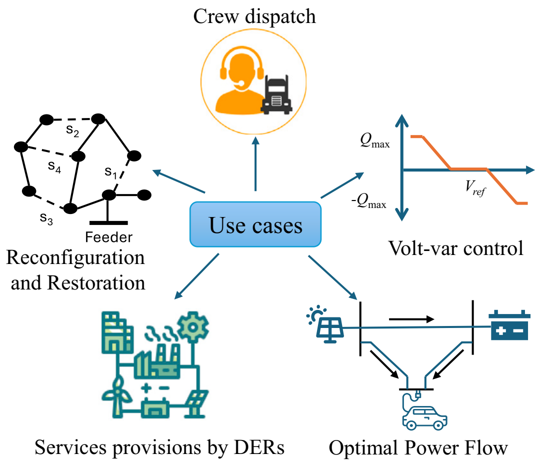

Fig. 1. Use cases for control, optimization, and decision-making in active distribution systems.

of existing optimization solutions. Furthermore, the emergence of physics-informed neural networks (PINNs) [15] marks a revolutionary step forward. These networks integrate physical laws into the learning process, providing a powerful tool for tackling complex problems where traditional data-driven models might fall short. By incorporating domain-specific knowledge, PINNs offer a promising avenue for improving accuracy and reliability in modeling and simulating active distribution systems, bridging the gap between data-driven insights and physical world constraints.

3. Summary of use cases in active distribution systems

As illustrated in Fig. 1, the use cases for control, optimization, and decision-making in active distribution systems can be grouped into five categories. A summary of the relevant publications and their corresponding methods is provided in Table 1. Additionally, a comparative analysis of five use cases in active distribution networks is given in Table 2 to highlight their distinctive characteristics. In the following subsections, we will explore each use case in detail.

3.1. Network reconfiguration and restoration

Large-scale blackouts, resulting from power system failures or extreme weather, necessitate the swift restoration of power supply to mitigate their impacts. Service restoration, aimed at resupplying power to de-energized loads [163], becomes crucial in such scenarios. The primary objectives of restoration efforts include safely and rapidly returning the power system to normal operating conditions, minimizing both losses and restoration time, and reducing the adverse effects on society [164]. From a technical standpoint, service restoration can be approached as a temporary system reconfiguration challenge, primarily involving the manipulation of switch on/off statuses.

Distribution network reconfiguration (DNR) serves to reorganize the topology of distribution networks, aiming to enhance network efficiency and stability by adjusting the statuses of switches, devices, and line flows [43]. The primary goal of DNR is to determine the optimal on/off statuses for all switches in a way that optimally balances loads and minimizes network losses while adhering to operational constraints [29]. Besides, Wang et al. [27] propose a Markov decision process framework-solved via approximate dynamic programming (ADP)-that dynamically reconfigures distribution systems during extreme weather events to enhance resilience. In addition, Wang et al. [28] develop a Markov decision process-based model with an ADP solution for real-time distribution network reconfiguration aimed at minimizing renewable generation curtailment and load shedding under operational constraints. Generally, DNR problems are typically divided into two main categories: static and dynamic reconfiguration [42]. Static reconfiguration is concerned with identifying the optimal configuration for the current network, focusing on a single point in time. In contrast, dynamic reconfiguration seeks

Table 1
Summary of publications, use cases and methodology.

Use case	Papers	Methods	Classification
Restoration and reconfiguration	[16–19]	Heuristic method	Mathematical optimization
	[20–25]	Meta-heuristic method	Mathematical optimization
	[26–28]	Dynamic programming	Mathematical optimization
	[29–48]	Mathematical programming	Mathematical optimization
	[49–58,58–69]	Reinforcement learning	End-to-end learning
	[70,71]	Supervised learning	End-to-end learning
	[72,73]	Supervised learning	Physics-informed learning
Crew dispatch	[74–77]	Mathematical programming	Mathematical optimization
	[78]	Meta-heuristic method	Mathematical optimization
	[79]	Reinforcement learning	End-to-end learning
Volt-VAR control	[80]	Dynamic programming	Mathematical optimization
	[81,82,82–89]	Mathematical programming	Mathematical optimization
	[87,90–92]	Meta-heuristic method	Mathematical optimization
	[93,94]	Supervised learning	End-to-end learning
	[95–108]	Reinforcement learning	End-to-end learning
	[109]	Learning iterations	Learning-assisted optimization
	[110–112]	Network embedding	Physics-informed learning
Services provisions by DERs	[113–116]	Mathematical programming	Mathematical optimization
	[117–119]	Supervised learning	Learning-assisted optimization
	[120]	Meta-heuristic method	Mathematical optimization
	[121,122]	Reinforcement learning	End-to-end learning
Optimal power flow	[123,124]	Dynamic programming	Mathematical optimization
	[125–133]	Mathematical programming	Mathematical optimization
	[134–146]	Supervised learning	End-to-end learning
	[147–149]	Extremum seeking control	Mathematical optimization
	[150–155]	Supervised learning	Learning-assisted optimization
	[156,157]	Network embedding	Physics-informed learning
	[155,158–162]	Loss embedding	Physics-informed learning

Table 2
Comparative analysis of data-driven use cases in active distribution networks.

Use case	Operational focus	Decision variables	Optimization characteristics
Reconfiguration and restoration	Topology adjustment, fault restoration in response to contingencies	Switch statuses (open/close)	Mixed-integer linear/nonlinear programming
Crew dispatch	Efficient coordination of repair crews under time/resource constraints	Routing and task scheduling (locations, time windows)	Combinatorial programming
Volt-VAR control	Voltage profile regulation and reactive power optimization	Tap positions; capacitor/reactor control; DER reactive output	Mixed-integer linear/nonlinear programming
Service provision by DERs	Coordination of DER assets for ancillary or market services	Active/reactive set-points; participation in grid services	Mixed-integer linear/nonlinear programming
Optimal power flow	Optimal dispatch of grid resources respecting system limits	Generator output; voltage levels; power flows; transformer taps	Nonlinear programming

to find a series of optimal network configurations over time, with the additional goal of minimizing the operations of mechanical devices [64].

A substantial body of research has been dedicated to solving this problem, with existing approaches generally classified into two main categories: model-based methods and data-driven methods.

Model-based methods further bifurcate into centralized and distributed approaches. Centralized methods encompass a range of techniques including heuristics or meta-heuristic algorithms [16,20], dynamic programming (DP) [32], and various mathematical programming methods such as mixed integer non-linear programming (MINLP) [31,41], mixed integer linear programming (MILP) [34,35,38,39], mixed-integer conic programming (MICP) [40], and mixed integer second-order cone programming (MISOCP) [36]. These methods rely on a central controller to aggregate information from across the system and dictate actions for each local agent. However, this centralization introduces vulnerabilities, notably a single point of failure, which can compromise system resilience. In contrast, distributed methods, exemplified by the multi-agent system (MAS) [47] and alternating direction method of multipliers (ADMM) [46], aim to enhance algorithmic resilience by distributing decision-making across multiple agents. Despite these advantages, the current literature on MAS provides limited insights into how decision-making protocols align with network-level optimal restoration problems [48]. Additionally, ADMM struggles to achieve convergence when applied to nonconvex MIP problems [165]. Both MAS and ADMM depend on decentralized communication and collaboration, making them vulnerable to data breaches, malicious attacks, synchronization issues, and communication failures. To ensure secure and reliable operations, they require the implementation of encryption protocols, privacy-preserving techniques, and trust mechanisms. To reduce the high communication rounds of ADMM, a layered architecture for distributed algorithms has been proposed in Sadnan et al. [48] for network restoration, designed to enhance grid resilience after disasters. This architecture coordinates the grid's controllable assets across multiple layers, enabling the support of critical services without relying on costly communication networks or data-processing infrastructure.

Model-based methods face notable challenges. The lack of accurate distribution network models complicates the direct application of these algorithms. Additionally, the intricacies of restoration and reconfiguration tasks stem from their discrete, multi-constrained, non-linear, and multi-objective characteristics [166]. Consequently, data-driven methods are increasingly being recognized as a viable alternative for addressing the complex issues of restoration and reconfiguration in active distribution networks.

Similar to model-based approaches, data-driven methods can also be divided into centralized methods and distributed methods. Data-driven centralized algorithms predominantly incorporate supervised machine learning and reinforcement learning (RL) techniques. Extensive research adopts deep Q-network (DQN) for distribution system restoration [49,55,56,58], static reconfiguration [50,53,59] and dynamic reconfiguration [51,60–62]. Furthermore, Tianqiao et al. proposed a graph-RL framework for the restoration problem. The proposed algorithm links the power system topology with a graph convolutional network, and then the latent features over graphical power networks produced by graph convolutional layers are exploited to learn the control policy using DQN [54]. Yuanqi et al. developed a data-driven batch-constrained soft actor-critic (BCSAC) algorithm for the dynamic DNR problem. The proposed algorithm can overcome the extrapolation error problem [64]. Similarly, Ji et al. developed an autonomous dynamic reconfiguration method for the active distribution network based on the deep learning method. The reconfiguration strategies are learned using a long-short-term memory (LSTM) network trained on historical datasets and real-time operation. A switch action function is combined with the LSTM model to perform dynamic control [70]. To enhance the training efficiency, an imitation learning framework was proposed for training such an agent, where the agent interacts with an expert built based on the mixed-integer program to learn its optimal policy, and therefore significantly improves the training efficiency compared with exploration dominant RL methods [57]. To provide a fast online response and optimal sequential decision-making support, the curriculum learning (CL) technique was adopted to guide the RL agent to learn to solve the original hard problem in a progressive and more effective manner [66].

The widely used data-driven distributed method is multi-agent reinforcement learning (MARL). Hybrid multi-agent frameworks with Q-learning algorithms [67–69] were developed to support rapid restoration of the active distribution system by using a framework that does not rely on a centralized controller, avoiding a potential single point of failure. Wu et al. developed a multi-agent soft actor-critic (MASAC) approach for the reconfiguration problem [65], where the proposed algorithms can reduce the computational burden and accommodate different system states and scales.

3.2. Crew dispatch

Restoring electricity service necessitates the coordination of multiple crews, each possessing unique skill sets, to undertake a variety of procedurally interdependent tasks with safety as a paramount concern [75]. The routing repair crews (RRC) can be modeled as a vehicle routing problem (VRP), a combinatorial optimization and integer programming problem aimed at determining the optimal routes for a fleet of vehicles [74]. Traditionally, this problem has been approached with model-based methods, including MILP [74,75], DP [77], and second-order conic programming (SOCP) [76].

However, given that the routing problem is an NP-hard combinatorial optimization, the complexity is poised to increase with the trend of integrating repair and restoration tasks. In light of this, the advent of data-driven methods has spurred a wave of innovative approaches to incorporate repair crew dispatch strategies into the outage management framework. For instance, Fanucchi et al. utilize a repetitive nearest neighbor algorithm and particle swarm optimization technique to identify patrol sequences for crew dispatch in a multi-objective setting [78]. Shuai et al. propose a novel AlphaZero-based utility vehicle routing method to determine the real-time dispatch strategy of repair crews after a storm [79].

3.3. Volt-VAR control

VVC selects appropriate settings for voltage regulation and reactive power compensation devices to manage voltage profiles and reactive power flow in distribution systems. VVC methods can be broadly categorized into two categories: legacy and advanced control methods [167]. Legacy methods encompass standalone controllers, line drop compensators, and rule-based approaches; while advanced control methods leverage mathematical programming or artificial intelligence techniques.

While these methods have been effective in various circumstances and have served the industry for years, they also present limitations. Legacy methods, being predominantly open-loop, lack the ability to adapt to changing operating conditions beyond their sensing areas. Moreover, defining appropriate rules can be challenging, rendering these methods inefficient in some situations. Additionally, the absence of coordination among different controllers often results in sub-optimal outcomes. These approaches struggle to accommodate the dynamic and complex nature of modern distribution grids, particularly with the increasing integration of DERs. Moreover, the recent IEEE Standard 1547–2018 requires that inverter-fed DERs contribute reactive power to support grid voltage.

Advanced control methods have been extensively researched to integrate inverter-based DERs into VVC and overcome the limitations identified in legacy VVC techniques. These methods are generally divided into physical model-based methods and data-driven approaches. Physical model-based VVC algorithms commence by constructing an accurate and reliable model for the distribution network, followed by the collection of field measurements from the distribution management system (DMS). The VVC problem is subsequently formulated as a mathematical programming problem, which is tackled with commercial solvers. This scheme facilitates closed-loop, coordinated control that reflects the broader operational conditions of the system. Techniques within the realm of physical model-based VVC include MILP [81], mixed-integer quadratically constrained programming (MIQCP) [82], bi-level mixed-integer programming [83], MINLP [84], SOCP [85], and MISOCP [86]. Furthermore, to accelerate the optimization of the inverter-based VVC, a tuned ADMM method incorporated gradient projection algorithm is proposed for the data-driven optimization paradigm [109].

Although physical model-based VVC algorithms offer significant theoretical advantages, they encounter numerous practical challenges. First, these methods presuppose the availability and accuracy of distribution network and load models. Unfortunately, the network data maintained in utility companies' GIS are often incomplete or inaccurate [167], making it difficult to construct a precise and reliable physical model of the distribution network for the application of physical model-based VVC algorithms. Second, the computational time required by many physical model-based algorithms remains a bottleneck, particularly due to the complexities underlying MIPs. This issue is exacerbated in the context of large-scale distribution networks, where the computational demands become even more challenging.

In response to the limitations of physical model-based methods, data-driven algorithms employing advanced signal processing and artificial intelligence techniques have emerged as promising alternatives. In Sun et al. [89], a data-driven, two-stage real-time VVC method is proposed to address rapid voltage violations caused by the high penetration of inverter-based DERs. Additionally, to prevent conflicts among parallel inverters and maintain VVC control stability while considering the physical constraints of inverters, a novel VVC strategy based on Artificial Neural Networks (ANN) is proposed in Li et al. [94]. This strategy operates at the grid edge through the control of distributed DER inverters. Unlike their predecessors, these methods do not depend on constructing a physical model of the distribution network. Instead, they derive control policies directly from online or historical operational data, thereby offering broader applicability. Machine learning-based approaches for VVC, as developed in Refs. [93] and [168], exemplify this shift. Furthermore, RL gained traction as a potent algorithm for sequential decision-making tasks and has been studied in the VVC context. This category encompasses a variety of methods, such as DQN [101,102], Q-learning [106,107], SAC [103–105], DDPG [98–100], etc.

To enhance the performance and robustness, some studies have integrated RL with graph neural networks [97], while others have introduced novel concepts like mutual information regularization [95]. To mitigate fast voltage violations while minimizing the network power loss, Sun and Qiu [98] proposes a two-stage deep reinforcement learning (DRL)-based real-time VVC method. To improve the communication efficiency and resilience, the VVC problem is formulated as a networked multi-agent Markov decision process, which is solved by using the maximum entropy RL framework and a novel communication-efficient consensus strategy [96]. To ensure stability and safety, a stability-constrained RL method for real-time VVC is proposed in Feng et al. [108]. This approach leverages an explicitly constructed Lyapunov function to guarantee stability by enforcing monotonically decreasing policies. In contrast to physical model-based VVC methods, data-driven methods could achieve coordinated control without requiring accurate and complete system parameter information.

3.4. Services provisions by DERs

The integration of DERs into the power grid has revolutionized the provision of ancillary services, traditionally dominated by large, centralized power plants. Demand response (DR) in active distribution systems can be treated as DERs and it can participate in energy and capacity markets, as well as provide multiple ancillary services to the grid, such as frequency regulation and contingency reserve [169]. This subsection explores the ways in which DERs contribute to electricity market service provision.

The increasing penetration of small-scale intermittent DERs in the power system poses frequency regulation challenges due to the reduction in system inertia. In Zhang et al. [113], a new entity called Renewable Energy Aggregators (REA) is proposed, enabling DERs to enhance frequency stability in low-inertia systems. The REA participates in the electricity market and provides frequency regulation services through dynamic scheduling and control strategies. Additionally, in Stanojev et al. [114], a centralized controller is proposed for the provision of Primary Frequency Control (PFC) by aggregating DERs in active distribution systems. This controller aims to determine the optimal setpoints for DERs to regulate power flow in accordance with PFC requirements. To include the varying inertia due to the presence of DERs, Hidalgo-Gonzalez et al. [117] proposed a new framework to obtain a constant data-driven controller for frequency regulation with uncertain and time-varying power system dynamics. The flexible wireless access for DERs makes the cloud's optimized deployment of edge regulation tasks possible. In Zhang et al. [115], a cloud-edge collaboration and wireless communication coordination framework is proposed to facilitate DER frequency regulation. This framework enables DER users to participate in fast auxiliary markets with high returns.

The effective integration of DERs into the active distribution systems requires close coordination between Transmission System Operators (TSOs) and Distribution System Operators (DSOs). This collaboration is crucial for ensuring that DERs can provide ancillary services at both the transmission and distribution levels without compromising grid reliability. In Ullah and Park [116], a decentralized transactive energy market strategy is presented, which integrates wholesale and local energy markets through coordinated interactions among TSOs, DSOs, and DER owners. In Silva et al. [120], a data-driven methodology is proposed to estimate the power flexibility at the TSO–DSO interface for meshed grids, addressing the limitations revealed by the application of Interval Constrained Power Flow (ICPF) in such cases.

DR refers to changes in end-users' consumption behavior in response to direct control signals, time-varying electricity prices, or other forms of incentives. Consumers' DR services generally include load shedding, load shifting, and the utilization of onsite generation or energy storage [170]. In distribution networks, DR plays an important role in efficiency and reliability improvement [171,172].

For load-serving entities, the development of rapid optimization algorithms to coordinate the vast array of heterogeneous, distributed DR resources is crucial for operational efficiency enhancement. The lack of a standardized model for DR resources further complicates the optimization problem. To address these complexities, a variety of methodologies have been proposed to model and optimize the operation of DR resources, with embedded data-driven methods to handle the aforementioned complexities. In Behl et al. [118], Behl et al. proposed a data-driven method called DR-Advisor, which serves as a recommender system for facilities managers of large buildings. This method provides control actions to achieve the required load curtailment and maximize economic rewards. Additionally, in Yoon et al. [119], a price-based DR strategy is formulated using an explicit ANN to generate data on optimal HVAC (heating, ventilation, and air-conditioning) system load schedules. Subsequently, another ANN is trained online to directly predict these optimal load schedules.

In addition to analytically solving optimization-based DR models, a substantial body of research has explored the use of RL to achieve optimal DR control across various devices, such as electric vehicles and air conditioners. Ref. [121] provides a comprehensive review of RL algorithms and modeling techniques tailored for DR applications. The study in Wen et al. [122] formulates the rescheduling problem of a fully automated energy management system (EMS) as an RL problem. It suggests that this RL problem can be approximately solved by decomposing it over device clusters, avoiding the need for explicit modeling of user dissatisfaction due to job rescheduling. This novel formulation permits the EMS to initiate jobs autonomously, granting users the flexibility to submit more versatile requests. Remarkably, this approach maintains a computational complexity that is linear with respect to the number of device clusters.

3.5. Distribution system optimal power flow

Traditionally, OPF algorithms have been formulated to tackle a diverse array of challenges within transmission system operations. These challenges encompass a wide range of optimization objectives related to both active and reactive power management. Specific goals include economic dispatch, optimizing power transfer, minimizing losses and costs, achieving the minimum control shift, and reducing the number of controllers that need to be adjusted. Each objective plays a crucial role in enhancing the efficiency and reliability of power system operations. For example, a system operator might implement an advanced economic dispatch strategy based on stochastic dual dynamic programming (SDDP) [123,124] that simultaneously minimizes generation costs, reduces energy losses, and streamlines control actions by optimizing both active and reactive power flows, thereby maintaining voltage stability and minimizing the need for frequent controller adjustments.

In distribution systems, the application of traditional OPF methods is less prevalent. This is partly because they necessitate extensive communication with a wide array of devices, presenting a logistical challenge. Moreover, traditional OPF methods often lack the robustness required to effectively address the inherent nonlinearities and non-convexities associated with three-phase power flow. These complexities introduce significant obstacles to the straightforward application of OPF algorithms, underscoring the need for adapted or alternative approaches that can accommodate the unique characteristics of distribution systems.

In recent years, there has been considerable academic progress in bringing OPF methods closer to distribution system operation. Most efforts have focused on making distributed optimization schemes more robust. In addition, concepts from control theory and statistical learning have been integrated to overcome challenges towards safely and efficiently implementing OPF. As the role of OPF in distribution systems attracts broader attention, we direct the interested reader to several survey papers [173–175]. Here we discuss recent advances in data-driven techniques for OPF.

3.5.1. Using feedback measurements to run OPF in a closed loop – "feedback OPF"

These methods use control-theoretic techniques to actively track a reference based on an OPF solution. As such they are data-driven by virtue of their online measurements and feedback. Bolognani et al. first propose the technique using duality-based methods for reactive power control for voltage regulation and loss minimization [125]. In [126–129], various authors further conceptualize the methods for *closed-loop feedback optimization* to steer a power system in real-time to the optimal operating point without explicitly solving an AC OPF problem. Instead, it treats the power flow equations as implicit constraints that are naturally enforced by the physical grid and then uses adaptive feedback control. The feedback approach can be effective in overcoming model uncertainties commonly found in OPF models. Picallo et al. combine the approach with dynamic state estimation to control unmeasured states [130]. The approach has gained academic traction but remains challenging to apply in practice. One of the main challenges of this approach is that it requires a careful analysis of theoretical stability conditions, which are typically derived for continuous dynamics and have to be translated to the more realistic discrete and stochastic nature of practical OPF systems. Other issues are a lack of quantitative results on the rate of convergence, the robustness against noise, and the tracking performance for time-varying problem setups [176].

3.5.2. Using data to robustly solve OPF

OPF is a complex computational task. It requires having adequate information about the network model, including models of various assets relevant to OPF calculations and variables that provide input to OPF calculations. Distribution system models are never perfect; they have errors and uncertainties within them. Input variables, such as voltages, nodal injections, or power flows may come either as forecasts with errors or as real-time measurements with noise- or delay-induced errors. In addition, OPF for distribution grids is also a highly nonlinear and non-convex computation, which may not necessarily yield a solution or take time to converge. As a result, solving OPF in a centralized offline fashion is challenging. Error distributions are typically assumed to follow some probability distribution and many techniques have emerged to develop more stochastic OPF methods that integrate these distributions into the formulation and numerical solving, see [132] for an overview. However, these probability distributions are typically not known and merely available through finite data sets or online measurements. Data-driven techniques may help alleviate some of these challenges, by exploiting convex relaxations based on Wasserstein techniques [133]. Guo et al. incorporate these ideas in the feedback optimization schemes [131,132] covered in Section 3.5.1.

3.5.3. Using learning to apply OPF in an open loop – "feedforward OPF"

These methods use learning techniques to mimic OPF solutions, typically in a decentralized fashion. Particularly, Sondermeijer et al. [134] and Dobbe et al. [135] used a linear regression approach to learn control policies using a training set generated offline from solving an OPF. The designed controller decides on reactive power injections for rooftop solar photovoltaic (PV) in a balanced, single-phase, distribution network. The controllers only rely on local information, making their approach a robust proposition that does not require a communication network between DERs. This work was extended by Serna Torre and Hidalgo-Gonzalez [136] where they propose a linear regression framework to learn reactive power controllers for each rooftop solar PV that would be robust to topological changes (e.g., expansion of branches, new nodes). Furthermore, the work in [134,135] was extended by Karagiannopoulos et al. [146] where the authors, similar to the previous works, generate a training set from solving an OPF offline. This training set differs from the approach in previous works by taking into account uncertainty from renewable energy (as a chance constraint), modeling unbalanced three-phase operation, and also considering a broader set of control actions: reactive power, active power curtailment, load shifting, and battery management. The work in Lei et al. [156] is based on the stacked extreme learning machine (SELM) framework and innovates by incorporating a physics-informed data-driven OPF approach, which enables the overall framework to be tractable (which is not possible by only using SELM). One of the key aspects of this approach is the identification of active constraints to extract features more effectively while reducing the learning complexity. The proposed framework does not require knowledge of the network topology or its parameters, making it ready-to-use for different cases. There exist other contributions that rely on a different set of machine learning techniques. For example, the work in [142,145] uses a deep RL approach to mimic OPF, and [137,138] uses a kernel-based approach. We also refer the reader to the work in [139,140].

3.5.4. Model-free methods

These methods use model-free techniques to estimate the gradient of OPF problems based on real-time measurements. The work in [147–149], uses extremum seeking control for near-optimal management of DERs for voltage regulation in distribution networks. By broadcasting real-time information, each DER can adjust its output to move the system towards the global optimum. This methodology does not depend on prior knowledge of the system's topology, DERs' locations, renewable energy power generation, or forecasts.

The feedback-optimization method covered in Section 3.5.1 is also applicable without an explicit power flow model by using voltage sensitivities [177].

4. Summary of algorithms

Different decision-making problems in distribution networks are modeled and solved in a variety of ways. Before summarizing existing algorithms, we first focus on classifying the use cases into different categories. Depending on whether decision variables are continuous or discrete and whether a single action or a sequence of actions needs to be made, optimization problems in distribution networks can be divided into four categories: discrete variables and single action, discrete variables and sequence of actions, continuous variables and single action, and continuous variables and sequence of actions. In general, sequential decision-making problems are usually more difficult because a sequence of decision variables at different times must be determined. Optimization problems that involve discrete variables are also more challenging due to the non-smooth solution space and NP-hard nature of the problem.

As highlighted in Section 3, a diverse array of algorithms has been developed to address the four categories of problems encountered in active distribution systems. Given this variety, it becomes imperative to organize these algorithms into distinct classes for better understanding and analysis. In this section, we categorize the algorithms into four main approaches: mathematical optimization, end-to-end learning, learning-assisted optimization, and physics-informed learning, as illustrated in Fig. 2. The following provides a brief overview of each approach:

(1) **Mathematical optimization:** This approach formulates decision-making and control problems in the distribution network as optimization problems. Optimal solutions are sought through traditional mathematical techniques, such as heuristic algorithms, dynamic programming, linear approximation techniques, and convex relaxation. Each method aims to find optimal or near-optimal solutions by systematically exploring the problem space within predefined mathematical frameworks.
(2) **Learning-assisted optimization:** Combining the strengths of machine learning and traditional optimization, this approach employs machine learning algorithms to enhance or solve optimization problems. Machine learning models may predict system behaviors or identify patterns that inform optimization strategies, effectively acting as an intelligent layer that supports decision-making processes.
(3) **Physics-informed learning:** Physics-informed learning incorporates the physical principles governing the distribution system directly into data-driven models, such as embedding the power grid model within a neural network. This method ensures that the learned models and solutions are not only data-compatible but also adhere to fundamental physical laws, enhancing the reliability and applicability of predictions and controls.
(4) **End-to-end learning:** End-to-end learning seeks to establish a direct mapping between the states of the power grid and DERs and the resultant decisions or desired control signals. This approach leverages deep learning models to learn complex relationships entirely from data, bypassing the need for explicit intermediary steps or feature engineering. Although supervised learning and reinforcement learning are structured differently, both are classified as end-to-end learning because they optimize the complete mapping from inputs to outputs in a unified training process.

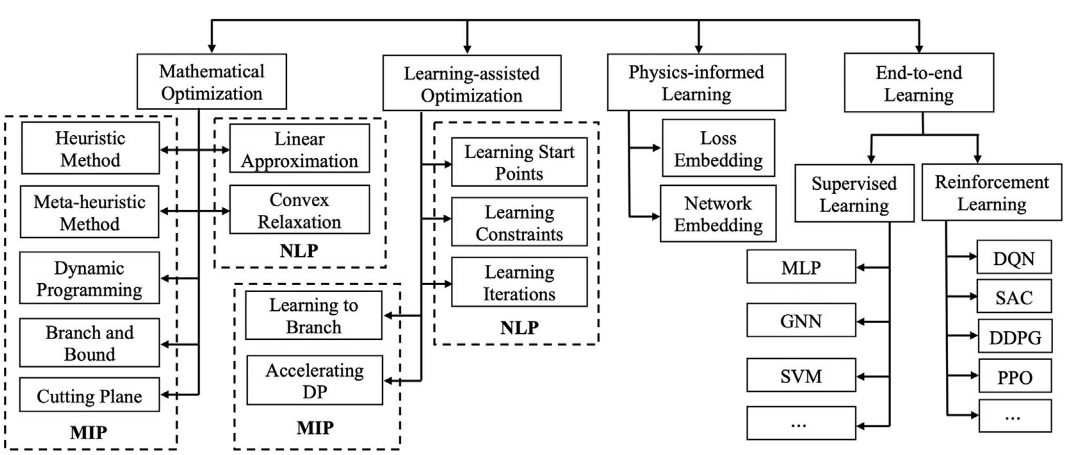

Fig. 2. Classification of algorithms for distribution system decision-making and control problems.

4.1. Four widely-adopted approaches to solve decision-making and optimization problems in active distribution systems

4.1.1. Mathematical optimization

Decision-making problems in distribution networks are often framed as optimal control problems, which can be formulated through MIP or NLP.

Mathematical optimization for MIP. Algorithms for solving MIP are categorized into exact algorithms and heuristic or meta-heuristic algorithms. Exact algorithms, such as branch-and-bound [178], cutting plane algorithms [179] and DP [80], aim to find precise solutions. For comparison, the heuristic or meta-heuristic algorithms don't guarantee the optimal solutions and try to obtain near-optimal solutions. Consequently, the heuristic or meta-heuristic algorithms must strike a good balance between exploration and exploitation, in order to trade off between performance and computational efficiency.

Mathematical optimization for NLP. The primary challenges of NLP in distribution networks are their non-linearity and non-convexity. Apparently, if NLP problems can be reduced to linear or convex ones, the problems would be much easier to solve. Therefore, many researchers leverage convex relaxations and linear approximations to simplify the NLP problems. Taking the OPF problem as an example, the AC power flow model, inherently non-linear and non-convex, can be linearized into a DC power flow model or relaxed into convex optimization problems, such as semidefinite programming (SDP) relaxation for general networks and an SOCP relaxation for radial networks [173]. Both relaxation techniques significantly alleviate computational demands while maintaining acceptable solution accuracy. However, the relaxed solution may not always correspond to a feasible or optimal solution of the original non-convex problem. For instance, in unbalanced three-phase distribution systems, taking the convex hull of the original region expands the feasible set, leading to higher-rank physically infeasible solutions when using SDP [180].

Despite their widespread application, mathematical optimization approaches face two significant limitations: the necessity for precise model parameters and the lack of scalability, with computational time escalating rapidly as the problem size increases.

4.1.2. Learning-assisted optimization

Learning-assisted optimization approaches leverage machine learning to accelerate the solution process of optimization problems, showing significant advancements in recent years. This approach not only improves computational efficiency and solving speed but also enhances the scalability and tractability of optimization problems in active distribution systems and beyond.

Learning-assisted optimization for MIP: Recent developments in learning-assisted optimization for MIP have focused on expediting the search procedure in the solution space. This group of methods includes formulating optimization as an RL problem [14], learning meta-heuristic algorithms [181], accelerating DP [182], learning to branch [183,184], and mixed-integer optimization with learned constraints [185]. In Qin and Yu [72], MIP for the distribution network reconfiguration problem is solved by synergistically combining a physics-informed Graph Neural Network framework (GNN) with an optimization model. Similar ideas are extended to transmission systems. To solve the security-constrained unit commitment (SCUC), Álinson et al. use machine learning techniques to extract information from previously solved problems to significantly improve the computational performance of MIP solvers when solving similar instances in the future [186].

Learning-assisted optimization for NLP: Learning-assisted optimization approaches for NLP include learning warm start points, learning constraints, and learning to perform iterative updates. Instead of predicting the NLP solution directly, supervised learning methods are used to predict a better starting point for solvers. With the learned warm start points, solving the problem takes a smaller number of iterations and computation time [187]. The existing works that try to learn constraints can be further subdivided into learning active constraints (binding inequalities) [188], umbrella constraints (necessary and sufficient for covering feasible solutions) [189] and inactive constraints [190], Baker and Bernstein [191]. Active constraints are those inequality constraints that are binding upon solving the optimization problem. The umbrella constraints are necessary and sufficient constraints to cover the OPF feasible solution. By using the learned active constraints or umbrella constraints, it is easier to obtain the optimal solution. Learning inactive constraints enables solvers to concentrate on the most critical aspects of the problem, leading to faster and potentially more accurate solutions. Furthermore, deep neural networks can also be used to perform iterative updates. For instance, Kyri Baker et al. avoided calculating the Jacobian matrix by replacing the Newton–Raphson step with a purely data-driven machine learning (ML) model that learns subsequent iterations' solutions [155]. The ML model is trained on Newton–Raphson iterations and learns to imitate the Newton–Raphson algorithm without having to construct Jacobian matrices or calculate matrix inverses.

4.1.3. Physics-informed learning

Recent works in physics-informed learning aim to reduce the amount of required training data and achieve higher accuracy by embedding physical system information into learning processes.

Network embedding: Some researchers focus on embedding physical information into neural networks. Ref. [157] introduces a framework to incorporate AC power flow equations inside neural network's training and integrates methods that rigorously determine and reduce the worst-case constraint violations across the entire input domain while maintaining the optimality of the prediction. Ref. [156] develops a new framework to reduce the learning complexity of a SELM by embedding features of the physical system. This approach can avoid the time-consuming iterative updates in OPF calculation. In Authier et al. [73], an end-to-end physics-informed GNN is proposed to solve the dynamic reconfiguration problem by modeling switches as gates in the GNN message passing and embedding discrete decisions directly within the framework.

Loss Embedding: Embedding physical system information into loss functions represents another innovative direction. Ref. [160] proposed an integration of deep neural networks and Lagrangian duality to capture the physical and operational constraints. Ref. [161] solves OPF by differentiating through the operations of a power flow solver that embeds the power flow equations into a holomorphic function. In Zhang et al. [159], Karush-Kuhn-Tucker (KKT) optimality conditions are used to construct the training loss function. To ensure that the power-flow balance constraints are satisfied, a penalty approach was adopted in the deep neural network training to respect the inequality constraints [142]. To enhance the robustness against anomalous measurements, Ref. [110] proposes a physics-informed global graph attention network and a deep auto-encoder to extract features of the measurements, then the extracted features are fed into the SAC algorithm.

4.1.4. End-to-end learning

End-to-end learning algorithms have emerged as a predominant method for addressing decision-making and control problems within active distribution systems. These algorithms aim to completely supplant the traditional optimization models with machine learning techniques, including supervised learning and RL. The key advantage of end-to-end learning lies in its computational efficiency: once the machine learning models are adequately trained, they require only straightforward function evaluations to operate, providing a significant boost in speed compared to traditional iterative optimization methods [159].

Supervised learning for non-sequential decisions: For non-sequential decision-making tasks in active distribution networks, supervised machine learning models process system and DER states as inputs and generate decisions or control signals as outputs. These models are typically trained on historical operational data, enabling them to execute swiftly during online operations, far outpacing the runtime of iterative algorithms [159]. The specific supervised learning models employed in this domain include: feed-forward neural network (FNN) [141,142], kernel-based regression [137,138,146] and multiple linear regression [134].

RL algorithms for sequential decisions: RL algorithms are instrumental in addressing sequential decision-making problems in active distribution systems, typically framed within the context of Markov decision processes (MDPs). In this RL framework, an agent learns to interact with its environment by observing states, taking actions based on those observations, and receiving rewards for its actions. The ultimate objective is to learn a policy – a mapping from states to actions – that maximizes the expected discounted return [13]. RL algorithms such as Q-Learning [106,192], actor–critic [193], and Markov chain Monte Carlo (MCMC) [194], are only applicable to distribution system control and decision-making problems with small state and action spaces. To tackle problems with high-dimensional state and action spaces, DRL algorithms are pursued. The most commonly used DRL algorithms include DQN [49,50,55–57], SAC [64,103,105], deep deterministic policy gradient (DDPG) [63,195–197], and proximal policy optimization (PPO) [66]. DRL algorithms have significantly expanded the applicability of RL in active distribution systems, providing robust solutions to complex and high-dimensional problems.

4.2. Enhanced algorithms

In addition to the four widely used approaches, this subsection introduces three enhanced data-driven algorithms to solve decision-making and optimization problems in distribution systems.

4.2.1. Non-centralized methods

Centralized algorithms have traditionally dominated optimization and control tasks within active distribution systems. Despite their widespread use, these centralized approaches exhibit several significant drawbacks. First, centralized controls are often not resilient against the failure of the centralized controller [96]. This is because each agent communicates with a centralized controller that performs computations and sends out commands [173]. Second, centralized control requires a high data transmission rate and reliable communication conditions which are not always available in the distribution network. Third, the user's information is required as input for centralized control, which puts users' privacy at risk. Therefore, many researchers have tried to develop non-centralized algorithms.

In light of these challenges, there has been a significant shift towards developing non-centralized algorithms. These methods are particularly relevant to the rising integration of DERs into the distribution grid. Non-centralized optimization and control offer several benefits over their centralized counterparts, including improved system resilience, reduced communication burdens, and enhanced privacy protection.

Non-centralized methods encompass a broad spectrum of approaches, ranging from mathematical optimization techniques like distributed optimization to machine learning strategies such as MARL. These diverse methodologies provide flexible and scalable solutions for managing optimization and control in active distribution systems, addressing the shortcomings associated with centralized control.

Distributed optimization: Distributed optimization enables agents within an active distribution system to collaboratively minimize a global function, which constitutes the sum of local objective functions [198]. This collaborative approach to optimization is divided into two principal categories based on the foundational algorithms utilized. The first category encompasses methods based on augmented Lagrangian decomposition, such as dual decomposition [199], the ADMM [88], analytical target cascading (ATC) [200,201], and auxiliary problem principle (APP) [202,203]. These methods are particularly adept at breaking down the global optimization challenge into smaller, more manageable sub-problems, thereby facilitating a more efficient solution process. On the other hand, the second category relies on the KKT necessary conditions, including techniques like optimality condition decomposition (OCD) [204,205], consensus + innovations [206], and gradient dynamics (GD) [207]. These approaches leverage the optimality conditions to guide the distributed optimization process, enhancing the ability to achieve consensus among agents and ensuring that the global optimization objectives are met. One of the key advantages of distributed optimization methods is their ability to bolster cybersecurity measures by mitigating the risks associated with centralized control systems. Furthermore, these methods significantly reduce the dependency on extensive and costly communication infrastructure, making them a highly attractive option for enhancing efficiency, resilience, and security within modern active distribution systems [173].

MARL: MARL represents a synergistic blend of MAS and RL, garnering significant attention for its application in the data-driven control of active distribution systems in recent years. MARL leverages the strengths of both distributed methods and RL to offer a robust framework for optimizing decision-making processes within distribution networks. Specifically, notable implementations of MARL in this domain include MASAC [65,104], multi-agent Q-learning (MAQL) [107], multi-agent deep Q-network (MADQN) [101,102], and multi-agent deep deterministic policy gradient (MADDPG) [98,99]. MARL approaches integrate the benefits of distributed methods and RL. These approaches collectively enhance control performance while concurrently mitigating the communication overhead and the risk of private data exposure. By distributing the decision-making process across multiple agents, MARL enables more scalable and efficient solutions, allowing for simultaneous optimization of numerous objectives across the network. The integration of RL principles further ensures that each agent can adaptively learn from the environment to improve its policy over time, leading to optimized network operations with reduced reliance on centralized control mechanisms. This dual benefit of enhanced performance and security makes MARL an increasingly preferred choice for tackling the complex challenges of active distribution system management.

Game theory: Game theory represents a mathematical framework designed for analyzing strategic interactions among rational decision-makers, gaining substantial attention for its application in active distribution networks in recent years. As a fundamentally non-centralized method, game theory models interactions as cooperative or non-cooperative games, effectively capturing the complexity inherent in decentralized decision-making processes involving diverse stakeholders. Prominent applications within active distribution networks include cooperative bargaining games for distributed battery balancing [208], Stackelberg games for integrated energy system management [209], non-cooperative games for retail electricity market operations [210], and coalition formation strategies for distributed energy resources (DERs) [211,212]. Game theory leverages the strengths of distributed coordination and strategic decision-making to enhance network performance, reduce operational costs, and mitigate stakeholder conflicts. By facilitating decentralized decision-making and coalition formation, game-theoretic approaches offer scalability, efficiency, and fair resource allocation. Additionally, cooperative game theory methods such as Shapley value and Nucleolus ensure equitable profit distribution among collaborating entities, thereby fostering stable and effective coalitions. Consequently, the dual benefits of optimized performance and improved stakeholder coordination position game theory as an increasingly attractive approach to addressing the multifaceted challenges of active distribution system management. However, game theory approaches can suffer from complexity and computational overhead, especially as the number of stakeholders or actions increases. Additionally, achieving equilibrium solutions may require extensive communication and iterative negotiation, potentially leading to inefficiencies in practical real-time implementations.

4.2.2. Robust and stochastic methods

To ensure the operational safety and reliability of the active distribution system, optimization algorithms must exhibit robustness against uncertainties and measurement noise. Robust optimization approaches are designed to address control problems by preparing for the worst-case scenarios. These strategies have been developed to achieve optimal distribution system reconfiguration [43,44] and to tackle VVC problems amidst uncertainties in load demands and distributed generation outputs. On the other hand, stochastic optimization methods focus on optimizing the expected control objectives [45], accounting for the probabilistic nature of system uncertainties. Such methods have been utilized to address complex problems, including the optimal EV charging scheduling problem in an iterative procedure [213] and solving a multistage stochastic OPF problem [131,132]. By incorporating the unpredictability of future events and variations within the system, stochastic methods provide a framework for making informed decisions that enhance the efficiency and resilience of active distribution operations. Both robust and stochastic optimization approaches play crucial roles in navigating the inherent uncertainties of active distribution systems, ensuring that operational decisions are both safe and reliable under a wide range of operating conditions.

However, robust and stochastic optimization methods possess significant limitations. Robust optimization methods, for instance, often exhibit overly conservative behavior. By accounting for worst-case scenarios, these methods tend to produce solutions that are suboptimal under typical operating conditions, potentially leading to increased operational costs. Additionally, robust formulations, such as the column-and-constraint generation (CCG) method [214], can become computationally intensive, especially in large-scale systems where the worst-case scenario search space expands significantly. On the other hand, stochastic optimization methods, although capable of addressing uncertainty through the optimization of expected performance, also encounter notable drawbacks. Primarily, their effectiveness heavily depends on accurate probabilistic modeling of uncertain parameters, which can be challenging to achieve in practice due to limited or noisy data. Furthermore, stochastic methods frequently necessitate extensive scenario generation, thereby increasing computational complexity and hindering timely real-time decision-making.

To address these limitations, data-driven distributionally robust optimization (DRO) has emerged as a promising alternative. This methodology combines the advantages of robust and stochastic approaches by constructing an "ambiguity set" of probability distributions consistent with available empirical data. Consequently, it effectively captures both forecast and sampling errors inherent in real-world datasets, resulting in solutions that strike a better balance-avoiding excessive conservatism while maintaining adaptability. Data-driven DRO has demonstrated notable effectiveness in various applications, including network reconfiguration [215,216], restoration [217], Volt-VAR control [209,218], energy trading [219], and optimal power flow [220,221].

4.2.3. Online learning

Online learning (OL) has emerged as a powerful data-driven and machine learning technique in the management of DR resources within active distribution systems. Initial investigations into the deployment of DR resources leveraged the multi-armed bandit framework, focusing on index policies informed by Markov chains for effective load dispatching [222]. As the field has evolved, OL has been increasingly applied to refine the management of DR resources by learning from real-time data. OL can be used as a tool to learn probability distributions and behavior of the loads to properly dispatch them [223]. Recent works have used OL to provide load shedding while learning the parameters and deciding the best available loads to curtail [224]. Henríquez et al. [225] follows a similar approach while considering load dispatch constraints. In Lesage-Landry and Taylor [226], an OL approach is used to select loads to provide load-shifting services while learning load parameters. Lesage-Landry and Taylor [227] use online convex optimization to track setpoints with uncertain and flexible loads in DR programs. Overall, by continually updating and refining load dispatch strategies based on real-time data and evolving system conditions, OL enables a more dynamic and efficient response to the key challenges of DR management.

5. Relevant data sets and testing systems

5.1. Simulation environment and datasets

5.1.1. Simulation environments

When it comes to active distribution systems simulation platforms for data-driven applications, most researchers have used proprietary environments. One of the main reasons is that the electric utility industry is heavily regulated and quite conservative. Being safety-critical, the real-world distribution system topologies, control settings, and DERs data are proprietary and often not shared with researchers. Despite these constraints, several well-known distribution system simulators have emerged as valuable tools for researchers and engineers. OpenDSS [228], Matpower [229], Pandapower [230], and PSASP [231], GridLAB-D [232] are among the leading simulators that offer capabilities for modeling active distribution networks. These platforms facilitate the calculation of power flows and the analysis of network faults, thereby simulating the operational state of active distribution networks.

Such simulation environments are crucial for generating sufficient labeled data needed for the training and validation processes of data-driven methods. By providing a virtual representation of active distribution systems, these simulators enable the development, testing, and refinement of data-driven applications in a controlled and accessible manner, bridging the gap between theoretical research and practical utility operations.

Beyond those conventional simulation tools, researchers have also developed a few gym-like simulation environments tailored for specific data-driven tasks such as machine learning-based applications. These specialized environments are crucial for simulating the dynamics of active distribution networks under various states, actions, and observations, closely mirroring real-world responses. Such gym environments are instrumental for training and testing RL agents, providing a realistic and controlled setting to explore and validate different control strategies.

One notable example is a Gym-like VVC environment developed for the IEEE 13-, 123-, and 8500-bus test feeders, which served as a testbed to conduct RL-based VVC research [233]. Gym-ANM [234] is another environment designed for training agents in active network management tasks, including control schemes of generators and DERs. PowerGym [235] is an open-source RL environment for VVC in active distribution systems. Besides, an OpenDSS-cum-SimPy based Gym environment [236] is presented to train agents for network reconfiguration to address network congestion and cyber threats. Recently, a Resilient RL Co-Simulation (ResRLCoSIM) framework has been developed in Mukherjee et al. [237], leveraging GridLAB-D and Hierarchical Engine for Large-scale Infrastructure Co-Simulation (HELICS) [238]. This framework is compatible with the Gym environment and can be applied to various benchmark RL methods, offering a versatile platform for testing and enhancing the resilience of RL agents in power system simulations.

Moreover, due to the complex nature of operation and control for multiple devices concurrently, the active distribution system can serve as a natural test field for multi-agent algorithms. A few multi-agent application simulation environments are constructed to test algorithms in this setup. For example, PowerGridworld [239] enables users to instantiate diverse multi-agent scenarios, which integrates power flow solutions into the agents' observation spaces and rewards. A MARL simulation environment [240] is established to focus on solving the active voltage control problem in active distribution networks.

Additionally, several studies have explored simulation environments for microgrids. Pymgrid [241] is built to focus on the tertiary level for microgrids, i.e., concerning the long-term dispatch of the various generators for optimizing the operational cost. OpenModelica Microgrid Gym (OMG) [242] is an open-source platform designed to simulate, control, and optimize microgrids based on energy conversion through power electronic converters. The above platforms support Gym-like usages such as reset, step, random action sampling, and visualization. Hence, they can be used to validate most of the developed RL algorithms [97,243]. Power system researchers can make fair comparisons on the developed RL algorithms without worrying about proprietary information leakage.

5.1.2. Datasets

The data-intensive nature of the aforementioned methods makes it imperative to create benchmark datasets and authoritative testbeds for active distribution network applications. These kinds of standardization are crucial for testing algorithms and promoting equitable performance comparisons. There are several open-source datasets [233,244–249] providing the topology data of real-world active distribution networks, including the information on line resistance, reactance, and network topology. Moreover, load data in distribution networks is prevalent in several datasets. For instance, the dataset by [250] details a real-world Norwegian low-to-medium voltage distribution grid, encompassing both grid data and load data. Another dataset by [251] supplies network and loading data for an actual distribution network in North East England. Additionally, the ATTEST dataset [252] includes information about a realistic distribution network in Croatia, covering grid topology, nodes, generators, and power consumption. The collection of multi-energy load data, e.g., electric vehicles [253–257], electrified buildings [258–260], and heat pumps [261], is also included in many datasets. A specific example is the Pecan Street Dataport [262], which provides high-resolution energy data, including flexible loads, inflexible loads, generators, and power quality from volunteering participants.

5.2. Physical test systems

5.2.1. ERIGrid 2.0

ERIGrid 2.0 (European Research Infrastructure supporting Smart Grid) is led by the Center for Energy of the Austrian Institute of Technology, which unites 20 innovation partners from 13 European countries to create a transnational platform for the benefit of research, industry, and network operators. The project allows industrial and academic researchers to test smart grid control algorithms on-site or virtually, and they also develop and make publicly accessible e-learning tools, webinars, and workshops to provide remote lab access for educational purposes. This platform can support developing, testing, and validating modern power supply systems, the integration of renewable energies, and the digitalization of networks and intelligent energy systems. ERIGrid 2.0 is composed of 21 physical and 10 virtual laboratories. On-site testing is supported by their technical staff. Access to their facilities is free and they support the cost of travel. For more technical details and information on how to request access, please refer to [263].

5.2.2. DERConnect, UC San Diego

DERConnect is a National Science Foundation Mid-Scale Research Infrastructure at the University of California, San Diego that received $42 million in funding in 2020. DERConnect establishes, for the first time, a grid-connected, customizable, and dedicated power system with all the required components and DER types for large-scale distributed control in one place. DERConnect features actual (i.e., functional devices at scale in addition to hardware emulators) and advanced DERs; testing equipment linked with a communication system; operation in grid-connected and islanded modes; and real-time remote access. DERConnect's controllable loads include heating, ventilation, and air conditioning systems, lighting, solar PV, battery energy storage, and EVs. DERConnect will enable near real-time distributed control trials on several levels of hierarchy via multiple separable sub-units and up to 2500 actual DERs and 2 million independent simulated DERs. DERConnect will open to the research community in 2025. An example of the research carried out in the earlier years of UC San Diego's microgrid can be found in Anderson et al. [264]. For more technical details and how to request access, please refer to [265].

5.2.3. ARIES, national renewable energy laboratory

The National Renewable Energy Laboratory has an on-site research platform called ARIES (Advanced Research on Integrated Energy Systems) [266], which stands for advanced research on integrated energy systems. This platform is designed to de-risk and optimize current energy systems as well as provide insights into future systems that rely on renewable energy sources. ARIES has four research objectives: (1) increasing the penetration of variable generation and storage, (2) increasing the capabilities for power electronics-based management and control, (3) de-risking multi-sectoral energy systems deployment and operation, and (4) designing cyber-secure control strategies. To fulfill these objectives, ARIES has the following research areas: energy storage, power electronics, hybrid energy systems, future energy systems, future energy infrastructure, and cybersecurity. ARIES is composed of real equipment and devices, emulated devices, hardware-in-the-loop experiments, high-performance computing, and assets at other national laboratories to allow full experimentation of integrated energy systems at a scale that replicates the real world. For more technical details about how to collaborate, please refer to [266].

5.2.4. Princeton island grid

Princeton Island Grid (PIG) is a microgrid located in Princeton New Jersey with an islanding function. The PIG consists of a controllable building load, a 1 MWh battery energy storage system, 836 kW of solar PV, and six 7.2 kW EV chargers. Siemens in-house software is used to manage the PIG (such as DECIGO CC, Mindsphere Application Center for Distributed Energy Systems, and Siemens Energy Workplace for Analysts). PIG is a living lab for testing microgrids, grid-level controls, IoT, energy-related performance monitoring and analysis, simulation and digital twin, and cyber security. Some examples of the data-driven applications that can be tested on PIG are: microgrid energy demand monitoring and analysis, microgrid-based demand response, short-term solar power predictions using cloud images, power systems cyber attack analysis, etc. For more details about the resources of PIG, please refer to [267].

6. Challenges, opportunities, and pathway in realizing data-driven distribution networks

Data-driven algorithms serve as an innovative approach to solving decision-making problems with increasing complexity in active distribution networks. Despite their potential, a significant divide persists between the practical applications in the industry and the advancements in academic research. This section first delves into the primary challenges and opportunities that data-driven methods face in addressing real-world decision-making, optimization, and control problems in active distribution networks, then outlines a pathway to deploying data-driven methods in active power distribution networks. An overview of challenges and research opportunities is presented in Fig. 3.

6.1. Challenges

6.1.1. Generalization

While data-driven approaches can greatly reduce the computation time and improve the solution quality of optimization problems in active distribution systems, their generalization performance cannot be guaranteed. The distribution system's network topology may change over time, new DERs may be introduced into the feeders, and the spatio-temporal distribution of the electric load in the testing period could be different from that of the training data. In general, it is very difficult to guarantee that the data-driven algorithms could adapt and react properly to every previously unseen distribution network and operation conditions. Practically, retraining the model periodically may only partially mitigate the issue.

6.1.2. Interpretability

Interpretability describes the degree to which distribution system operators can understand the decisions made by machine learning

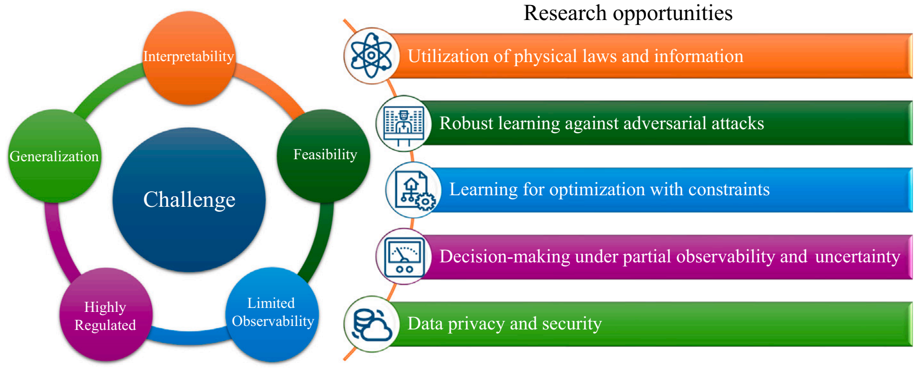

Fig. 3. An overview of the challenges and research opportunities.

algorithms and data-driven approaches. Low interpretability is the main hindrance to the wider deployment of learning algorithms in distribution networks, especially end-to-end deep learning algorithms which are widely regarded as "black box" models. These models cannot be readily understood by system operators or provide desired operational safety guarantees. Developing models that combine high interpretability with advanced analytical capabilities is essential for meeting the operational standards and safety requirements of distribution system operators.

6.1.3. Feasibility

Sensor data from real-world active distribution systems must follow physical laws, such as Kirchhoff's laws and conservation of energy. Most decision-making problems in distribution networks are optimization problems with operational constraints. Violating these constraints will lead to infeasible and unsafe solutions. Unfortunately, naive data-driven algorithms typically cannot enforce these hard constraints in decision-making problems. Therefore, to make data-driven approaches applicable in actual distribution system operations, there is a need to develop machine learning algorithms for optimization problems with hard constraints.

6.1.4. Limited observability

Typically, the existing sensing and monitoring instrumentation in active distribution networks is insufficient [268], which offers system operators very limited observability. While some research efforts have concentrated on state estimation and decision-making with limited data [269], the challenge of ensuring model generalization and feasibility under partial observability remains significant.

6.1.5. Highly regulated industry

The power industry has traditionally been a highly regulated industry, partially resulting from its heavy infrastructural investments, proprietary data, and critical security requirements. Power distribution system operators have a systematic way of ensuring the secure operation of the active distribution grid after decades of operational experience. Compared to other industries, it takes more time for the market to transition from human-centric decision-making to the regime of its data-centric counterpart.

6.2. Research and development opportunities

6.2.1. Utilization of physical laws and information

Integrating physical laws and information into ML algorithms can significantly improve the reliability and accuracy of predictive models. This class of methods has revolutionized many application areas in a variety of ways. For instance, physics-informed neural networks have been developed to solve supervised learning tasks while respecting any given laws of physics described by general nonlinear partial differential equations [15]. To follow the law of conservation of energy, Hamiltonian and Lagrangian mechanics are embedded into the neural networks [270,271]. In physics-informed RL, incorporating physical principles can enhance the effectiveness, sample efficiency, and training speed, facilitating complex problem-solving and real-world applications [272].

6.2.2. Robust learning against adversarial attacks

The input-output mappings learned by deep neural networks can be highly discontinuous functions. This means that small perturbations to the inputs of data-driven decision-making models for distribution networks can lead to huge prediction errors [273]. Furthermore, the data-driven models in distribution networks may be vulnerable to adversarial attacks. Thus, it is necessary to learn a control policy, which is robust to uncertain system operation conditions, network topology, and vulnerable sensor data. In the area of RL, Lerrel et al. proposed robust adversarial reinforcement learning (RARL) to improve the robustness of RL algorithms [274], which can improve the anti-interference ability of the RL models. In the area of active distribution systems, researchers find that several competition-winning, state-of-the-art RL agents proposed for power system control are vulnerable to adversarial attacks [275]. To address this problem, they propose to use adversarial training to increase the robustness of RL agents against attacks and avoid infeasible operational decisions. In Liu and Wu [276], an adversarial RL algorithm is developed to train an offline agent robust to the model mismatch for VVC. However, the approach does not address data privacy concerns between different entities. To safeguard data privacy across microgrids, a data-driven federated RL method is introduced in Mukherjee et al. [237], aimed at mitigating adversarial attacks in networked microgrids. Additionally, a hierarchical control layer is integrated alongside the primary controls of grid-forming inverters. Nonetheless, further research is needed to incorporate safety-constrained RL techniques to ensure secure and reliable operations.

6.2.3. Learning for optimization with constraints

To meet the constraints of optimization problems, many scholars began to pay attention to learning algorithms for optimization with constraints. This approach is crucial for ensuring that solutions not only achieve optimal performance but also adhere to the physical and operational parameters that govern real-world systems. In general, two main types of constraints can be imposed on neural networks: soft constraints and hard constraints. The former introduces additional terms (e.g., those derived from Lagrangian duality [277]) into the loss function, which is minimized during training. However, imposing soft constraints does not guarantee the satisfaction of physical laws, which is a significant limitation for applications in active distribution systems where compliance with such laws is non-negotiable. Research has demonstrated that imposing hard constraints is computationally feasible and yields satisfactory outcomes. For instance, Márquez-Neila et al. [278] shows that imposing hard constraints can in fact be done in a computationally feasible way and delivers reasonable results. Donti et al. [279] present deep constraint completion and correction (DC3) to solve this problem. Specifically, this method enforces feasibility via a differentiable procedure, which implicitly completes partial solutions to satisfy equality constraints and unrolls gradient-based corrections to satisfy inequality constraints.

6.2.4. Decision-making under partial observability and uncertainties

The real-world active distribution systems have a limited number of sensors that could provide real-time measurements, which leads to feeders with limited observability. To navigate this challenge, sequential decision-making problems are often formulated as partially observable Markov decision processes (POMDPs) [280,281], with tailored RL algorithms developed to provide solutions. There are a few papers that touched on the topic in active distribution systems. In Bahrami et al. [193], Shahab et al. studied the users' long-term load scheduling problem and modeled the changes in price data and electric load as a Markov decision process, which enables us to capture the interactions among users as a partially observable stochastic game. Hangyue et al. formulated VVC as a partially observable Markov game. Then, a MADDPG algorithm was adapted to solve this problem [99]. By integrating constraints directly into the learning process and developing algorithms capable of operating under partial observability, researchers are paving the way for more robust and efficient active distribution operations. Decision-making under uncertainty is another crucial aspect of active distribution systems, where various methods have been developed to address the unpredictability of real-world conditions. Two leading approaches in this domain are stochastic optimization and robust optimization. However, many decision-making problems in active distribution systems involve MIP, which remains computationally challenging to solve efficiently. To accelerate the solving process, two recent learning-based approaches, Neur2SP [282] and Neur2RO [283], have been introduced to tackle classical decision-making problems under uncertainty. These methods show significant potential for application in active distribution systems, offering improved computational efficiency and scalability.

6.2.5. Data privacy and security

In distributed energy markets involving DERs and microgrids (MGs), prosumers are increasingly concerned about data privacy and security during energy transactions. Some ADMM-based privacy-preserving methods have been developed in [284,285], but as discussed earlier, distributed algorithms like ADMM remain vulnerable to malicious attacks [286,287]. Moreover, ADMM requires two-time-scale calculations, limiting its scalability to large networks and making it less robust to noise and inexact solutions. To address these challenges, a privacy-preserving distributed energy transaction approach was proposed in Chang et al. [288], which enhances security by adding a noise term and a secret function to the information exchange process. However, this method may not perform well in high line congestion scenarios or when managing frequent bus injections and withdrawals, requiring further investigation. Additionally, distributed privacy-preserving algorithms involve frequent data exchanges, which can lead to communication delays and high computational overhead, particularly with limited computing resources. Recently, outsourced computation has emerged as a solution, allowing prosumers with constrained resources to delegate complex tasks to a power cloud center. For instance, a proactive deception approach introduced in Han et al. [289] utilizes virtual network encryption and asynchronous decryption to enhance both speed and accuracy. However, further research is needed to address challenges related to uncertainty aggregation in DERs and the generalization to nonconvex models.

6.3. Pathway to realizing data-driven distribution networks

The transition towards fully operational, data-driven methods in active power distribution networks involves bridging the gap between theoretical frameworks and their practical deployment. This subsection articulates a comprehensive roadmap that identifies strategic pathways essential for this transformation, underpinned by advancements in digitalization, sensing, and communication technologies.

6.3.1. Integration of advanced data acquisition systems

A fundamental step is the establishment of robust data acquisition infrastructures that can monitor network parameters at high resolutions. This entails the deployment of smart sensors, micro-phasor measurement units (μPMUs), and IoT devices across the distribution network. The comprehensive real-time capture of operational data-ranging from voltage profiles and load variations to behind-the-meter renewable energy outputs-is crucial for enabling accurate situational awareness and subsequent data analytics.

6.3.2. Development of scalable data management platforms

With the influx of high-frequency and high-volume data, there is an urgent need for scalable and secure data management platforms. Cloud-based solutions and edge computing platforms can facilitate the storage, processing, and retrieval of large datasets while ensuring data integrity and low latency. These platforms must be designed with cybersecurity in mind to protect critical infrastructure and sensitive customer information.

6.3.3. Adoption of robust data analytics and data-driven models

Robust data analytics and data-driven models form the cornerstone of data-driven solutions for active distribution networks. As summarized in Section 4, there is a wide spectrum of data-driven strategies-ranging from mathematical optimization to learning-assisted optimization, physics-informed learning, and end-to-end learning-that collectively offer powerful tools for control, optimization, and decision-making in active distribution networks.

6.3.4. Fostering interdisciplinary collaborations and stakeholder engagement

Realizing a data-driven future necessitates a multidisciplinary approach that brings together electrical engineers, data scientists, and policy makers. Collaborative frameworks can drive the integration of emerging technologies and standardize practices across utilities. Additionally, fostering partnerships between industry and academia will support pilot projects and testbeds, ensuring that theoretical advancements are continually validated against real-world operational scenarios.

6.3.5. Emphasizing regulatory and standardization frameworks

For widespread adoption, regulatory bodies must develop clear guidelines that support innovation while ensuring system reliability. Establishing industry-wide standards for data exchange, interoperability, and cybersecurity is imperative. These standards will not only facilitate the integration of diverse technological systems but also ensure that emerging data-driven methods align with national and international regulatory policies.

6.3.6. Continuous validation through demonstration projects

Continuous validation is essential to transition data-driven methods from theory to practice in active distribution networks. As detailed in Section 5, simulation environments and physical test systems offer two complementary platforms for this purpose. Simulation environments provide a controlled setting to assess algorithm performance under varied scenarios, while physical test systems offer real-world insights for validating operational resilience. Integrating lessons learned from these platforms through demonstration projects ensures that the developed methods are robust, scalable, and ready for practical deployment.

7. Conclusion

This paper provides a comprehensive literature survey of recent data-driven optimization and decision-making algorithms in active distribution networks. We summarized the data-driven algorithms for optimization and decision-making problems by major active distribution network applications, including restoration and reconfiguration, crew dispatch, Volt-VAR control, dispatch of distributed energy resources, and optimal power flow. Then, we divide these algorithms into four categories: mathematical optimization, learning-assisted optimization, physics-informed learning, and end-to-end learning. The relevant datasets and testing systems for data-driven control, optimization, and decision-making in active distribution networks are also covered in depth. Finally, we highlight the key challenges of existing approaches and point out research and development opportunities.

CRediT authorship contribution statement

Nanpeng Yu: Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Shaorong Zhang:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis. **Jingtao Qin:** Writing – review & editing, Methodology, Investigation, Formal analysis. **Patricia Hidalgo-Gonzalez:** Writing – original draft, Methodology, Formal analysis. **Roel Dobbe:** Writing – original draft, Conceptualization. **Yang Liu:** Writing – original draft. **Anamika Dubey:** Writing – original draft. **Yubo Wang:** Writing – original draft. **John Dirkman:** Writing – original draft. **Haiwang Zhong:** Writing – original draft. **Ning Lu:** Writing – original draft. **Emily Ma:** Writing – original draft. **Zhaohao Ding:** Writing – original draft. **Di Cao:** Writing – review & editing. **Junbo Zhao:** Writing – review & editing. **Yuanqi Gao:** Writing – original draft, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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