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Smart optimization in battery energy storage systems: An overview

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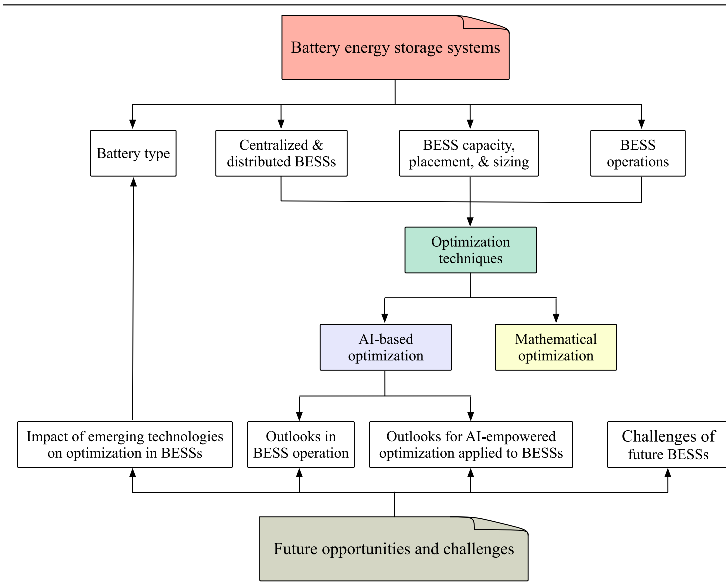
HIGHLIGHTS

- We first provide a review of BESSs operation that includes grid-scale applications, community, microgrid, and residential settings, and how they enhance the power system performance.
- We summarize the BESS optimization approaches from the viewpoint of mathematical programming to AI-based optimization techniques and explain how these approaches are applied to BESS optimization scenarios.
- We present some outlook on BESS optimization, how future AI contributes to BESS optimization, the issues of future BESS, and how the development of AI, big data, and internet of things (IoT) impact future BESSs.

GRAPHICAL ABSTRACT



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ABSTRACT

The increasing drive towards eco-friendly environment motivates the generation of energy from renewable energy sources (RESs). The rising share of RESs in power generation poses potential challenges, including uncertainties in generation output, frequency fluctuations, and insufficient voltage regulation capabilities. As a solution to these challenges, energy storage systems (ESSs) play a crucial role in storing and releasing power as needed. Battery energy storage systems (BESSs) provide significant potential to maximize the energy efficiency of a distribution network and the benefits of different stakeholders. This can be achieved through optimizing placement, sizing, charge/discharge scheduling, and control, all of which contribute to enhancing the overall performance of the network. In this paper, we provide a comprehensive overview of BESS operation, optimization, and modeling in different applications, and how mathematical and artificial intelligence (AI)-based optimization techniques contribute to BESS charging and discharging scheduling. We also discuss some potential future opportunities and challenges of the BESS operation, AI in BESSs, and how emerging technologies, such as internet of things, AI, and big data impact the development of BESSs.

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Nomenclature

ADP	Approximate dynamic programming	MOO	Multi-objective optimization
AI	Artificial intelligence	MOPSO	Multi-objective particle swarm optimization
α	Constant value within [0, 1]	MT	Microturbine
BESS	Battery energy storage system	NLP	Non-linear programming
BDC	Battery degradation cost	NN	Neural network
DE	Differential evolution	PI	Proportional-integral
DER	Distributed energy resources	P	Battery size (MW)
DOD	Depth of discharge	P_b	Battery charging/discharging power
DP	Dynamic programming	P_b^{max}	The maximal battery charging/discharging rate
DPR	Deep peak regulation	P_b^{min}	The minimal battery charging/discharging rate
DQN	Deep Q-networks	PFR	Primary frequency response
DR	Demand response	P_l	Load power
DRL	Deep reinforcement learning	PPO	Proximal policy optimization
DSO	Distribution system operator	P_{pv}	PV generation
EA	Evolutionary algorithm	P_r	Electricity price
E	Battery capacity (MWh)	PSO	Particle swarm optimization
ESS	Energy storage system	PV	Photovoltaics
EV	Electric vehicle	QP	Quadratic programming
FFR	Fast frequency regulation	RES	Renewable energy source
GA	Genetic algorithm	RL	Reinforcement learning
GD	Gradient descent	RO	Robust optimization
G2H	Grid to home	SC	Supercapacitor
G2V	Grid to vehicle (charge)	SDP	Stochastic dynamic programming
GT	Generation and transmission	SFR	Secondary frequency regulation
HESS	Hybrid energy storage system	SG	Smart grid
HES	Hydrogen energy storage	SOC	State of charge
H2G	Home to grid	SOH	State of health
IoT	Internet of things	SOO	Single-objective optimization
LCC	Life cycle cost	SP	Stochastic programming
LP	Linear programming	TD3	Twin delayed deep deterministic policy gradient
LS-BESS	Large scale BESS	TID	Tilt-integral-derivative
LV	Low voltage	T	The total time stamps
MDP	Markov decision process	VPP	Virtual power plant
MG	Microgrid	V2G	Vehicle to grid (discharge)
MILP	Mixed integer linear program	WP	Wind power
MIP	Mixed-integer programming	WT	Wind turbine

1. Introduction

The rapid development of the global economy has led to a notable surge in energy demand. Due to the increasing greenhouse gas emissions, the global warming becomes one of humanity's paramount challenges [1]. The primary methods for decreasing emissions associated with energy production include the utilization of renewable energy sources (RESs) and the implementation of diverse energy-saving technologies to reduce power consumption. This motivation drives the advancement of RESs as a major way to diminish reliance on fossil fuel reservoirs and alleviate carbon emissions [2–4]. Nonetheless, the remarkable increase of RESs challenges the secure operation of power systems and the balance between power supply and demand [5]. Available services in power grids may not be able to mitigate the uncertain and intermittent characteristics inherent in RESs, resulting in poor power quality [6,7]. Besides, the existing power distribution grids are experiencing technical challenges which they have not been designed to tackle. Possible voltage increase because of electricity export during daytime from households with rooftop photovoltaics (PV), uncertain consumption/export profiles [8], uncertain wind power (WP) generation [9], and the emergence of eco-friendly technologies like electric vehicles (EVs) [10], have been challenging distribution system operators (DSOs). The issue becomes worse considering that distributed energy resources (DERs) are often behind the meter, which means that the consumption/generation is managed behind the households' electricity meters, which are out of access to DSOs [11].

Battery energy storage systems (BESSs) have attracted significant attention in managing RESs [12,13], as they provide flexibility to charge and discharge power as needed. A battery bank, working based on lead–acid (Pba), lithium-ion (Li-ion), or other technologies, is connected to the grid through a converter. Adding batteries to the transmission system can enhance the operational flexibility of the grid through less wind and solar power curtailment [14]. They can also provide ancillary services, such as primary frequency control and peak shaving, for power grids at different time scales [15]. Similar to any other technology, BESSs have their optimal design and operational requirements, including sizing and location [16,17], matching with other technologies, such as PV [18–20], scheduling and control [21], demand response (DR) [22], frequency and voltage control [23–25], energy arbitrage [26], and bidding strategy [27–29], considering the high initial cost of batteries.

Various stakeholders consisting of microgrid (MG), customers, generators, and DSOs can benefit from scheduling and managing the power in BESS optimally [30]. An optimization model was developed utilizing mixed integer linear programming (MILP) to examine the economic viability of integrating solar-PV systems with energy storage and load management strategies across various rate structures in [31]. In addition to the batteries integrated into solar-powered sensor nodes, a hybrid energy storage system (HESS) incorporating another adaptive charge scheduling was designed in [32] to reduce PV power losses and prolong battery longevity. Shu et al. [33] focused on maximizing the profit for both wind farms and BESS by finding the optimal BESS charging and discharging strategy for each time slot. In [34], a home energy storage system (ESS) was constructed by minimizing the cost consisting of purchased electricity (G2H), daily operation and maintenance cost of the ESS, and the incomes of the energy sold to the main grid (H2G). With the increasing penetration of electric devices, BESS optimization is involved in the charging and discharging schedule of EVs and electric buses, where optimization is applied to realize the technical, economic, and environmental benefits. An online coordinated optimization approach for a plug-in hybrid electric bus was designed to minimize energy consumption expense and battery degradation cost (BDC) [35]. Nizami et al. [36] targeted EV battery coordinated charging (G2V) and discharging (V2G) resource optimization to minimize the cost of EV owners using a mixed-integer programming (MIP)-based optimization model. To overcome the uncertainties caused by renewable energy, Jonban et al. [37] developed a robust real-time energy management system with renewable energy, such as PVs, wind turbines (WTs), and microturbines (MTs), where a reinforcement learning (RL) model was applied to optimize the energy cost in MG. Xiong et al. [38] formulated the cost function involving degradation, capital, and operation costs for the ESS and hydrogen energy storage (HES), where an interpretable deep reinforcement learning (DRL) model was designed to obtain naturally explained scheduling strategies.

Poullikkas [39] summarized various battery technologies utilized in the context of large-scale energy storage and their performance comparison have been comprehensively reviewed. Sparacino et al. [40] discussed the operating characteristics and modeling techniques of battery models. Hidalgo-León et al. [41] reviewed the architectures of BESSs and their applications in grid-scale operations. Yang et al. [42] provided a comprehensive overview encompassing the criteria, methodologies, and utilization of battery sizing across diverse RESs. Saboori et al. [43] reviewed the optimal ESS planning problem, addressing aspects such as the determination of optimal bus placement, power ratings, and energy capacities within distribution networks. Castillo et al. [44] introduced a method to use ESSs to perform grid services aimed at mitigating the impacts of uncertainty and variability linked to intermittent and non-dispatchable RESs. It also summarized the existing approaches to assess grid-integrated storage and highlighted persistent challenges to grid-scale ESSs. The applications of evolutionary multi-objective optimization (MOO) methods in hybrid RESs were reported in [45]. Fathima et al. [46] presented a review of different hybrid RESs and the applications of the optimization methods from the MG level, similar to [3]. Hoppmannet al. [47] provided a comprehensive overview of existing studies investigated the economics of integrated PV-battery systems on the residential level. Abdalla et al. [48] provided an overview of the roles, classifications, design optimization methods, and applications of ESSs in power systems, where artificial intelligence (AI) applications for optimal system configuration, energy control strategy, and different technologies for energy storage were covered. Hannan et al. [49] provided a comprehensive overview on technologies, optimization objectives, constraints, approaches, and the issues to be addressed. Worku [50] summarized the applications of ESSs in grid integration, different types of storage technologies and power converters. Jafari et al. [51] reviewed the role of ESSs played in decarbonizing power systems. Olabi et al. [52] dived into the applications from the classification, types, and operational characteristics of ESSs. Prakash et al. [53] given an overview on ancillary services in distribution grids from voltage support, frequency regulation, peak shaving, congestion relief, power smoothing, etc. Choudhury [54] mainly presented the categories and the control services of BESSs, the challenges in the development, management, and environmental impacts of BESSs in MG. Sayed et al. [55] provided on overview of different RESs and how they are managed with batteries. Based on a PV-BESS system, Rana et al. [56] conducted an overview encompassing enhancements in lifespan, cost reduction assessments, sizing optimization, mitigation strategies for diverse power quality concerns, optimal power system control, and strategies for peak load shifting and minimization. Numan et al. [57] summarized how the integration of ESSs with smart grid (SG) technologies, such as dynamic thermal rating, optimal transmission switching, and DR, contribute to improving system reliability and economic efficiency.

The aforementioned reviews have focused on the BESS optimization [49,56], battery materials and categories [39], how BESS is integrated with RESs [42,55], etc. Due to the increasing penetration of RESs in the power grid and the complexity of power scheduling, it is essential to have an overview of the optimization tasks and solvers involved in BESSs to help choose or develop problem-driven optimization methods. Also, with the development of AI in techniques, data, equipment, etc., exploring how BESSs influence and benefit from future AI is essential. However, none of the existing overviews provide the core optimization tasks involved in the existing BESS optimization problems and the summary of mathematical programming (optimization) and AI-based optimization methods. In this paper, we provide a comprehensive overview on the optimization tasks and methods applied in BESSs including optimal BESS capacity, placement, sizing, scheduling, coordination, and control. The main contributions are summarized as follows:

- We first provide a review of BESSs operation that includes grid-scale applications, community, MG, and residential settings, and how they enhance the power system performance.
- We summarize the BESS optimization approaches from the viewpoint of mathematical programming to AI-based optimization techniques such as evolutionary algorithms (EAs) and RL-based methods, and explain how these approaches are applied to BESS optimization scenarios.
- We present an outlook on BESS optimization, how future AI contributes to BESS optimization, the issues of future BESSs, and how the development of AI, big data, and internet of things (IoT) impact future BESSs.

The rest of this manuscript is organized as follows. The operation of BESSs in SG is introduced in Section 2, which includes the optimization and control frameworks for the BESS operation. Section 3 classifies the optimization methods including mathematical programming, EAs, and RL-based approaches. Section 4 presents the core optimization tasks in BESS and how the existing methods address these optimization problems. Section 5 summarizes challenges and potential future opportunities and challenges. Section 6 concludes the paper with some mentioned future work.

2. Overview of BESS operation and control

2.1. Battery types

For an ancillary service provider to the power grid, there are three main components in the BESS, which are shown in Fig. 1. The function of the power conversion system is connecting BESS to the MG, and converting AC/DC input with a different frequency to DC/AC output with the standard frequency. Battery monitoring and control systems focus on monitoring the BESS status and making the optimal decisions by controlling battery charging/discharging activities in each control time slot. The battery module is the component to store the energy. Diverse battery types bring different advantages and disadvantages to the application scenarios.

BESS can be generally categorized by two criteria, i.e., storage medium and storage duration [58]. There are five major storage medium types in the current BESS: Li-ion, Pba, nickel–cadmium (Ni–Cd), sodium–sulfur (Na–S), and flow batteries. From the storage duration perspective, Li-ion and Na–S batteries are classified as high energy density and high power density. Both types are designed with a longer energy storage duration and a higher charge/discharge rate than other battery types. However, Na–S requires an extreme operation environment (more than 300 °C) and has a high risk of fires and explosions. Li-ion battery costs more than others and cannot perform well in a low-temperature environment. Pba, Ni–Cd, and flow batteries are identified as low energy density and low power density, which have advantages

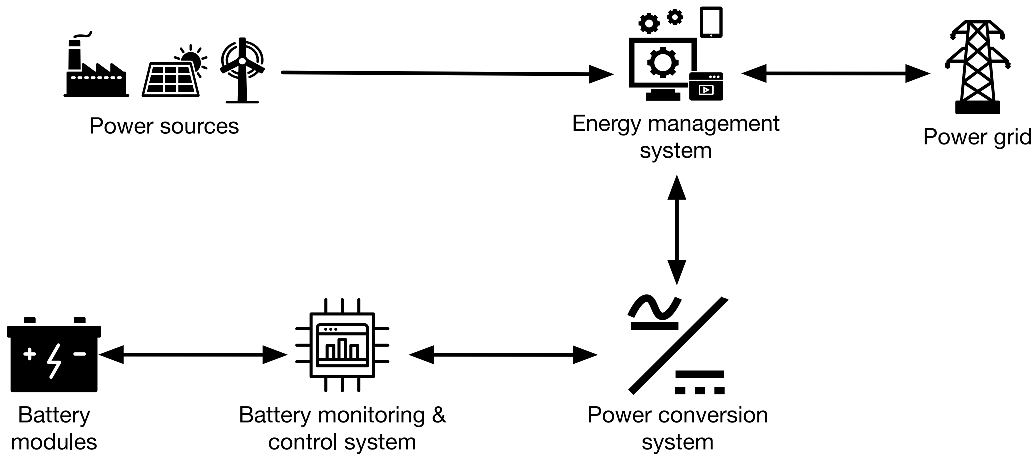

Fig. 1. The major components of the BESS.

in the investment cost and lifespan. Pba is an environmentally friendly battery type, but difficult to transport. On the other hand, Ni–Cd is easy to transport and store but difficult to recycle. [1] Except for the low charge/discharge rate, the flow batteries are flexible in scalability and fast in response time.

2.2. Centralized grid-scale and distributed residential BESS

The BESS operational framework can be generally divided into two categories: centralized BESS, such as large battery farms, and distributed BESS in residential or commercial buildings. A centralized BESS offers a comprehensive range of system services. These services span from short-term balancing and operating reserves to ancillary services aimed at enhancing grid stability and deferring investments in new transmission and distribution lines. Furthermore, a centralized BESS also facilitates long-term energy storage and plays a crucial role in restoring grid operations following a blackout. Recently, centralized BESS has been used as an auxiliary system of RESs, resulting in reducing the power generation cost [59]. The surplus RES can be stored in the battery and released to the power grid when electricity generation cost is expensive. The BESS can be used as a new secondary factor for frequency control [60,61]. Among the BESS frequency control studies, the optimal control scheme [62] and the minimal BESS size [63] are the main issues that have been addressed in the literature. Centralized BESS has advantages in the optimal decision-making operation for all battery packs controlled by a single operator. Namely, the benefits of the BESS can be considered together to reduce uncertainty factors such as battery charging/discharging activities made by other operators to increase their own profit. Despite the numerous advantages it offers, energy storage continues to encounter several obstacles that hinder its widespread implementation. These barriers include high costs, insufficient incentives, and technical challenges. Energy storage technologies are often expensive in comparison to conventional generation sources, and their value is frequently underappreciated, resulting in inadequate compensation. Moreover, the integration of these technologies with the existing grid infrastructure and operations, as well as their compatibility with various devices, platforms, and protocols, can present additional complexities. Furthermore, ESSs must undergo rigorous testing, certification, and monitoring to guarantee both safety and optimal performance.

Compared to centralized BESS, distributed BESS emerges as a formidable asset for our energy system, especially during the ongoing transition to renewable energy sources. It serves as a valuable tool for facilitating the widespread integration of renewable by effectively mitigating temporal discrepancies between energy supply and demand. By enabling residential and commercial buildings to actively participate in the electricity distribution system and store energy, distributed energy storage empowers us to optimize our utilization of clean energy sources. This capability significantly enhances our ability to embrace and leverage the potential of sustainable energy. Namely, distributed BESS has more flexibility in storage capacity and location selection. BESS distributed and installed in residential and commercial buildings can reduce the fixed cost of battery farm construction. In addition, the distributed BESS brings the benefit to both power grid operators and end users [64]. Among these kinds of researches, the building baseload, RES [65], and BDC [66] are mainly considered to reduce/enlarge battery operation cost/revenue [67]. Dynamic programming (DP) is widely recognized as an effective method for optimizing residential BESS in conjunction with RESs, as highlighted in [68–70]. Traditional DP algorithms require the computation and storage of state functions, a process that becomes increasingly challenging as the state space expands. This exponential growth in the solution space significantly restricts their practicality for addressing DER coordination challenges [71]. To navigate these limitations, the power and energy sector has turned to approximate dynamic programming (ADP). ADP offers a robust modeling and algorithmic approach for managing complex, stochastic, sequential decision-making tasks, effectively sidestepping the DP's notorious "curse of dimensionality" [72–74]. However, the incorporation of distributed BESS with conventional power grids necessitates the development of customized topologies and control systems tailored to specific requirements. This requirement leads to a costly and time-consuming process of designing and debugging each single component and control system whenever a utility decides to incorporate an ESS. Despite the growing need for advanced integration, the development of standardized architectures, methodologies for distributed intelligence and intelligent power systems, alongside scheduling tools and models to facilitate the seamless integration of ESSs, is still significantly lagging behind.

2.3. BESS optimization framework

In this section, we summarize the overall BESS optimization framework that could be applied to residential virtual power plants (VPP) [75–77] and grid-scale [78] application scenarios, as illustrated in Fig. 2. The core components include the RESs, the network topology [79], objective functions and constraints, algorithms to address the formulated problem, and outputs that consist of the expectations of each investigator.

RESs include different types of energy sources and devices. For EVs, the framework mainly focuses on the EV battery charging and discharging schedule. The network topology is a low voltage (LV) network [80].

[1] https://www.edina.eu/power/battery-energy-storage-system-bess.

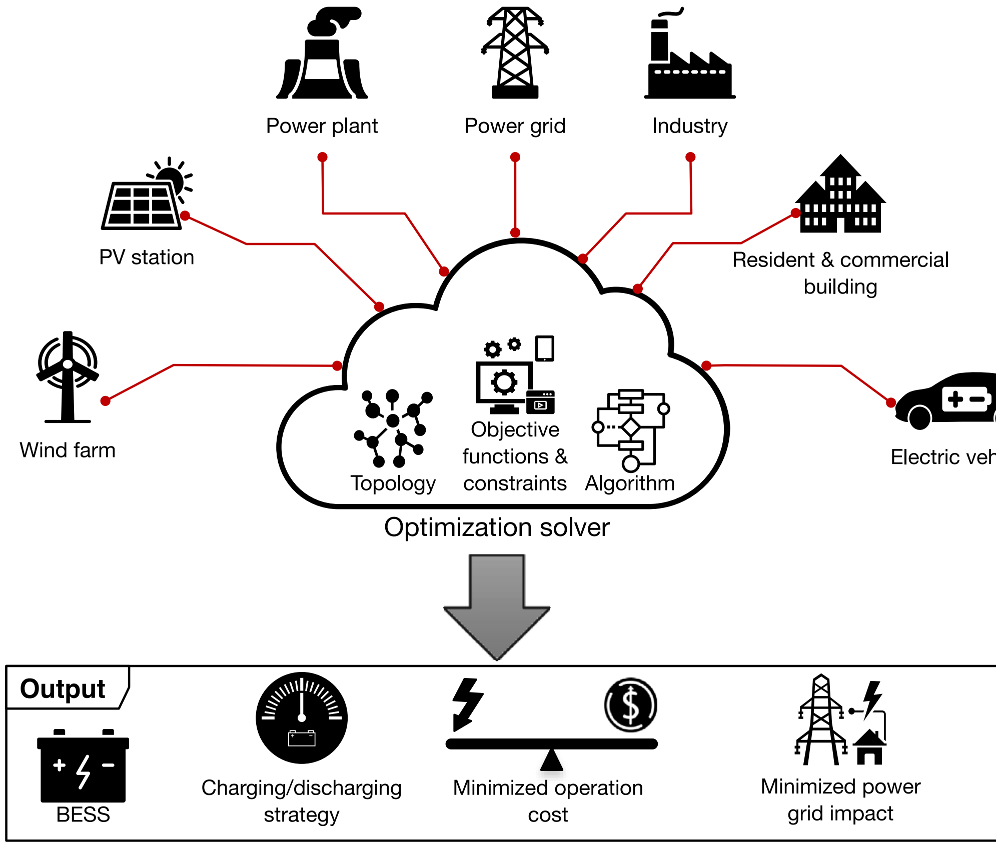

Fig. 2. The framework of BESS optimization in power grid.

The related objectives and constraints are the functions having decision variables to be optimized. The optimization algorithms [45] are used to address the formulated problem over different application examples. The outputs of the optimization algorithms often consist of BESS control and operation, the charging and discharging schedule, the cost over different stakeholders and batteries, as well as the system management, the grid network impact, and environmental benefits.

2.4. Optimal BESS capacity, placement and sizing

In the past few years, the grid-scale BESS optimization problem has attracted increasing attention. The existing studies can be largely classified into two groups: optimal sizing and placement problem [81] and optimal charging and discharging strategy problem [78].

As the first step of grid-scale BESS optimization, the optimal BESS sizing and location in distribution networks will not only increase operation benefit and reduce operation cost [82], but also lead to technical benefits that consist of improving the power grid reliability [83], reducing frequency deviation [84], providing voltage support [85,86], shifting and shaving peak load [87]. The optimization objectives may involve obtaining the minimal annual total cost [88], levelized cost of electricity and storage [89], battery and unit life cycle cost (LCC) [90], and the maximal profit from energy trading [91].

Based on the optimization methodology, the BESS location and sizing problems can be generally divided into single-objective optimization (SOO) and MOO. In [92], a framework of BESS location and capacity definition was proposed to minimize the power generation cost over every cycle of operation by peak load shifting with a fixed available storage budget. The BESS charging and discharging efficiencies have been considered in the BESS candidate location. For the multi-objective BESS allocation optimization problem, the grid voltage deviations, feeders congestion, network losses, and the expense associated with supplying loads can be considered to minimize voltage magnitude deviations, feeders/lines congestion, load supply costs, and investment expenditures pertaining to BESS deployment. Nick et al. [93] showed that the capabilities of the optimal allocation of BESSs significantly enhance the reliability of service in active distribution networks by mitigating voltage deviations, alleviating line congestion, and reducing the overall cost of locally utilized electricity and battery investment.

2.5. BESS operation in power grids

The operational objectives of BESS in the generation and transmission (GT) of a power grid are different from those in the distribution level. Problems of BESS in GT are mainly about services they can provide for voltage and frequency support of the grid [94,95], while in the distribution grid, scheduling, coordination and control are of high interest [96,97].

2.5.1. BESS operation in power generation and transmission systems

Batteries can help renewable-based generation units by reducing fluctuations in their output power. Fig. 3 shows how batteries can be integrated into power plants. In addition to the battery size, which is important in optimal hybrid energy storage [98], efficient coordination between the generated power and stored energy to the battery is required.

The storage system can be either a single battery [99] or hybrid including supercapacitor (SC)-BESS [100] and BESS-Flywheel [101]. The battery integrated into wind or PV power plants requires efficient control with the general structure as Fig. 3. The control objective is to regulate the output power in the presence of fluctuation in generation while the state of charge (SOC) of the battery varies in an acceptable range. A classic proportional control technique was proposed in [102], where the charging setpoint values for a large-scale BESS are updated if

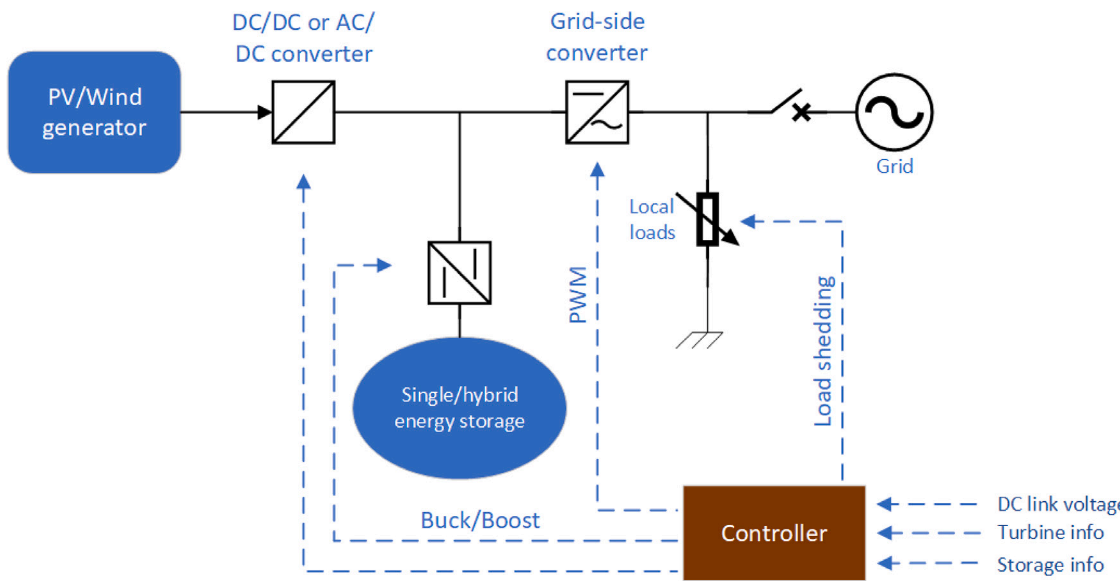

Fig. 3. Control of BESS in generation section.

the power fluctuation rate goes beyond a predefined threshold. A phase-lead compensator was proposed in [103] which tunes the rate of BESS charge based on the output power of the wind farm. If a prediction of the wind farm output power profile is available, control methods like model predictive control, can also provide an efficient BESS control for smoothing fluctuations [104,105]. Lakshminarayana et al. [106] proposed a Lyapunov optimization-based online algorithm to make decisions only on the current state of demand and renewable generation. In [107], an iterative Lyapunov real-time control was developed for the battery control in distribution grids. A hybrid control scheme based on neural networks (NNs) and a classical proportional-integral (PI) controller was proposed to improve the time response for a DC MG [108]. Singh et al. [109] presented an efficient (1 + TD) - tilt-integral-derivative (TID) cascade controller for frequency control in a MG. In the presence of uncertainties in the prediction of generated power, intelligent control approaches have also been applied to smoothing fluctuations. For example, parameters of a Kalman filter were updated in [110] using fuzzy control rules. Applying a recurrent fuzzy NN based power smoothing to a wind farm resulted in small fluctuations using an optimal BESS capacity [111]. A recent comprehensive review on WP smoothing techniques using BESS can be found in [112].

With the technological advancements, large-scale BESS can directly connect to the power grid and provide different services for grid stability, such as frequency and voltage support and power flow optimization. For example, the 100 MW Tesla battery, installed in South Australia in late 2017, has had successful frequency recovery performance since then.[2] A well-located BESS with the appropriate size is able to provide inertial and fast frequency response services to the grid if its operation is controlled intelligently [113]. A combined STATCOM/BESS setup could suppress oscillations in the Chinese grid by exchanging active/reactive power with the grid [114]. In all these applications, the size of the BESS and its control algorithm should be precisely matched.

2.5.2. BESS operation in power distribution grids

Reduction in the cost of BESS in recent years has been a motivation for electricity end-users to invest in batteries. This technology, if well matched with PV, can reduce electricity consumption by 60 to 80 per cent, which results in a significant electricity bill saving for consumers [115]. From this perspective, maximizing customer benefits by optimizing their return of investment as well as reducing their electricity bills is an objective of BESS operation in distribution grids [116]. However, the strategies that are in favor of only consumers may lead to a significant power export to the grid, resulting in voltage rise issues in some situations [117]. Therefore, another objective in any BESS operational activity is to control the voltage of the distribution grid. This can be done by either combining BESS and PV curtailment [118,119] or introducing appropriate tariff policies to promote self consumption [120]. Another approach is to apply smart control and scheduling algorithms on batteries to prevent over-voltage and perform peak shaving [121].

Control of BESS has been studied heavily in the context of MGs. A MG includes a set of generation and load units as well as ESSs, which can work in the island or grid-connected modes. Different hybrid generation/storage configurations have been studied in the literature such as PV/wind/fuel cell/battery [122] and PV/battery/hydro [123]. The control objective varies between frequency and voltage control and load shifting based on the operation mode of MGs.

3. Optimization methods

Optimization techniques can be classified into mathematical optimization (alternatively, mathematical programming) and AI-based optimization approaches (mainly computational intelligence-based optimization and RL-based methods) [124–128], as shown in Fig. 4. Mathematical optimization methods focus on the selection of the best solution based on some criteria from a set of available alternatives so that they work well for smooth unimodal problems, such as linear programming (LP), MIP, non-linear programming (NLP), DP, stochastic programming (SP), etc. AI-based optimization methods mainly refer to EAs, such as genetic algorithm (GA), differential evolution (DE), particle swarm optimization (PSO), etc., which use heuristic search as the local search to find the global optimum and are more suitable for the complex optimization problems, e.g., non-convex, nondifferentiable, or multi-modal problems. It also includes RL-based models, particularly DRL-based models developed using NNs, wherein optimization techniques primarily rely on gradient descent (GD)-based methods, such as deep Q-networks (DQN) [129].

[2] https://reneweconomy.com.au/tesla-big-battery-outsmarts-lumbering-coal-units-after-loy-yang-trips-70003/.

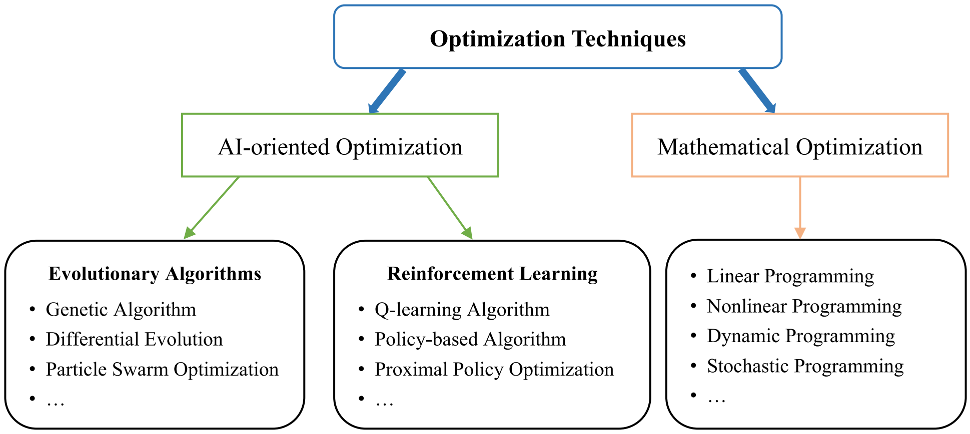

Fig. 4. Categorize of different optimization techniques.

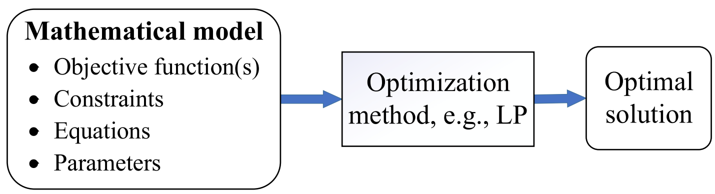

Fig. 5. The work process of mathematical methods.

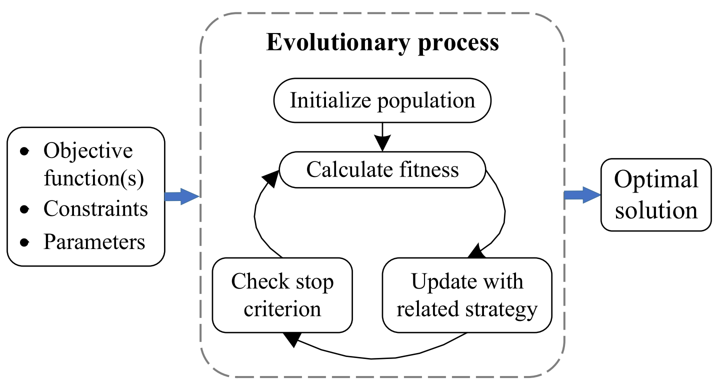

Fig. 6. The work process of EAs.

The workflow of mathematical optimization is shown in Fig. 5, where some mathematical descriptions are essential to obtain the optimization parameters. Also, each of them has its own usage in addressing optimization problems, e.g., LP mainly focuses on addressing linear optimization problems while robust optimization (RO) aims to the problems with uncertain parameters in a uncertainty set. Different from mathematical optimization, which starts the search with a single solution, EAs, illustrated in Fig. 6, are population-based approaches that do not require the problem to be mathematically formulated. This makes them suitable for problems that can or cannot be addressed using traditional mathematical (e.g., GD-based) approaches. They start with a population of randomly generated solutions and update with the related strategy in the employed algorithm, such as mutation, crossover, and selection in GA. Unlike mathematical optimization, almost each of them can solve all optimization problems. The other type of AI-based techniques, as described in Fig. 7, refers to RL-based methods, wherein an agent interacts with the environment, featured the state s^t, the action a^t, and the reward r^t at time stamp t. Unlike EAs, this type of AI-based methods requires an optimization approach, such as DQN to optimize the objective functions.

4. Optimization methods for BESS applications

In this section, we first introduce the core optimization tasks in BESS optimization problems. Then, we discuss BESS applications using mathematical programming and AI-based optimization.

4.1. Core optimization tasks in BESSs

The optimization in BESSs is mainly performed from the aspects of BESS operation in power generation, transmission, and distribution in the grids. BESS in power generation and transmission are mainly about services provided for voltage and frequency support of the grid [23,24,94,95], while in the distribution grid, scheduling, coordination, bidding, and control are of high interests [28,96,97,130]. In this context, the key optimization tasks consist of battery sizing and placement [81] and charging and discharging schedule for different operation purposes [78].

The optimized BESS location and capacity in distribution networks will not only increase operation benefit and reduce cost [82], but also promote technical benefits like improved power grid reliability and

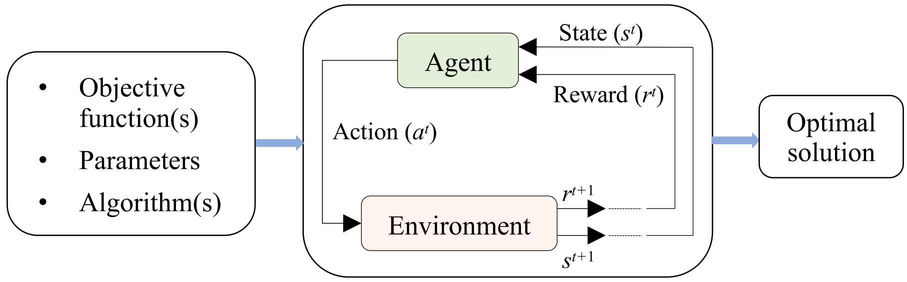

Fig. 7. The work process of RL-based methods.

security [83,131], frequency deviation reduction [84], voltage support [85], and peak load shifting and shaving [87]. The optimization objectives could be the annual total cost [88], levelized cost of electricity and storage [89], battery and unit LCC [90], and energy trading profit [91]. For example, a framework of BESS location and capacity definition was proposed [92] to minimize the power generation cost over every cycle of operation by peak load shifting with a fixed available storage budget. The study in [93] showed that the capabilities of the optimal allocation of BESSs significantly improve the supply quality of distribution networks in mitigating voltage deviations, eliminate line congestion, and minimize the total cost of BESS installation. The minimal capacity of BESS that can cover a maximum number of buses was obtained according to the location of PV and the penetration level of RESs, to solve the over-voltage and under-voltage issues in a distribution system [132]. Considering uncertainties in wind and PV power generation, the BESS placement problem was studied for a DSO to mitigate the transaction risk in a power market [133].

The charging/discharging scheduling problem aims to identify a charge/discharge/no-action timing for BESS to reduce the cost of stakeholders (e.g., consumers) [115,134,135], improve the frequency/voltage control[2] [113,114], adjust the market bidding behaviors [136–138], decrease the grid impacts [121], improve system reliability [139], improve the computational efficiency [140], maintain energy balance [9], achieve long-term battery operation [141], improve interaction and coordination among a variate of RESs [37], maximize the efficiency of energy stakeholders [142], enhance the usage of renewable energy [38], etc. Normally, the charging and discharging activities over the same battery cannot be active simultaneously during the same time slot. The significant electricity bill saving (60%−80%) for consumers [115,134,135] motivates the electricity end-users to invest in batteries. The benefits such as reduced maintenance and operation cost [143], the decreased peak load [144], the minimal potential series and peak-to-valley difference [145], lead to the increased application of grid-scale BESS. For example, the optimal time slots and the related amount of power for charging and discharging have been studied in [31,34,146–150] to obtain the maximal profit or minimal electricity cost. Except for optimizing battery schedule, the operation or parameters of PVs having batteries [151–153], power generations of RESs [84,154,155], and battery life lost cost [156], were also involved in the optimization tasks for economic, technical, or environmental benefits.

For both battery sizing/placement and scheduling optimization problems, the involved optimization tasks are not only limited to the battery itself, but also include penetrations of RESs as well as the optimization in the control systems.

4.2. Mathematical optimization in BESS applications

As illustrated in Fig. 4 in Section 3, mathematical optimization (programming) methods include approaches like LP, DP, MILP, or SP. LP has been mainly used for obtaining the optimal charging and discharging schedule [34,144,157], searching the optimal solutions of electricity price, feed-in tariff, and battery modeling parameters to reduce the overall cost [158], and EV charging rate [159]. In these tasks, the aims consist of flattening the peak load and reducing the cost (or energy bill) and BDC. One of the representative models is residential BESS integrated with PV [144,158], as shown in Fig. 8. The charging/discharging schedule over each 15-min for one day (T = 96) is optimized with the defined objective [144]:

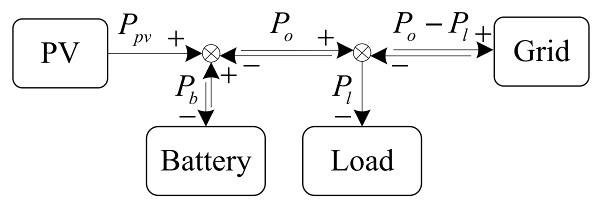

Fig. 8. The schematic of BESS integrated with PV.

$$\min \quad \sum_{t=1}^{T}(P_{lf}^t - P_o^t)\Delta t \tag{1}$$

$$s.t. \quad P_{lf}^t > 0, P_{lf}^t < P_{pf}^t \tag{2}$$

$$P_{pf}^t + P_b^t = P_o^t, \forall t \in \{1, \dots, T\} \tag{3}$$

$$P_b^{min} \le P_b^t \le P_b^{max} \tag{4}$$

where the left side of Eq. (3) can replace P_o^t in Eq. (1), P_{pf} and P_{lf} refers to the predicted PV power and customer's load, P_b^t represents the battery charging/discharging power (to be optimized) at time stamp t, P_b^{min} and P_b^{max} denote the minimal and maximal charging/discharging rate. Eq. (1) focuses on minimizing the net PV BESS output P_o level that falls below the customer's predicted load P_{lf}. The objective function and constraints from Eqs. (1)–(4) illustrate an LP problem. EV BESS is another important LP case [159]. To obtain the minimal cost over N EVs charging schedule $P_b^t, \forall t \in \{1, \dots, T\}$ in community area, the objective is formulated as:

$$\min \quad \sum_{t=1}^{T}\sum_{i=1}^{N}(Pr_t + \eta_c C_b)P_b^{t,i}\Delta t \tag{5}$$

where Pr_t is day-ahead electricity price at each time stamp, C_b is the BDC rate, η_c is the charging efficiency, $P_b^{t,i}$ is the ith EV charging rate at time stamp t, Δt is the time stamp (in hour). The constraints [159] are used to control the value of $P_b^{t,i}$ within the boundary, which are also linear.

For the model illustrated in Fig. 8, Atia et al. [147] considered the renewable energy from WTs, where mixed-integer decision variables such as PV, WT size (integer), BESS, inverter capacities, and the hourly power dispatch decisions are involved. MILP is applied to the problems having integers and continuous values [36,124,160]. C_b in Eq. (5) is a constant value, dynamically influenced by different temperature ranges [156,161]. Parameters such as state of health (SOH) and BDC [146,151], the fuel, operation and maintenance cost are the factors considered [162,163] in the model, resulting in a DP problem.

For example, in [151], the maximal economic benefit for the customer with BESS is formulated as:

$$\begin{aligned}
\max \quad & \sum_{t=1}^{T} C^t - B_c^t - B_a^t \qquad (6)\\
& B_c^t = \gamma_c P_b^t \Delta t, if \ P_b^t > 0, \gamma_c = \frac{C_{im}}{E_l}\\
& \Delta SOH = aSOC^2 + bSOC + c\\
& B_a^t = \gamma_a \Delta SOH^t E \Delta t, \gamma_a = \frac{C_{im}}{E - E_{eol}}
\end{aligned}$$

where C_{im} is the investment and maintenance cost, E_l is the battery lifetime, E is the nominal capacity, E_{eol} denotes the end of life capacity, C^t represents the cost that is linear with battery power schedule P_b^t, B_c^t and B_a^t denote the BDC due to cycling (when $P_b^t \neq 0$) and calendrical aging (when $P_b^t = 0$), respectively. The uncertainties in B_c^t and B_a^t and the non-linear constraints lead to the applications of DP or stochastic dynamic programming (SDP).

Another method that resists uncertainties is RO, which mainly focuses on addressing the problems that involve the uncertainties caused by renewable energy [164–167]. To against the power disturbance due to inaccuracies in prediction and fluctuations in WP and load, Zhang et al. [167] proposed a day-ahead dispatch optimization approach aimed at obtaining the minimal operation costs:

$$\begin{aligned}
\min \quad & \sum_{t=1}^{T} C_G^t + C_S^t + C_{W,cur}^t \qquad (7)\\
& C_G^t = \sum_{i=1}^{M} (C_{G,b}^{t,i} + C_{G,e}^{t,i} + C_{G,op}^{t,i} + C_{G,SFR}^{t,i} + C_{G,DPR}^{t,i})\\
& C_S^t = C_{S,FFR}^t + C_{S,PFR}^t + C_{S,SFR}^t + C_{S,op}^t\\
& C_{W,cur}^t = c_W (P_{W,act}^t - P_W^t)\Delta t\\
s.t. \quad & \sum_{i=1}^{M} P_G^{t,i} + P_{S,dis}^t - P_{S,ch}^t + P_W^t = P_l^t\\
& \sum_{i=1}^{M} (u^{t,i} P_{S,max}^t - P_G^{t,i}) + (P_{S,max} - P_{S,dis}^t + P_{S,ch}^t) > 8\% P_l^t
\end{aligned}$$

where C_G^t and C_S^t denote the operational expenses associated with conventional units and a large scale (LS) BESS, respectively, while $C_{W,cur}^t$ is the WP curtailment cost at time stamp t. M represents the number of conventional units. At time stamp t, $C_{G,b}^{t,i}$, $C_{G,e}^{t,i}$, $C_{G,op}^{t,i}$, $C_{G,SFR}^{t,i}$, and $C_{G,DPR}^{t,i}$ describe the startup, shutdown, power production, reserved secondary frequency regulation (SFR), and deep peak regulation (DPR) cost in unit i. $C_{S,FFR}^t$, $C_{S,PFR}^t$, and $C_{S,SFR}^t$ denote reserved space expenses for the LS-BESS in fast frequency regulation (FFR), primary frequency response (PFR), and SFR at time slot t, respectively. The unit operation expense of LS-BESS and the unit cost of WP curtailment are represented by $C_{S,op}^t$ and c_w, respectively. P_W^t denotes WP exported to grids. $P_{W,act}^t$ is the actual WP, which is also the uncertain factor, deciding the uncertainty set for the budget related to WP output due to the prediction value and error.

Unlike the above-mentioned cases, some formulated objective functions or the related constraints may be quadratic [168,169], such as:

$$\min \quad \alpha \Delta U_{\mathrm{rms}}^{\mathrm{peak}^2} + (1-\alpha) S_{\mathrm{rms}}^{\mathrm{peak}^2} \qquad (8)$$

$$U_{\mathrm{rms}}^{\mathrm{peak}^2} = \frac{1}{n_d} \sum_{d=1}^{n_d} \max_{\substack{k \in \mathcal{K}_d, h \in \mathcal{H}_m\\ p \in \{1,2,3\}}} (|U_{p.h.k}| - U_{\mathrm{norm}})^2 \qquad (9)$$

$$S_{\mathrm{rms}}^{\mathrm{peak}^2} = \frac{1}{n_d} \sum_{d=1}^{n_d} \max_{\substack{k \in \mathcal{K}_d,\\ p \in \{1,2,3\}}} |S_{p,k}^{\mathrm{tot}}|^2 \qquad (10)$$

$$S_{p,k}^{\mathrm{tot}} = P_{p,k}^{\mathrm{inv}} + jQ_{p,k}^{\mathrm{inv}} + \sum_{h \in \mathcal{H}_p} P_{h,k}$$

where $\alpha \in [0,1]$, $U_{\mathrm{rms}}^{\mathrm{peak}}$ and $S_{\mathrm{rms}}^{\mathrm{peak}}$ represent the voltage regulation and peak shaving over the decision variables like the nominal battery capacity, the nominal inverter power, the DC-link nominal power, the inverter active, the battery effective capacity, reactive power set points at each time slot and phase. $|U_{p.h.k}|$ is the complex line-to-neutral voltage in house, U_{norm} represents the nominal grid voltage, n_d is the number of investigated days, $\mathcal{K}_d$ denotes time steps in day d, $P_{h,k}$ represents the load profile of house h, $\mathcal{H}_m$ represents the set of houses associated with the pth phase. Eqs. (9) and (10) lead to a quadratic optimization problem as Eq. (8), where quadratic programming (QP) is required.

4.3. AI-based optimization in BESS applications

4.3.1. EAs in BESS applications

With the development of battery systems and renewable energy penetration, BESS optimization problems have become more complex, e.g., discontinuous, non-differentiable, stochastic, or having highly non-linear objective functions and constraints. This motivates the application of AI-based optimization methods such as GA [148,170], DE [171], and PSO [156] in this domain. These approaches can solve the problems not only solvable by mathematical programming, but also that mathematical programming is unable to solve. For example, to evaluate an optimum size of BESS (power P/MW and capacity E/MWh) for the stand-alone MG in [84], the objective function is formulated as:

$$\begin{aligned}
\min \quad & \alpha(f_1 + f_2) \qquad (11)\\
& f_1 = P\\
& f_2 = C_p P + C_W E + C_{Mf} P + W_a C_{im}
\end{aligned}$$

where f_1 and f_2 represent the size and the total cost of BESS, respectively. They are combined into one single objective with the same weight α. C_p (\$/MW), C_W (\$/MWh), and C_{Mf} (\$/MW/year) are battery specific power cost, capacity cost, and fixed cost. W_a (MWh/year) is the annual discharge energy. PSO was applied to address the linear optimization problem in Eq. (11), which can be addressed by LP as well. Considering the advantages of AI-based techniques, GA has been applied to obtain the optimal PV battery systems such as battery capacity and solar panel size [153,170,172], and energy management strategies [148]. Similar to the PV system in Fig. 8, the benefit of a grid-connected residential power system [148] over the optimal energy schedule (the discharge ratio) for a specified period $[t_0, t_f]$ is formulated as:

$$\begin{aligned}
\max \quad & \int_{t=t_0}^{t_f} (C_{sell}^t - C^t + C_{sub}^t)\, dt \qquad (12)\\
& C_{sell}^t = (P_{pv}^t - P_l^t)\omega_t C_0\\
& C^t = P_g^t P_{r_t}, C_{sub}^t = P_{pv}^t P_{r_p}\\
s.t. \quad & P_g^t + P_{pv}^t + P_b^t - P_n^t - P_l^t = 0\\
& (P_{pv}^t - P_l^t)(1-\omega_t) + P_b^t = 0\\
& (P_{pv}^t - P_l^t)\omega_t - P_n^t = 0, 0 \le \omega_t \le 1
\end{aligned}$$

where C_{sell}^t and C_{sub}^t represent electricity sale income and government subsidy. ω_t is the dispatch ratio to be optimized. C_0 and P_{r_p} are the benchmarking and subsidy price of PV generation. P_g^t is the electricity purchased from grid. This non-linear optimization problem is addressed by GA.

Specifically, BESS optimization problems always involve more than one conflicting objectives to balance benefits from different stakeholders including customers, SG, the system controller, or the distribution network. Even though some existing works have considered two or more objective functions [84,150,161,171,173], they were transformed into an SOO problem with weight α. For example, given two objectives f_1 and f_2, they can be converted to an SOO with a weight value $\alpha, \alpha \in [0,1]$ [168,169] so that the only objective function $f = \alpha f_1 + (1-\alpha) f_2$. Kerdphol et al. [84] is an example where the objective has same weight, i.e., $\alpha = 0.5$.

AI-based MOO has been widely applied to battery sizing [174], and battery energy scheduling in the PV system [175] and EVs [145,176] with multiple objective functions. Instead of providing one optimal solution over objectives, MOO generates multiple Pareto-optimal solutions, all of which are feasible solutions [177]. Even though MILP has been applied to MOO scenarios [150,178], it is only limited to LP problems. For example, in [145], to obtain the optimal load scheduling for EVs, the load stabilizing function and power fluctuation elimination (f_1) and revenue loss (f_2) are formulated as follows:

$$\min \quad f_1 = \alpha L/L' + (1-\alpha)P/P' \tag{13}$$

$$L = \sum_{t=1}^{24}(P_b^t + \sum_{i=1}^{M} P_i^t - \sum_{t=1}^{24} P_b^t/24)^2$$

$$L' = \sum_{t=1}^{24}(P_b^t - \sum_{t=1}^{24} P_b^t/24)^2$$

$$P = \max_{1\le t\le 24}(P_b^t + \sum_{i=1}^{M} P_i^t) - \min_{1\le t\le 24}(P_b^t + \sum_{i=1}^{M} P_i^t)$$

$$P' = \max_{1\le t\le 24}(P_b^t) - \min_{1\le t\le 24}(P_b^t)$$

$$\min \quad f_2 = \sum_{t=t_1}^{t_2} P_b^t \cdot P_{r_t} - \sum_{t'=t_3}^{t_4} P_b^{t'} \cdot P_{r_{t'}} \Delta + C \tag{14}$$

where M represents the number of charging piles, Δ is the discount made by the supplier of electricity to attract users to join their scheduling plan. Considering the complexity of this problem, this optimization problem including f_1 and f_2 is solved by multi-objective PSO (MOPSO). The modeling of BESS optimization is not limited to the aforementioned cases. With the increased penetration of RESs, EVs, electric buses, and other inverter-based devices, the BESS system is becoming more complex, where more advanced techniques are required to be developed.

4.3.2. RL-based methods in BESS applications

With the increasing uncertainties of load and renewable energy generation [179], WP generation [9], multiple deferrable demands during joint energy schedule [128], community energy-sharing [180], energy arbitrage [26], RL [128] and DRL [181] based methods have been designed and used to find the optimal energy storage scheduling strategies. Since these methods mainly focus on maximizing the rewards and agents between states and actions in a dynamic and uncertain environment, the objective functions or reward formulations include maximization of BESS reliability [141], the reward (profit) [182], operation profit [26], and minimization of electricity cost [183], etc. Among these applications, Markov decision process (MDP) [37] was a popular method to formulate the sequential decision process of battery charging and discharging over a specified period T, which were often addressed by twin delayed deep deterministic policy gradient (TD3) [179], proximal policy optimization (PPO) [184], Q-learning algorithm [26], policy-based algorithm [142], DQN [129], etc.

Specifically, some algorithm like DQN is developed based on GD. One of the representative DRL-based models is a MG power system integrated WP [9]. Similar to the diagram in Fig. 8, where the renewable energy, i.e., PV power, is replaced by WP generation. To obtain the optimal BESS charging and discharging schedule, the maximal system benefits, i.e., the minimal cost, is defined as:

$$\min \sum_{t=1}^{T} C_g^t + C_{op}^t \tag{15}$$

$$C_g^t = Pr_t \times P_g^t = Pr_t \times (P_l^t - P_{wp}^t + P_b^t) \tag{16}$$

$$C_{op}^t = k \times |SOC^{t+1} - SOC^t| \times E \tag{17}$$

where C_{op}^t describes the operation cost. P_g^t and P_{wp}^t represent the power exported from grid and the WP generation at time slot t, respectively. As mentioned above, at each time stamp t, the BESS can only have one action regarding charging or discharging, so that SOC and the cost coefficient k can be formulated as:

$$SOC^{t+1} = \begin{cases} SOC^t + \frac{a^t \times P \times \eta_c \times \Delta t}{E} & a^t \ge 0 \\ SOC^t + \frac{a^t \times P \times \Delta t}{E \times \eta_d} & a^t < 0 \end{cases} \tag{18}$$

$$k = \frac{C_{im}}{\eta_d \times E \times \delta \times N_c} \tag{19}$$

where a^t is the action coefficient of BESS, and η_d is the discharging efficiency. δ and N_c denote the depth of discharge (DOD) and the life cycle at rated DOD, respectively. P_c^t, P_d^t, and SOC^t should not exceed the maximal value and lower than the minimal threshold of each item. Different from mathematical and EA-based optimization models, DRL-based models require outside environmental information for BESS charging and discharging actions over different states. The dynamic of BESS is formulated as a MDP, so that the agent in DRL can interact with environment, where MDP is featured with state space $\mathcal{S}$, action space $\mathcal{A}$, and reward R measured hourly over time period T. The state and action spaces in MDP can be expressed as:

$$s^t \in \mathcal{S} = \{P_t^l, P_{wp}^t, P_{pi}^t, Pr_t, Pr_t^{avg}, SOC^t\} \tag{20}$$

$$a^t \in \mathcal{A} = \{-1, -0.8, \dots, 0.8, 1\} \tag{21}$$

P_{pi}^t is the WP prediction intervals using a real-time forecasting model. Pr_t^{avg} represents the average electricity price over the past T period. a^t consists of a number of charging or discharging actions, where each time slot t has an action. The positive value denotes charging activity while negative represents discharging action in BESSs. After each performed action, the BESS dynamics can be updated via:

$$E^{t+1} = \begin{cases} E^t + \eta_c \times a^t & a^t > 0 \\ E^t + \frac{a^t}{\eta_d} & a^t < 0 \end{cases} \tag{22}$$

where E^t is the electromotive force at time slot t. An efficient reward is formulated for obtaining the meaningful actions from agent according to the environment for minimizing the cost of the MG, as shown in Eq. (23).

$$r(s^t|a^t) = -(\omega_1 \times C_g^t + \omega_2 \times C_{op}^t + \omega_3 \times Pnt_{SOC}^t + \omega_4 \times Pnt_{wp}^t + \omega_5 \times Pnt_{res}^t) \tag{23}$$

where $\omega_i, i \in \{1, 2, \dots, 5\}$ denotes the coefficient of each item. Pnt_{SOC}^t, Pnt_{wp}^t, and Pnt_{res}^t illustrate the penaties of the over-limit BESS capacity, not sharing excess WP, and emergency reserve, respectively, all of which are related to the BESS SOC^t. DQN is considered to address this problem after the MDP of energy storage management problem is defined.

With the increasing penetration of RESs such as MTs, WTs, and PV systems, the generation of renewable energy [156] involves more complex processes, e.g., non-linear, quadratic, dynamic and uncertain models, resulting in the non-linear or indifferentiable optimization problems that cannot be addressed by the traditional techniques. Also, the levels of RESs penetration require different BESS sizes and scheduling by considering complex dynamic frequency control problems [60] for grid-level BESSs. Since most BESS charging and discharging optimization is based on simulation rather than the real LV network, verifying the voltage/frequency control of the optimization results poses another challenge [77]. Moreover, considering the electricity price model [185] that is a quadratic function changing with the real-time load demand, leads to more complex optimization such as multi-modal optimization when considering the total cost as the objective function. Additionally, the growing number of EVs and electric buses results in large-scale charging/discharging problems, which require optimal coordinated scheduling to reduce the negative impact on the power grid and the transmission line. The dynamics and uncertainties caused by renewable energy generation, which heavily relies on weather conditions, lead to significant unpredictability in RESs. As a result, the optimization of BESSs across each investigated state becomes less accurate. Such problems require the development of advanced AI-based optimization methods.

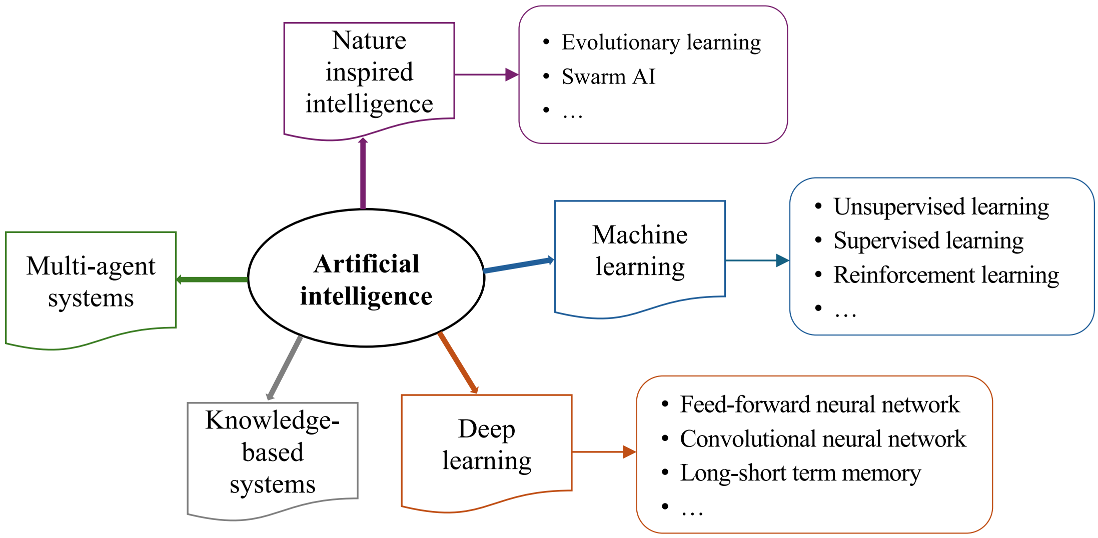

Fig. 9. Brief categories of future AI developments.

5. Future opportunities and challenges

5.1. Outlooks in BESS operation

The vigorous developments of clean energy suppress the environmental pollution caused by fossil fuels, attracting more attention of the research community around various research related to BESS, from battery material development to battery sizing, placement, and scheduling. Some of the important challenges resulting from high uptake of RES and BESS in power grids are as follows:

- The ESS design consists of integrating technical and theoretical feasibilities of the system and achieving the aims of less environmental impact, higher engineering economy, and safety.
- Increasing residential BESS with a PV system, WTs, and EVs leads to more uncertainties in the power scheduling and distribution and requires a more flexible energy scheduling system that can adaptively manage the power and maintain the reliability and stability of the SG, especially when the weather changes significantly.
- Considering the economic and environmental benefits of RESs, larger communities can be fully covered by RESs, which will motivate further technical deployment of large-scale BESSs. The increasing number of objective functions and constraints is another challenge. Advanced optimization methods need to be developed and applied to BESS sizing problems so that promising outcomes from cost, capacity, power loss, power quality improvement, and carbon emission can be achieved.
- The scheduling activities can lead to voltage and frequency rise that may violate the allowable limits, and extra power flows from the distribution system to the transmission system. More attention should be paid to the LV network simulation with BESS for frequency or voltage control and network stability [60].
- The increasing of EV charging and discharging scheduling coordinated with RESs and energy consumption may result in the development of techniques to enhance the overall power system reliability and flexibility [186].
- Increased uptake of various types of RESs will further motivate the improvement of current power transformation systems and power system reliability [187,188]. Also, it refines the energy transmission mechanism within the distribution network and the control system of the wayside ESS. For instance, considering the variations in impedance across the power supply network with distance, it is essential to modify the wayside ESS control model to be a dynamic voltage and current model, which will motivate the development and application of non-wire alternatives by managing the peak-load [189,190].
- The increasing penetration of RESs will lead to a significant reduction in power generation from traditional fossil fused based resources. Since meteorology is the core factor that will influence the RES output power and the demand is always fluctuating, to achieve a more stable system, some predictive strategy that integrates with optimization-based control should be considered. Also, since many RESs are noncontinuous, power quality issues should be considered in the related problem formulation.

5.2. Outlooks for AI-empowered optimization applied to BESSs

The development of future AI is briefly illustrated in Fig. 9. The increasing complexities of real-world clustering, classification, regression, and feature engineering problems will motivate innovations in machine learning techniques. The disadvantages of existing non-explainable AI and the development of big data contribute to future directions of deep learning. The increasing number of constraints, objective functions, decision variables, and parameters in practical multi-modal, non-linear, or non-differentiable optimization problems inspires the improvements of intelligent optimization methods. The growing complexity and difficulties of problems that are impossible to be addressed by the individual agent will motivate the enhancement of the existing multi-agent systems. As the traditional AI, knowledge-based systems still have some advantages in solving real-world problems and deserve further development in the future [191]. The categories are not independent of others, and some may have interactions or overlaps.

The applications of BESS will benefit from AI-based optimization techniques in the following aspects:

- The RESs can provide customers with a variety of loads such as unbalanced, non-linear, and pulse loads [192]. The BESS configured for such load patterns may exhibit inadequate dynamic responsiveness and suffer from reduced battery lifetimes. AI-based optimization methods can offer accurate contextual solutions in such scenarios with high-quality electricity and enhance the longevity of BESSs.
- The increasing penetration of RESs will significantly reduce reliance on generation from traditional fossil flues. However, since renewable energy is highly dependent on climate information and future severe weather events are not always accurately predictable, this will require high-performance AI-based optimization to schedule the power optimally.

- Even though various optimization methods have been developed for different application examples, with the increasing of RESs penetration [193–195] in people's daily lives, BESSs have become more complex, and the research challenges arising from battery storage, battery life, cost from different stakeholders, impacts on the distribution network, and grid network are urgent to be resolved.
- The conflicting benefits from different aspects require more suitable MOO methods to balance the trade-offs. With the increase of BESSs installed and increased uptake of EVs, one will have more decision variables in the optimization, resulting in increased difficulties in BESS optimization. The approaches that can address large-scale optimization problems, especially for MOO problems (MOOPs), must be developed.

5.3. Challenges of future BESSs

RESs bring significant economic and environmental benefits, especially when integrating with BESS. However, there are a number of challenges with the increasing number of BESSs.

- As shown in [120], the increasing penetration of BESS brings new challenges to the electricity price and tariff structures to balance the benefits for different stakeholders while maintaining the stability and reliability of the power grid.
- Discharging activity can benefit the EV customers and households with PV systems, but it impacts the battery lifetime [159]. Frequent discharging will lead to quick battery degradation; one has to make a trade-off between battery life and the discharging profits. An MOO setting is the best to address this issue. Also, this will cause another problem of how to recycle the batteries and reduce the environmental impact.
- EV charging and discharging scheduling will result in additional challenges within power grids. With the growing adoption of EVs and RESs such as PVs and WP in SGs, there is an increasing need for accurate predictions and joint scheduling optimization to improve system stability and reliability.
- Variability and uncertainty of both generation and loads in the distribution grids are big challenges that severely impact optimal control and scheduling algorithms. This will consist of RO, predictive models, and integrating forecasting algorithms into control systems to reduce the level of uncertainty, but both of them matter for further research, especially considering different generation and storage technologies in MGs.
- With the increased rollout of smart meters, consumption/export data from presumes are becoming available, which indeed paves the way towards data-driven control and optimization approaches.
- Fast charging infrastructure improves the EV charging efficiency, but how the charging speed can be maximally improved with minimal impact on the battery life is still an issue to be further investigated.
- Some well-known barriers to ESSs include technological maturity, cycle efficiency, and the associated capital, operating, and maintenance expenses. Due to the increasing penetration level of RESs, the balancing and power quality requirements that focus on non-dispatchable and intermittent RESs are varying. In fact, only storing energy cannot address the challenges arising from renewable energy integration. This has been investigated and studied by the existing works, which show that involving energy curtailment or DR leads to growing RESs utilization as well as more grid stability support.

5.4. Impact of emerging technologies on optimization in BESSs

With the widespread usage of IoT in SG management, EVs, and e-buses, the energy demand efficiency and fast system response will keep increasing. The growing complexity of the system leads to more challenges for the traditional control models to detect the faults or failures in a short response time so that the optimal decision may not be made as quickly as possible. Also, if the system works in low intelligence scenarios, the operator will have more workload, which might lead to incorrect operation and further security risks. Reliable AI-based optimization algorithms and models from machine learning can accurately capture the environmental features and make the optimal decision of BESS based on renewable energy generation, load fluctuation, and the events that may happen to manage the whole system.

The promising performance of AI techniques has led to different types of real-world applications, especially in optimization, learning, and analyzing. As illustrated in Section 5.2, the AI-based optimization and its improvement will significantly contribute to BESS optimization. Also, AI-based machine learning models have outstanding performance, which will contribute to the prediction tasks in BESS operation. The applications of the aforementioned technologies are not limited to existing focuses. Even though AI has addressed many aspects of BESS such as its development and management, the research gaps include developing mathematical and physical-based models, degradation mechanism analysis, large-scale battery design and optimization, failure or fault detection, and prediction [196]. Moreover, from the development of new materials, the traditional approach may take 20–30 years to discover new materials and then apply them to practical scenarios. When using AI to find new materials, the database provided by research contains a variety of materials data, such as electronegativity, first ionization energy, chemical bond energy, and unit cell parameters. AI can help analyze these data and find useful patterns, which will reduce the time for the development of battery materials.

The increasing penetration of renewable energy and BESS lead to more data to be collected, preprocessed, and analyzed. The recordings of smart meters often vary from 5 min to 1 h, resulting in the usage of big data analytics, e.g., cloud-based platforms to manage the data. Big data analytics can contribute to power grids since it can provide important insights into how energy storage assets perform and influence electricity markets. Due to this, the operators can make informed decisions and predict the battery life to optimize the operation process. Also, the battery data can contribute to monitoring the battery performance and help maximize the investment so that operation and maintenance costs can be reduced. Moreover, with more EVs and PV systems, the development of big data contributes to the optimization, modeling, and analysis tasks in BESS from testing the data-driven models and accurate power grid operation, leading to more reliability and safety criteria of energy storage technologies [197].

6. Conclusions

In this manuscript, we have provided a survey of recent advancements in optimization methodologies applied to design, planning, and control problems in battery energy storage system (BESS) optimization. We first briefly introduced the BESS operation, which consists of the battery types, technology, and the operation in the power distribution grid. Then, the optimization methods were introduced, and the difference between mathematical programming and AI-based optimization techniques was discussed. We detailed the core optimization tasks in BESS optimization and summarized the optimization models for addressing this problem over different scenarios. Moreover, we pointed out the advantages of AI-based optimization methods and their potential contributions to the future BESS optimization problem. We also gave some future opportunities and challenges for the BESS operation, the issue of BESS, and the impact of new technologies on BESS optimization. In the future, we will focus on the challenges and potential research opportunities mentioned in Section 5.

CRediT authorship contribution statement

Hui Song: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Chen Liu:** Conceptualization, Investigation, Writing – review & editing, Writing – original draft. **Ali Moradi Amani:** Investigation, Writing – original draft, Writing – review & editing. **Mingchen Gu:** Investigation, Writing – review & editing. **Mahdi Jalili:** Funding acquisition, Investigation, Project administration, Writing – review & editing, Supervision. **Lasantha Meegahapola:** Funding acquisition, Investigation, Project administration, Writing – review & editing, Supervision. **Xinghuo Yu:** Funding acquisition, Supervision, Validation, Writing – review & editing. **George Dickeson:** Validation, Writing – review & editing.

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

Data will be made available on request.

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