Archives of Computational Methods in Engineering
https://doi.org/10.1007/s11831-023-10046-7

REVIEW ARTICLE

Computation and Optimization of BESS in the Modeling of Renewable Energy Based Framework

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Received: 18 October 2023 / Accepted: 28 November 2023

Abstract
Incorporating Battery Energy Storage Systems (BESS) into renewable energy configurations offers numerous apparent advantages. Nonetheless, to fully capitalize on these advantages, it is imperative to implement management strategies that facilitate optimal system performance. Various approaches and methods can be employed to optimize the functionality of BESS within renewable energy systems (RES), encompassing specific dispatch goals as well as financial, technical, or hybrid objectives. These optimization methods are categorized into three primary groups: directed search-based (DSB), probabilistic, and rule-based strategies. Historically, research has heavily focused on tailoring systems based on the renewable energy sources for specific purposes, such as distributed generation (DG). This investigation not only offers a comprehensive overview of battery management measures but also assesses these endeavors in terms of their alignment with application objectives and the chosen optimization strategy. This approach unveils connections between distinct optimization goals and preferred strategies. The findings reveal that DSB approaches and control strategies, commonly employed for technical objectives, are more likely to succeed in addressing financial goals. Moreover, the extent to which a problem can be analytically defined emerges as a critical consideration. Upon comparing the merits and demerits of different reported optimization methodologies, it becomes evident that hybrid approaches, amalgamating the strengths of various optimization techniques, will increasingly shape future operational procedures. This study not only equips researchers with valuable insights into viable optimization strategies for forthcoming generation applications but also provides a cutting-edge overview of battery applications and optimization techniques.

Keywords Battery · Modeling · Optimization · Renewable Energy

Abbreviations

ADALINE	Adaptive Linear Neuron
ADP	Approximate Dynamic Programming
AI	Artificial Intelligence
BEMS	Battery Energy Management Systems
BMS	Battery Management Systems
CAES	Compressed Air Energy Storage
DR	Demand Response
ESS	Energy Storage Systems
EV	Electric Vehicle
FLC	Fuzzy Logic Controller
GA	Genetic Algorithms
GAMS	General Algebraic Modelling System
HESS	Hybrid ESS
HH	Hyper-Heuristic
HRES	Hybrid Renewable Energy System
IP	Integer Programming
LP	Linear Programming
MILP	Mixed-Integer Linear Programming
ML	Machine Learning
MPC	Model Predictive Control
NaS	Sodium-Sulfur
NLP	Nonlinear Programming
NSGA	Non-Dominated Sorting Genetic Algorithm
OLTC	On-Load Tap Changers
PSO	Particle Swarm Optimization
PV	Photovoltaic
QP	Quadratic Programming
RC	Resistor–Capacitor
SDP	Stochastic Dynamic Programming

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1 Introduction

Battery energy storage systems (BESS), commonly referred to as BESS, have become increasingly integral within contemporary electric power systems. Their importance originates from their distinctive capacity to manage the sporadic characteristics of renewable energy sources, offer technical assistance to power networks, and play a role in the advancement of intelligent grids [1, 2]. BESS has undergone extensive scrutiny across a spectrum of RES to enhance the integration of renewable energy. These cover a wide range of scales, spanning from small-scale distributed renewable sources [3] and micro-grids [4] to extensive independent HRES [5] and large-scale plants [6]. Furthermore, battery storage is increasingly being adopted for a range of essential functions within electricity grids [7, 8], including addressing overloading in the transmission network [9], assisting in maintaining stable voltage and frequency, and postponing the necessity for upgrades to the transmission network [1].

Despite its pivotal role in managing renewable energy intermittency, the broader adoption of BESS faces a significant hurdle: the relatively high investment costs associated with these systems [10]. This challenge persists despite batteries being recognized as among the most effective solutions for addressing the variability of renewable energy sources. Another key concern revolves around the operational lifespan of the battery, raising questions about maximizing its utility throughout its functional span. This issue highlights the importance of optimizing battery size, an area previously examined in-depth by the authors [11]. The current study builds on this sizing exploration by delving into systems with pre-determined battery capacities.

A paramount consideration is the specific application of BESS, which significantly shapes the intended functioning of these systems. Accordingly, the selection of the application target holds immense significance. Therefore, the review extensively investigates battery optimization, emphasizing the anticipated roles batteries must fulfill and exploring effective management strategies. This scrutiny centers on delineating the required functionalities of batteries within different applications and assessing potential approaches for their efficient management.

Lately, there has been a notable increase in the number of research articles and evaluations focused on ESS or BESS, each concentrating on particular facets. Several of these inquiries explore synopses of BESS technology on a substantial scale [2, 12], systems for managing batteries [13, 14], thorough examinations of costs over the lifespan and complex models for battery expenses [15, 16], in addition to regulations related to energy storage [17]. Earlier studies exploring battery optimization have explored various renewable energy frameworks, including distributed energy systems, microgrids, and extensive RES installations, among others. In each of these contexts, battery storage emerged as a crucial component. For example, a thorough examination was undertaken on diverse ESS to enhance the utilization of wind power [18]. This analysis sought to accomplish objectives such as reducing fluctuations, regulating voltage, mitigating oscillations, tracking loads, and similar goals. Additional research [19] concentrated specifically on ESS in the context of integrating wind power. This study not only identified appropriate ESS technologies but also delved into the complexities associated with designing, operating, and controlling wind power installations. Furthermore, there are assessments that particularly focus on specific functionalities, like the regulation of power output fluctuations in wind farms [20, 21] and solar power plants [22], along with the utilization of batteries for maintaining frequency stability in contemporary electrical grids [23]. These focused review articles offer the advantage of delivering more precise summaries within their specific scope. Nonetheless, they might not offer a comprehensive depiction of the extensive array of conceivable BESS applications. Recognition should be given to the fact that there are evaluations specifically centered on BMS [24], with the goal of improving control and management at a more foundational level of battery cells. Nonetheless, this isn't the primary emphasis of the current research. Additionally, it's important to acknowledge that there are reviews with a primary focus on BMS.

Furthermore, in addition to comprehensive evaluations at a large scale, the functionality of distributed energy systems has also been extensively addressed. This comprehensive exploration of applications includes an in-depth analysis of BESS in residential solar PV systems, as outlined in the reference provided [25]. This reference underscores the economic viability of utilizing BESS in this context. Similarly, other research works have summarized the implementation of ESS for PV based DG, with a primary focus on the advancement of BESS technology [3] and optimization strategies [26].

Moreover, the concept of HESS, particularly the integration of batteries and supercapacitors, has garnered significant attention due to their complementary attributes. Extensive research has been conducted on microgrids [27], specifically concentrating on the applicability of HESS. A separate examination of HESS has also been conducted, exploring its relevance not only to the smart grid but also to other applications like electric vehicles [28]. Recent studies have delved into optimizing aged EV batteries and virtual power plants [29, 30]. However, it's important to note that while this review touches upon optimization objectives and methodologies for HESS and virtual power plants, the unique considerations associated with the operation of HESS.

The mentioned review articles possess a common characteristic: each concentrates its attention in a separate energy setup or the application of ESS and BESS. However, there are still ongoing debates about the core purpose of integrating batteries with RES and the rationale for selecting particular models or strategies to enhance battery performance. This assessment aims to address these inquiries by amalgamating operational objectives and testing approaches from various battery evaluations.

The main aim of this study is to illuminate on the intricate connections between different BESS modeling techniques, the specific optimization goals chosen, and the preferred methodologies adopted to tackle the associated challenges. It is evident that the nature of the BESS application and its complexity significantly influence the selection of appropriate BESS modeling approaches. Moreover, the integration of battery deterioration impacts into the modeling procedure heavily relies on the intended goals of the BESS application and the extent of battery usage. This examination also encompasses an exploration of the underlying relationship between the chosen optimization goals and the recommended BESS optimization strategies, which is a pivotal aspect of this review. This is because particular optimization strategies are developed or selected with the purpose of addressing predefined issues.

Recent reviews have been published, concentrating on the wider uses of BESS. To emphasize the applications of versatile ESS in integrating renewable energy sources, a comprehensive summary was conducted. This summary was organized based on various storage technologies, including batteries, hydroelectric pumped storage, compressed air energy storage, magnetic storage, and also biomass and gas storage [31]. Nevertheless, this method renders the task of pinpointing shared objectives and resolutions among ESS applications difficult, even though it streamlines the process of comparing technologies. Another summary involving bibliometric analysis yielded intriguing insights into BESS integration. While survey-based methods offer statistical insights, they may not always uncover deeper underlying insights. Reference [32] provided an evaluation of the existing literature, focusing on diverse technologies and their roles in grid sustainability and renewable energy integration. Yet, it did not cover the crucial battery optimization process.

This study offers a comprehensive summary of specific BESS applications, categorized by modeling approaches, application targets, and optimization methodologies. Additionally, it includes a discussion of the fundamental connections between BESS optimization goals, approaches, and battery energy management advancements. Notably, this study concentrates on BESS and ESS within predetermined capacity RES. The following sections outline the structure of this review: Sect. 2 provides an explanation of the three-layer BESS architecture. Section 3 discusses BESS modeling techniques, while Sect. 4 summarizes various BESS applications for financial, technical, and hybrid purposes across diverse RES. Section 5 offers conclusions based on the findings presented. Section 6 delves into insights gained, and finally, Sect. 7 concludes with general remarks.

2 The Operational Structure of BESS in RES

A diverse array of BESS objectives exists, involving battery optimization to achieve the best possible economic results encompassing battery optimization for attaining optimal economic outcomes, battery power regulation to adhere to specific performance benchmarks, and battery current and voltage management to ensure consistent outcomes within renewable energy systems. As an illustration, battery optimization can be harnessed to achieve the most favorable economic results. In the realm of microgrid research [33, 34], frequently involving the integration of battery storage, a widely adopted hierarchy with three control layers is prevalent. Positioned at the foundational layer, primary control primarily focuses on the fundamental control aspects of converters. On the other hand, the uppermost layer, known as tertiary control, serves as an intermediary connecting the primary control layer with the tertiary control layer.

This collection of research introduces a similar idea rooted in the three-tier control structure for a microgrid. Figure 1 displays the configuration of the three-tier control framework employed for overseeing battery management and control. The intentions of each tier are visualized using solid and dashed lines, symbolizing energy and information transfers, respectively.

This process occurs while the BESS undergoes charging or discharging. Simultaneously, the controller aims to maintain system stability by adhering to the reference signal from the secondary control, thus ensuring alignment with the set reference.

To achieve the highest level of RES performance, either economic or technical criteria can be employed, based on steady-state conditions. A reasonably sized battery can facilitate diverse energy management tasks, including but not limited to maximizing overall profits, minimizing operational expenses, peak shaving, arbitrage, and related activities.

It is important to highlight that this analysis primarily focuses on the function's batteries should perform within a RES and the methodologies required to fulfill these functions. The time spans under consideration for these tasks typically encompass minutes, hours, or even the entire project lifespan. Secondary and tertiary controls oversee these aspects of the process.

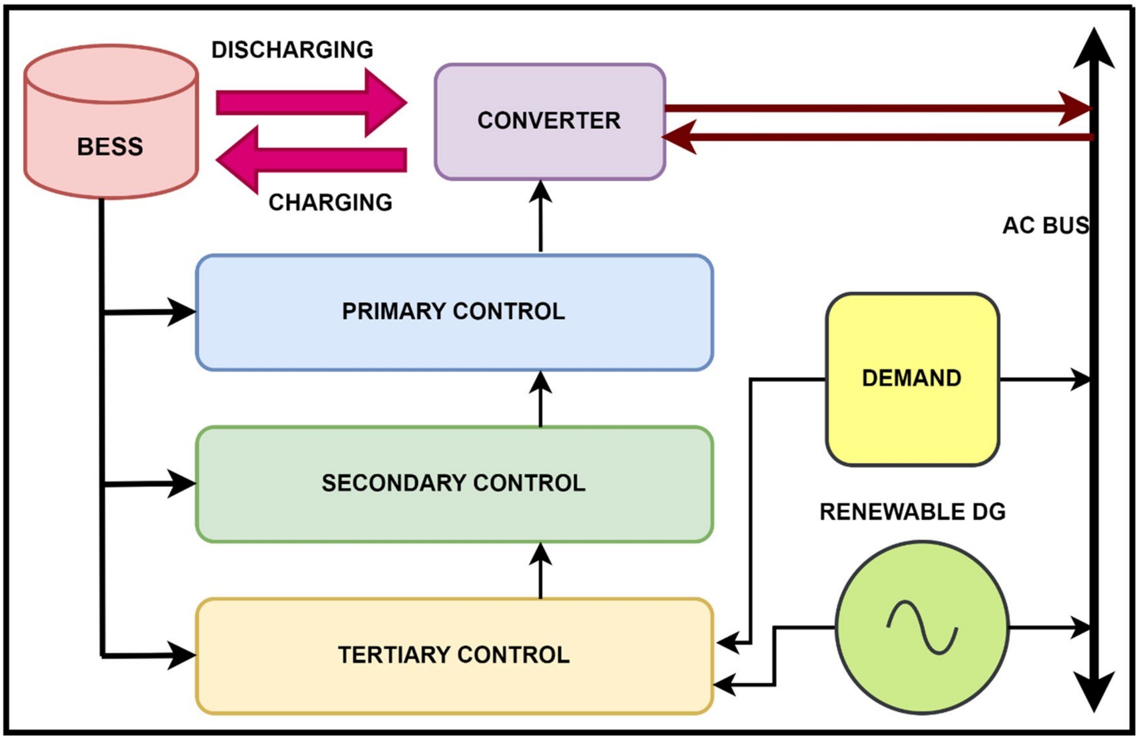


Fig. 1 Three-layer control in the coordination of BESS

Hence, the goal of this research is to furnish a concise overview of the potential applications of BESS, with a predominant emphasis on exploring how BESS functions in secondary and tertiary control roles.

3 Modeling of BESS for the Management of Energy Storage

A BESS comprises battery cells arranged in parallel and series configurations, complemented by converters for efficient charging and discharging operations. Various battery technologies, such as lead-acid, NaS, lithium-ion, and redox flow batteries, find promising applications in grid and RES setups. Notable examples include lithium-ion, lead-acid, and NaS batteries. While this study does not extensively explore the impact of materials-physics models on BEMS, readers can refer to earlier comprehensive investigations for a deeper understanding. Understanding the underlying physics of different battery technologies is critical for informed decision-making regarding state-of-charge limitations, round-trip efficiency, degradation profiles, and other crucial factors. This consideration bears significant importance. For a deeper comprehension, readers are directed towards earlier comprehensive investigations as provided in References [7, 35, 36]. Table 1 represents the comparison of promising battery technologies for ESS.

In BESS modeling, the battery characteristics are illustrated using mathematical equations. An indispensable facet of BESS management and regulation involves constructing a BESS model. These models are employed at varying levels of detail and complexity to meet the diverse demands of

Table 1 Comparison of promising battery technologies for ESS

Battery technology	Advantages and Applications	Disadvantages	References
Lead-acid batteries	Cost-effective; suitable for specific applications	Lower energy density; higher self-discharge rate	[37, 38]
NaS batteries	High-temperature operation; suitable for large-scale applications	High cost; flammable electrolyte	[38, 39]
Lithium-ion batteries	High energy density; widely used in consumer electronics and various industries	Higher cost; sensitive to heat and high discharge rates	[38, 40]
Redox flow batteries	High scalability; long cycle life	Slow charging and discharging rates; higher cost	[41–43]

BESS management. Employing simplified models is suitable for broader energy management challenges, while employing more intricate models is justified for specialized control issues. For example, in the process of comparing diverse battery technologies, a fundamental and universal battery model was employed, featuring unique characteristics tailored to each battery variant. This facilitated a meaningful and efficient comparative analysis [11]. For the purposes of this assessment, BESS models can be categorized into two groups: generic models and dynamic models. This classification stems from the chosen modeling methods and simulation settings, including the application of comparable circuit representations.

The typical model finds its most frequent application in representing stable-state scenarios for the purpose of energy management goals. On the other hand, dynamic models offer increased benefits in the representation of transient scenarios for the intent of dynamic control. The degradation processes of BESS are modeled in Sect. 3.3, emphasizing the importance of considering these processes during BESS operation.

It's essential to note that this section will primarily focus on the BESS model concerning battery energy optimization within renewable energy systems. Enhancing economic outcomes and technological advancements across renewable energy or power systems stands as a primary objective of battery energy optimization, alongside other objectives. This concept is distinct from battery management, which primarily seeks to maximize the performance and lifespan of a given battery [44]. For instance, research into battery fractional derivative models [45], SOC estimation [46], and thermal management [47] all fall under the category of battery management. Assumptions pertinent to battery energy optimization can stem from insights gained in battery management studies, where the aim is to optimize specific battery performance and lifecycle. These assumptions could involve factors like upper and lower SOC thresholds, efficiency patterns, degradation attributes, variables within the resistance–capacitance model, and so forth.

3.1 The Universal Framework

The commonly employed standard framework for energy management of a battery predominantly centers on observing alterations in the battery's SOC, resulting from the inflow or outflow of electricity. SOC, frequently used to assess a battery's energy status, ranges from 0% (indicating complete depletion) to 100% (indicating full charge). It signifies the portion of the battery's total capacity that has been charged. Expressing SOC can involve measuring the stored energy relative to total energy capacity, assuming constant battery voltage. Furthermore, changes in SOC over a duration can be depicted as a time sequence comprising distinct SOC levels. Charging leads to an increased SOC, while discharging leads to decreased SOC, as depicted in Eqs. (1) and (2) [48], which mathematically summarizes this process, considering the efficiencies associated with both charging and discharging processes (c and d).

$$\text{Charging condition} \quad \mathrm{SOC}(t+\Delta t) = \mathrm{SOC}(t) + \frac{P_{BESS}(t)\eta_c \Delta t}{EC_{BESS}} \tag{1}$$

$$\text{Discharging condition} \quad \mathrm{SOC}(t+\Delta t) = \mathrm{SOC}(t) + \frac{P_{BESS}(t)\Delta t}{\eta_d EC_{BESS}} \tag{2}$$

P_{BESS} denotes the power for charging and discharging the BESS, with positive values indicating charging and negative values denoting discharging over a specific time interval, Δt.

The abbreviation EC_{BESS} stands for the energy level or capacity of the BESS. A crucial factor contributing to the broad acceptance of the general model is its capability to focus on BESS applications without specifying the exact technology or type of BESS/ESS. This capability is a primary driver behind the extensive usage of the general model. It allows for exploring how energy storage properties impact the entire system and determining which technologies best suit the application based on desired attributes identified using the general model.

In this study, several of the mentioned research works assumed constants c and d to simplify complexity. However, these values are influenced not only by battery technology but also operational conditions, including temperature, current, and voltage. Consequently, certain investigations have employed more intricate methodologies to gauge these efficiencies. Several of these methods encompass processes such as parameter derivation from empirical data [7, 49] or the utilization of curve fitting [50].

3.2 Dynamic Models

While the comprehensive structure aptly clarifies the connection between the power used for charging and discharging the battery and its SOC, it assumes that SOC changes resulting from energy surpluses or deficits are universally achievable. In other words, it presupposes the feasibility of achieving any required voltage or current adjustments to accommodate anticipated SOC changes.

In cases where precise control of BESS current and voltage parameters, including transients, is essential, dynamic models can be employed for BESS modeling [51]. Among the frequently used methods for constructing dynamic models are equivalent circuits.

The field of academic research offers a range of dynamic models, including simplified, first-order, and models with dynamics of the second order. Figure 2 portrays a simplified rendition of a dynamic model suitable for battery analysis.

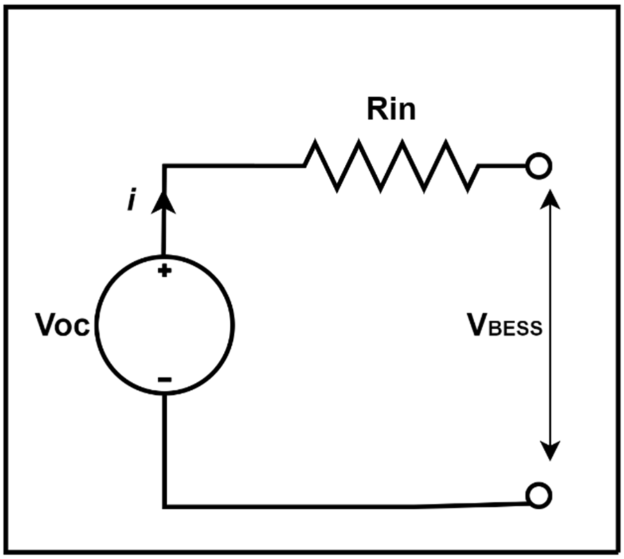


Fig. 2 First order equivalent circuit of BESS

This model comprises an equivalent voltage source *Voc* and a series-connected internal battery resistance *Rin* [52, 53]. When transient effects can be disregarded, utilizing this simplified dynamic model, governed by Eq. (3), proves highly advantageous.

$$v_{BESS} = v_{oc} - iR_{\text{in}} \tag{3}$$

$$v_{BESS} = v_{oc} - iR_{in} - v_1 - v_2 \tag{4}$$

$$i = i_{R1} + i_{C1} = i_{R2} + i_{C2} \tag{5}$$

$$\dot{v}_1 = \frac{i}{C_1} - \frac{v_1}{R_1C_1} \tag{6}$$

$$\dot{v}_2 = \frac{i}{C_2} - \frac{v_2}{R_2C_2} \tag{7}$$

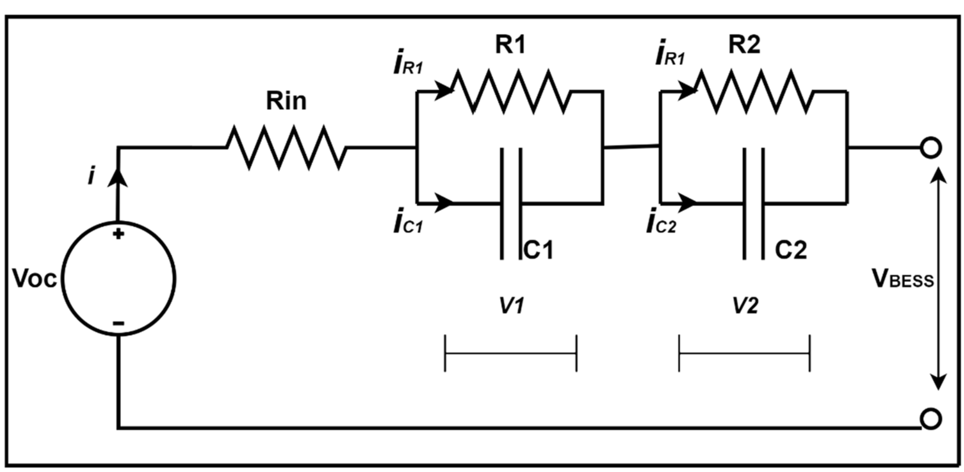
As shown in Fig. 3, both first-order and second-order dynamic models incorporate RC networks [54–56] to address transient impacts. By utilizing Kirchhoff's principles in the relevant circuit, it becomes possible to formulate a series of differential equations, which can subsequently define the voltage's dynamic attributes concerning time. Equations corresponding to the second-order equivalent circuit model depicted in Fig. 3 can be formulated using Eqs. (4) to (7) [54], where denotes the time derivative of V_1.

While the overarching model effectively elucidates the connection between the power used for charging and discharging the battery and its SOC, it operates under the assumption that alterations in SOC due to excess or deficiency of energy are consistently attainable. In simpler terms, it presupposes the attainability of any voltage or current shift to accommodate anticipated SOC changes. When precise control of BESS's current and voltage parameters, including transients, is crucial, dynamic models, like those utilizing equivalent circuits, come into play for BESS modeling [51].

Diverse dynamic models are available in academic research, including simplified versions, first-order models, and second-order models. Figure 2 illustrates a simplified dynamic model suitable for battery analysis. It is represented like a practical volatge source having a open circuit volatge and an internal series resistance [52, 53].

For an in-depth comprehension of battery operations, users turn to first-order and second-order equivalent circuit battery models, often involving solving a set of differential equations. Another widely-used dynamic technique is state-space modeling. It condenses a group of differential equations into a concise matrix equation by choosing an appropriate state variable [57] for determining the solution. The surge in these techniques' popularity can be attributed

Fig. 3 Second order equivalent circuit of BESS



to commercial software's availability for swift simulation of intricate circuits. MATLAB/Simulink and PSCAD are noteworthy examples of such software.

3.3 Battery Degradation Models

Over time, a battery's effectiveness diminishes, primarily due to chemical processes occurring in its electrolyte, anode, and cathode [58]. Battery deterioration can be classified into two forms: calendar aging and cycle aging. Calendar aging denotes the natural degradation of a battery as time passes, regardless of whether it is cycled or not. This aging process is impacted by temperature and the battery's SOC [59]. Cycling aging occurs during charge and discharge cycles. Its pace is determined by discharge depth, average state of charge per cycle, and cell temperature. Frequent cycles and deeper discharges, particularly below 20% state of charge [60] (varies by battery type), significantly reduce the operational life of batteries, particularly in lead-acid and lithium-ion variants [15, 60]. These cycles also diminish the battery's energy storage capacity.

Capacity fade, the reduction in storage capacity, significantly impacts battery deterioration in system modeling [61, 62]. Generally, if a battery's usable capacity falls below 80% of its initial value, it's considered reaching the end of its service life and replacement is recommended [63, 64], irrespective of its type. This remains accurate for both lead-acid and lithium-ion battery types.

Hence, it is essential to consider degradation when overseeing energy for extended projects and performing simulations spanning prolonged durations. The battery's SOH/SOC and proves effective in gauging battery degradation [49]. SOH is commonly defined using the reduction in rated capacity, with a new battery exhibiting $C_{act}=C_{nom}$, resulting in a 100% SOH. This SOH concept, as expressed in Eq. (8) [63], equates C_{act} with C_{nom} for a new battery and reaches 0% SOH at $C_{act}=C_{EOL}$, denoting the conclusion of its capacity for usable life. the end of its usable life capacity. Subsequent capacity losses are assessed through experimental data, quantifying the influence of cycles on the reduction of capacity. Previously, Nuhic et al. [63], it's common practice to consider 80% of a new battery's nominal capacity as its end-of-life capacity. This value is integrated into Eq. (9).

$$\mathrm{SOH} = \frac{C_{act} - C_{EOL}}{C_{nom} - C_{EOL}} 100\%, C_{act} \geq C_{EOL} \tag{8}$$

$$C_{EOL} = 0.8C_{nom} \tag{9}$$

Alternatively, an indicator of deterioration can be derived from the actual usable capacity of the battery. This capacity reflects the difference between a brand-new battery's nominal power and the incurred capacity loss [65]. As previously mentioned, battery aging involves both calendar and cycle degradation [66]. However, cycle deterioration is the predominant contributor to battery decline, and it is harder to measure. Consequently, various techniques have been developed to evaluate BESS deterioration due to cycling. The rainflow counting algorithm, often applied in structural engineering, power electronics, and mechanical vibration analysis, is commonly used [67, 68]. This method counts cycles occurring over a defined timeframe [67, 68], spanning a wide range of applications. Studies akin to this one has assessed these models for the optimization of BESS within a microgrid [69].

The effective management of battery degradation within BESS has become a significant aspect of optimizing their performance. One prevalent approach involves quantifying battery decline as a cost, which is then integrated into the optimization model. This strategy is commonly employed in various studies. For example, researchers have integrated a weighted Ampere-hour (Ah) aging model for BESS into multi-objective optimization scenarios [70]. One of the primary goals is to mitigate battery deterioration through optimized charge–discharge strategies, which contribute to the formulation of battery energy management systems [71]. A novel approach involves the use of a dual BESS system, where each unit alternates between charging and discharging states [72, 73]. Additionally, the emergence of HESS is gaining traction. These systems, which incorporate technologies like ultracapacitors (UCs) for high-frequency events, offer a promising avenue to enhance battery lifespan [74, 75]. Table 2 demonstrate a comparison of approaches utilized for the management of battery degradation.

4 BESS Energy Management Targets

BESS have a notable role within renewable energy setups, providing a spectrum of benefits that span from enhancing the overall profitability of the system to facilitating functions like peak mitigation, power steadiness, and regulation of grid frequency. The designated roles of BESS within a system are significantly shaped by the precise operational needs of the renewable energy configuration and the capabilities of the BESS itself. This section undertakes an evaluation of research projects emphasizing battery energy management. The assessment is structured according to the objectives guiding BESS management, which encompass financial, technical, and combined goals.

4.1 Economic Objectives

Owing to the substantial influence of economic efficacy, multiple research investigations have integrated financial aspect to enhance battery efficiency. Additionally, a diverse

Table 2 Battery degradation management strategies

Strategy	Approach	References
Cost integration	Battery decline quantified as a cost integrated into optimization models	[70]
Lifespan, depreciation, usage, wear costs	Consideration of various costs related to battery degradation, including lifespan cost, depreciation cost, usage cost, and wear cost	[57, 76–78]
Mitigating degradation	Techniques to minimize battery degradation, including avoiding deep discharge cycles and reducing charge–discharge cycle frequency	[79, 79–83]
Optimized charge–discharge strategies	Optimization of charge–discharge patterns for effective management of battery deterioration and formation of battery energy management systems	[71]
Dual BESS approach	Implementation of a dual BESS system where units alternate between charging and discharging states	[72, 73]
HESS	Incorporation of technologies like UCs in HESS to enhance battery lifespan in high-frequency event scenarios	[74, 75]

range of financial indicators have been employed as objectives in battery optimization. Examples of these indicators encompass minimizing total operational costs [84], maximizing operational profits [85], and maximizing the lifetime value of energy storage [86], among others. Table 3 offers an overview of pertinent literature focused on battery energy management with financial goals, including more detailed indications.

Of note, the most frequently pursued objective among the numerical indicators listed in Table 3 is the reduction of total operating expenses (equivalent to maximizing operating profits). However, different research has proposed varying definitions of operating expenses and the constituent elements of operating costs. For instance, in Ref. [84], the overall microgrid cost minimization encompasses factors like fuel costs for diesel generators, power exchange costs with the utility, and startup/shutdown costs of microgrid power sources. Conversely, distinct research [87] calculates total cost considering factors such as profits from power market participation, battery deterioration costs, and battery operation costs. As such, Table 3 has been constructed to underscore optimization goals in each study by comprehensively outlining the specified indicators, enabling the identification of the distinct components contributing to these objectives.

Numerous factors underpin the incorporation of diverse aspects in these investigations targeting specific battery applications. Initially, this phenomenon can be attributed to the integration of numerous components within the modeled system. For instance, in the microgrid scenario outlined in Reference [84], the inclusion of micro-turbines and fuel cells necessitated the consideration of fuel costs, alongside unit start-up and shut-down expenses. Conversely, a microgrid solely reliant on photovoltaic cells for power weighed electricity market gains and battery degradation costs [86]. The inclusion of controlled load delays in the total cost was essential, given their integral role in the simulated system [88].

The diversity in system types and their operational intricacies compels researchers to opt for specific metrics in their studies—this constitutes the second noteworthy aspect. An illustrative example is the investigation into whether engagement in the energy market is part of the operation of hybrid systems. This assessment decides the relevance of the cost-to-profit trade-off inherent within the dynamics of the power sector. Analyzing Table 3 reveals that for systems linked to utilities, the majority of studies factored in power consumption-associated costs and profits. However, when exploring autonomous hybrid renewable energy systems, considerations of electricity cost and profit often take a backseat in BESS optimization endeavors [89, 90]. Thirdly, specific metrics are integrated as a consequence of establishing a defined optimization objective for the BESS to achieve, or due to setting specialized goals for the renewable energy system. These objectives can be fulfilled either by the BESS itself or the RES. An excellent illustration of a specific objective is the involvement of the BESS within the market for reserve and regulation services [91, 92]. Participating in this market aims to enhance profits, and thus this type of objective becomes part of the BESS management's financial targets. In scenarios where this energy scheme was applied with distinct focuses, such as the consideration of feed-in-tariffs to minimize overall load delivery costs [93], specialized objectives are taken into account. Additional distinct objectives such as the expense related to curtailing renewable energy [90], the outlay associated with unmet energy demand [78], and the expenditure linked to emissions of gases that contribute to the greenhouse effect [94], though not included in Table 3 due to their infrequent use, are noteworthy. Additional attention to these aspects introduces supplementary costs or gains that must be accounted for in the overarching goal. Furthermore, recent studies tend to give more prominence to battery deterioration [76, 78, 95]. As discussed in Sect. 3.3, these investigations take into account the costs related to battery degradation as an extra specific consideration during the computation of total expenses and benefits.

Table 3 Relevant literature on battery energy management for financial goals

References	Key findings
[84]	The (θ)-PSO method proposed in this study was employed to address an optimal operation management challenge with the objective of minimizing the microgrid's overall operating cost
[89]	An analysis was undertaken to assess the financial viability of utilizing ESS for both main reserve and peak-shaving purposes
[104]	To gauge the efficacy of the suggested optimization technique, an 8-bus system was employed. Findings demonstrate that employing both photovoltaic systems and batteries can alleviate transmission congestion, lessen peak load, and diminish the need for expensive thermal units
[105]	The recommended control strategy for the weekly dispatch of the BESS involves a time horizon that not only reduces fuel consumption by 2% but also enhances the capacity to accommodate wind power output by 20% compared to scenarios without BESS integration
[90]	In spite of the initial greater upfront expenditure associated with the battery, the results indicate that the technical and financial benefits of a properly optimized BESS technology will outweigh the costs incurred over the battery's lifespan
[78]	The findings indicated that predictive techniques yield greater cost savings compared to non-predictive dispatch strategies, particularly in systems with higher renewable energy penetration
[95]	Conventional generators demonstrated greater commitment to the project to maximize the anticipated profitability of the VPP. This inclination arises from the considerably lower fuel costs for regular generators compared to battery degradation expenses
[76]	A controlled depreciation cost model was developed for lithium batteries, enhancing cost efficiency and mitigating battery aging through an optimized model. These advantages were achieved through the synergistic combination of the two models
[106]	In terms of both effectiveness and efficiency, the ADP-based real-time energy management technique exhibited superior performance compared to the DP and PSO methods. Furthermore, this method demonstrated resilience against uncertainties arising from PV, wind generation, energy demand prediction errors, and electricity price prediction errors
[107]	Assessed using three different approaches – first level, bilevel without and with SOC regulation – the suggested method exhibited superior performance by reducing overall operational costs and enhancing microgrid reliability
[85]	A two-scale DP strategy emerged as an optimal approach for power management in hybrid wind-battery systems. In contrast to the traditional 24-h DP strategy, this approach demonstrated substantial performance improvements
[108]	The described technique offers the potential to optimize the dispatch of electricity from wind farms, obviating the need for dispatch schedule adjustments. Additionally, this approach fosters wind power expansion within the grid, bolstering its competitiveness against alternative energy sources
[54]	The findings underscored the significance of factoring in battery wear and tear costs within the management plan, ensuring battery usage aligns with income surpassing expenses
[109]	Within the realm of a user-driven microgrid power market, an inventive economic model was introduced. This model incentivizes battery installation, enabling energy trading within microgrids
[110]	Simulation outcomes highlighted that synchronized optimal dispatch of ESS substantially decreased microgrid power costs compared to individual microgrid interactions with the grid
[111]	The study's results identified inaccurate energy price forecasts and constrained distribution network capacity as the foremost factors curtailing anticipated benefits
[112]	The proposed approach was assessed using the IEEE test system encompassing 37 nodes. Optimization outcomes demonstrated lowered operational costs across various BESS penetrations while maintaining voltage drop within permissible limits
[113]	The recommended algorithm possesses versatility to collaborate with diverse batteries, each characterized by distinct attributes, yielding cost savings in power consumption
[114]	Simulation results depicted a non-linear increase in financial gains with declining battery prices. Cooperative management of EVs and BESS proved effective in preventing performance degradation for both systems
[115]	Simulation findings illuminated that high PV penetration diminished benefits for PV-equipped households. Furthermore, analysis indicated lower profitability for sole battery-equipped households compared to those with both PV and batteries
[116]	The simulation results revealed that opting for battery purchase proved to be the superior financial choice compared to feed-in-tariff and net electricity metering programs that excluded battery acquisition
[117]	The simulation outcomes indicated a potential reduction of 41.68 percent in annual power expenses with the proposed solution, as opposed to scenarios devoid of both BESS and PV
[93]	The decision to incorporate battery replacement costs into the BESS management plan was driven by its substantial impact on the overall operational expenditure, in alignment with the findings
[118]	The simulation results validated the effectiveness of the recommended management strategy, facilitating PV utilization, peak demand reduction, and containment of power fluctuations arising from PV generation
[119]	The utilization of PV system simulation software yielded more favorable results, with increased yearly electricity production compared to actual PV power data. This achievement was attributed to a higher annual electricity output generated
[120]	End users were provided access to a decision support tool designed to assist them in optimizing their expenditure on PV-battery systems, thus reducing their monthly power expenses

Table 3 (continued)

References	Key findings
[86]	The proposed solution led to a substantial increase of approximately 160% in the battery's useful life compared to standard set-point control methods
[57]	Leveraging wind power and market data from Alberta, Canada, the recommended MPC limited optimizer demonstrated superior net daily profits with minimal trade-offs throughout the BESS's lifespan
[121]	In situations where precise predictions based on statistical knowledge of the system are challenging, the described method can be employed. Furthermore, incorporating relevant statistics into the algorithm's design process enhances the proposed algorithm's effectiveness
[122]	Findings from unit commitment research have been integrated into the BESS dispatch plan for a wind farm. The bidirectional energy flow capability enables power exchange in both directions
[123]	A resource consolidation and utilization approach for home energy systems has been formulated, resulting in reduced operational expenses while accounting for battery cycle aging costs
[124]	Simulation results indicated that energy price unpredictability exerted a more significant influence on community battery performance than power generation and consumption levels
[125]	The introduced reinforcement learning-based charging and discharging method effectively managed nonlinear battery behaviors, improved battery wear-out modeling accuracy, and addressed energy cost unpredictability
[126]	The suggested ESS management strategy succeeded in decreasing average power consumption and strategically deferring flexible load activation based on electricity prices
[127]	Data derived from the degradation experiment of a lithium-ion battery were employed for investigative purposes. A two-phase decomposition approach was introduced to streamline the process of solving time-domain problems
[91]	The impact of integrating energy, reserve, and regulation markets into battery storage system profits was demonstrated through market participation, influencing profits through battery dispatch
[128]	Simulation outcomes revealed that the suggested solution tended to overestimate BESS earnings by offering multiple services, even though the model provided an accurate earnings estimate
[92]	The recommended method aims to maximize long-term operational profits, enabling battery involvement in energy and regulation markets beyond fixed daily cycles, fostering enhanced market participation
[87]	Over two consecutive days, a bilevel supervision plan was implemented to maximize operational profitability, while considering the limitations of traditional generator ramping capabilities and network constraints
[129]	An optimized planning and control method was developed to enable BESS to participate in the primary frequency regulating market while maintaining an optimal SOC
[130]	Findings indicated that the utilization of CAES reduced diverted wind energy by 30%, while NaS batteries only achieved a 4% reduction
[131]	Simulation results demonstrated the effectiveness and reliability of the proposed two-stage coordinated microgrid operating approach, incorporating ESS supervision and direct load control
[132]	An optimization technique was devised to strike a profitable balance between minimizing ESS loss and optimizing revenue from power sales, achieving an optimal trade-off between the two
[88]	Comparative results revealed that the proposed integration of joint load scheduling and ESS control yielded superior financial performance compared to systems lacking storage or load scheduling, or those with storage alone
[133]	The showcased real-time coordination system has the potential to enhance wind power's role in frequency control, facilitating increased frequency control capability without adversely affecting battery longevity
[94]	Research outcomes underscored that lithium-ion batteries paired with mono-crystalline silicon photovoltaics represent a promising technology combination capable of reducing carbon emissions by 26%

4.2 Technical Objectives

The application of BESS is utilized not only the purpose of attaining financial objectives but also enhancing the technical efficiency of RESs. The primary objectives encompass reducing electricity losses within distribution networks, ensuring more consistent power generation from renewable sources, and more. The aggregated research findings concerning battery energy management are consolidated in Table 4, with a specific focus on achieving technical aims. Generally, applications aimed at technical objectives predominantly address secondary and tertiary control. These two upper control tiers are contingent on the BESS operational framework, as elaborated in Sect. 2. Concerning BESS control objectives, the objectives of these applications can be categorized into three major groups: I optimizing energy utilization; ii enhancing power profiles; and iii improving various performance aspects.

The majority of tertiary control objectives, such as optimizing battery schedules to improve the operational effectiveness of RESs on an hourly or daily basis, involve longer-term horizon optimization. This applies to most

Table 4 Relevant literature on battery energy management for technical goals

References	Key findings
[96]	When compared to an unoptimized technique, employing the Hyper-Heuristics algorithm resulted in a reduction of over 5% in consumption
[97]	Effective utilization of a battery in a PV generation system hinged on appropriate charging and discharging timing, leading to decreased distribution system line losses
[134]	The proposed multi-timescale approach synergizes the gradual correction actions of OLTC post-emergency with swift corrective actions of BESS and PV systems are utilized to reduce line losses and ensure the stability of voltage levels
[135]	Research findings demonstrate the optimization of microgrid costs by replenishing the battery with excess electricity from PV systems during periods of on-peak and MID-peak TOU
[72]	With an increase in predicted wind speed, the recommended dual-BESS technique exhibited smoother output, closely aligning with optimal charging and discharging timing
[74]	Employing a semi-Markov process model for representing PV power, accounting for intermittent factors like cloud cover, was enhanced through the use of an SDP planner over a rule-based planner, yielding efficiency gains and reduced fuel usage
[98]	The outcomes highlight the potential for substantial monetary rewards to be provided to household users, encouraging them to adopt storage solutions to trim the highest energy demand applications while utilizing TOU tariffs
[136]	The utilization of the system breakdown technique was expected to extend the lifespan of lithium-ion batteries to around 10–20 years, given mild cycling and infrequent deep drain cycles
[137]	The proposed method exhibited superior peak shaving performance compared to older techniques such as PSO, GA, and FLC controller
[138]	Traditional approaches like fixed demand boundary management and specified power barrier control demonstrated lower effectiveness compared to the innovative method
[139]	Daytime power outages were managed by employing the biomass energy generator as a local AC bus, while the load was powered using the photovoltaic generator and battery
[140]	A commercial space was used for a study involving a 20 kW (1 MWh) capacity battery, showcasing significant reduction in feeder peak load with the suggested alternative
[81]	The developed optimal control technique enabled wind farms to function akin to traditional generators, but with frequent battery charging and discharging. This underscores the need for long-life cycle battery technologies in the future
[99]	The proposed control approach effectively met targeted dispatch goals and maintained a favorable SOC range for the BESS
[141]	The economic advantages of BESS were clear in offsetting inaccuracies in wind power forecasts. Lead-acid and lithium-ion batteries, despite having shorter operational lives and higher initial expenses, demonstrated better performance compared to NaS batteries in simulated setups
[82]	Assessing the effectiveness of BESS in harnessing wind energy hinged on three primary metrics: estimated wind power threshold, expected wind power insufficiency, and likelihood of wind power shortfall
[142]	The suggested technique effectively regulate voltage, minimize peak power, and stabilize power distribution by minimizing active power deviation between the transformer and standard power graph
[71]	Enhancing wind power management, a distinctive BESS dispatch strategy shifted charge and discharge phases from pessimistic to optimistic scenarios to address wind power variability
[80]	In the recommended dispatch strategy, a LP approach identified a minimum demand threshold for cost-saving, utilizing projections of PV generation and anticipated load for the upcoming day
[143]	The SMPC controller introduced enabled the wind farm to provide an appropriate dispatch curve, allowing it to operate similarly to a conventional power plant
[73]	Two distinct methodologies for BESS dispatch were proposed to monitor predefined production. The concurrent state-swapping approach demonstrated better technical performance compared to the asynchronous method, whereas the asynchronous state swapping method exhibited superior financial outcomes
[144]	Employing a knowledge-based method not only fulfills island energy requirements but also reduces wind energy losses and load-shedding incidents, all achieved with a 20% reduction in storage space
[145]	Addressing power fluctuation extraction on tie-lines using storage, results indicated that coupling with DR programs significantly reduces traditional energy storage system sizes in microgrids. This enhancement also bolsters power quality, leveraging the responsiveness of DR programs to energy consumption changes
[83]	The dual-layer control strategy's initial layer determined BESS power commands for mitigation needs. The subsequent layer revealed that incorporating state-switching limitations tied to remaining energy diminishes the lifespan of battery level transitions in BESS
[102]	Simulation outcomes showed that a combination of BESS and SFES is more efficient for regulating wind farm output compared to exclusive BESS utilization, in contrast to solely using BESS
[146]	This study systematically defined three operational states—regular, notification, and alert—for the HESS

Table 4 (continued)

References	Key findings
[147]	The control strategy suggested using ADALINE demonstrated superior performance in both accuracy and speed when tracking wind farm production, surpassing the FLF-based technique. Furthermore, it showcased decreased utilization of battery capacity as opposed to the FLF-based method
[148]	Economic evaluation demonstrated that implementing the suggested incentive program would yield profit, with potential for increased profitability by aligning the distribution plan with market prices
[149]	The selected control loop adeptly followed the prescribed wind power dispatch while maintaining BESS SOC within intended ranges
[150]	The suggested rule-based control mechanism vigilantly managed required dispatch power while ensuring BESS SOC and current remained within reasonable thresholds
[100]	The simulation outcomes demonstrated that the suggested approach for reducing PV fluctuations achieves similar results to the moving average technique, all while demanding a smaller BESS capacity
[75]	By implementing the proposed power management method, the necessary power capacity of the UC could be decreased to only 20% of the VRB's capacity, effectively averting the VRB's operation at low power thresholds
[66]	Diverse suggested strategies to provide primary frequency service and restore SOC could potentially increase the operational life of a lithium-ion battery by 5 years, given the gradual reduction in its energy storage capacity
[151]	Employing the BESS for frequency control entailed a comprehensive assessment of power loss, system efficiency, reliability, and associated costs linked to grid-connected BESS utilization
[152]	The proposed approach comprises two control modes: the first mode fine-tunes the ESS to counter frequency fluctuations, while the second mode prioritizes energy conservation to prevent further frequency deviations
[153]	Research demonstrates that the BESS can rapidly recoup expenses associated with frequency regulation operations, with minimal impact on system frequency
[154]	Combining frequency control and peak shaving can yield earnings up to 10% higher than using frequency control alone, and twice as high compared to standalone peak shaving
[55]	The synchronized control approach for multiple distributed BESS exhibits superior power quality enhancement compared to the uncoordinated control strategy, especially when used alongside an on-load tap changer
[56]	Integration of a BESS into a wind-and-diesel-powered system enhances power quality and system reliability when operating on wind power alone
[155]	Effective management of a 0.6 MW/0.76 MWh BESS within a DER featuring 3.15 MW of PV has negligible impact on battery charging cycles
[77]	The developed online power management approach enables real-time monitoring of SOC/SOH across various scenarios, effectively preserving battery capacity from degradation
[156]	A decentralized real-time technique was implemented in lieu of the conventional central controller, reducing communication stress and enhancing responsiveness
[157]	The adaptable method accommodates seasonal load variations while ensuring optimal BESS unit usage
[158]	The evolved control strategy adeptly handles frequency and voltage changes within the islanded composite system, contributing to overall power quality improvement
[101]	The employed BESS dispatch method effectively stabilized PV capacity, showcasing enhanced smoothing properties in the integrated PV feeder
[159]	A comparison was conducted between the LP model and the renewable energy simulation program SAM. The investigation's results revealed a normalized root mean square error of 2.10 percent for yearly battery dispatch

tertiary control goals. For example, the financial objectives discussed earlier fall under the tertiary control category. Regarding technical objectives, tertiary control also encompasses energy optimization. The collected energy often functions as a measure to evaluate the achievement of objectives. As an illustration, in Reference [96], the battery was deployed to reduce the utility company's energy consumption, and in Reference [97], it was used to mitigate line losses within the distribution network.

A power transmission or distribution system experiences losses in real and reactive power, referred to as line losses, during a specified timeframe. This metric is pivotal in gauging network operational efficiency. Metrics relying on total energy accumulated contrast with financial goals as they do not take power expenses into account. In addition to the storage of energy, ensuring energy equilibrium is a fundamental objective of BESS within RESs. An instance is seen in Reference [74], where the battery discharges to balance microgrid electricity production and consumption.

Furthermore, power profile characteristics constitute another technical aspect vital to optimization (measured in kW or MW). These qualities encompass peak demand reduction, targeted dispatch tracking, and fluctuation mitigation. Peak shaving exemplifies battery utility by storing non-peak renewable energy for release during high-demand periods, as evidenced in Ref. [98]. Tracking desired dispatch is another BESS role achievable with substantial deployment. Forecasts often dictate the intended dispatch, prompting BESS intervention to rectify forecast errors [99], minimize actual vs. planned wind power differences [81], or adhere to power targets [71]. Furthermore, a substantial body of research focuses on the application of BESS to mitigate the inherent fluctuations in renewable generation systems arising from variability in resources.

In these studies, a comparative analysis is conducted, juxtaposing the processes and outcomes associated with different methods of electricity generation. Specifically, the research explores the facets of photovoltaic electricity generation, as outlined in references [100] and [101], delving into the intricate details and operational characteristics of PV systems.

Moreover, the investigation extends its scope to encompass solar photovoltaic farms, a distinct approach to harnessing solar energy. Reference [75] serves as a valuable source of information in this regard, shedding light on the operational intricacies and potential benefits of solar photovoltaic farms in electricity production. In a parallel exploration, the research also examines the domain of wind farms, as elucidated by references [102] and [103]. This segment of the study endeavors to unveil the nuanced aspects of wind energy generation, scrutinizing the operational dynamics and efficiency considerations unique to wind farm installations.

Apart from the technical goals that involve extended viewpoints within the tertiary control layers, a few crucial technical metrics will be encompassed by the secondary control, such as voltage and frequency regulation. In traditional power systems, frequency control involves dispatching spinning reserves or other thermal generators within the network. Voltage regulation, on the other hand, can employ various reactive power compensation methods like SVC. Battery technology advancements have reached a point where they can handle both active and reactive power, allowing them to contribute for the purpose of regulating frequency and voltage [55, 66], facilitated by sophisticated power electronic techniques.

Significantly, BESS have been incorporated for technical functions within the domain of primary control, encompassing very brief timeframes or operations in a quasi-real-time manner. Nonetheless, these elements will not be tackled in this examination. A more comprehensive investigation into microgrid battery control, offering greater understanding of real-time battery management, can be found in [34]. These applications can be categorized as "additional performance enhancements." For instance, some objectives involve decreasing battery capacity loss [77] and augmenting the firming of PV capacity [101]. "Capacity firming" involves the utilization of storage systems in conjunction with other methods to ensure a consistent amount of renewable energy over a specified period. A more comprehensive list of works delving into managing battery energy to achieve technical goals, the details are present within Table 4.

4.3 Hybrid Objectives

While the technical and economic aims of BMS discussed earlier constitute a significant portion of the research in this domain, a growing body of research are now focusing on not only a single battery type but also leveraging batteries to achieve both technical and economic objectives. This concept is termed "hybrid objectives." This trend is anticipated to persist, as it aligns logically with the often-intertwined nature of technical and financial objectives. This is especially evident when technical advancements translate into measurable financial gains. Addressing hybrid objectives often requires the application of multi-objective optimization methods, accommodating the simultaneous pursuit of multiple objectives. The process of amalgamating multiple objectives into a single optimization challenge through the utilization of weighted values is a fundamental approach applicable to hybrid objectives. This technique is referred to as "scalarization" [110]. When these weight distributions align with the costs associated with each objective, the summation of individual expenses across all unique aims will correspond to the total expenditure. Consequently, certain hybrid goals can be categorized within the financial objective cluster. Two instances of this can be observed in Reference [86], where objectives concerning energy price and battery degradation cost are discussed.

A glance at Table 5 reveals several research studies that encompass both technological and financial aims, consolidated through costs and gains. This is due to the recognition of these supplementary technical facets as routinely adopted metrics essential for assessing profitability. In fact, through financial integration methodologies, numerous investigations featuring a broad spectrum of cost/profit components, spanning both financial and technical intentions, may be classified as harboring hybrid objectives. An example involves the total of costs related to multiple factors, including expenses from load shedding, costs and profits from electricity purchase/sale, battery degradation expenses, penalties from transformer overheating, and costs or profits from providing primary frequency control, as depicted in Reference [160]. Certain of these elements might not typically arise within economic assessments, and this is evident.

When dealing with dimensionless weights, the process of aggregating different objectives becomes crucial. For instance, Duong and Khambadkone [170] illustrates a scenario where a particular combination of weight factors is employed to integrate power loss, power variation, and battery life reduction. Furthermore, the application of fuzzy

Table 5 Relevant literature on battery energy management for hybrid goals

References	Objectives	Key findings
[161]	Optimize the overall expected return, considering both energy costs and costs associated with energy loss	The results revealed that the suggested approach effectively extended the number of cycles achievable by the storage, albeit with only marginal improvements in energy cost and losses
[160]	Maximize the comprehensive performance of various services, encompassing primary frequency management, smoothing, and curtailment avoidance, to attain the maximum cumulative profit	In contrast to an approach that exclusively offered a single service, the findings revealed that the potential profits derived from constructing energy storage facilities can be doubled when multiple services are delivered
[162]	Minimize costs related to the integrated grid and storage, encompassing expenses for grid expansion, voltage control facility upgrades, curtailment costs, and revenue from electricity sales	The optimal investment choice is significantly influenced by factors such as the line length, surplus PV feed-in, market participation potential, and remuneration for curtailing renewable energy, as indicated by the research findings
[163]	Minimize energy usage costs, battery utilization costs, and penalties associated with battery signal smoothing and grid signal smoothing to the greatest extent possible	The concept of implementing incremental red-zone power rates for batteries was proposed as a strategy to enhance battery management. This approach permitted the battery to temporarily surpass its operational limits, aligning with one of the objectives outlined in the proposal
[164]	Minimize both operational and emission costs as much as possible	The simulation results revealed the possibility of an overall cost reduction of 8.5% with the incorporation of a battery in a microgrid
[165]	Minimize the expected electricity costs while maximizing the potential benefits of primary frequency control	The optimization results revealed that the simultaneous optimization of frequency control and self-consumption increased profits by 25% compared to relying solely on frequency control, and it tripled the profits achieved through self-consumption alone
[166]	Minimize energy costs and battery deterioration expenses while optimizing the delivery of aggregated flexibility services. These services encompass technical solutions addressing distribution network issues, increasing grid hosting capacity, and improving the overall efficiency of the electrical market	To address the optimization problem, a distributed approach was proposed and assessed in comparison to the centralized solution. The results indicate that the suggested distributed method not only delivered a solution with comparable performance to the centralized method but also achieved a five to twelve times faster convergence
[167]	Minimize expenses across various aspects, encompassing generation costs, emissions costs, electricity procurement costs, battery loss costs, and probabilistic risk costs	The results revealed that implementing peak shaving in the Vehicle-to-Grid (V2G) mode has the potential to decrease the cost associated with using Electric Vehicle (EV) batteries. Consequently, this reduction in cost can contribute to an augmentation of the economic advantages offered by the proposed solution
[168]	Minimizing prosumers' net energy costs involves optimizing the utilization of photovoltaic (PV) generation, minimizing purchased power from the utility company, and maximizing the shared energy among prosumers	The peer-to-peer model holds the potential to substantially reduce overall energy costs. Home prosumers experience a 62.71% reduction in costs during the summer and a 68.99% reduction in the winter. For business prosumers, the cost savings are 81.31% lower in the summer and 31.69% lower in the winter
[169]	Maximize the anticipated total income by considering profits from the power market, curtailment costs, and battery degradation expenses	The suggested Distributionally Robust Optimization (DRO) exhibited superior resilience compared to stochastic optimization with a normal distribution. The proposed DRO successfully accommodates all created scenarios, each with distinct transmission line limitations, establishing its superiority over stochastic optimization

logic controllers proves advantageous for integrating diverse goals. This approach was employed by [171] to establish an optimal SOC range for BESS, ensuring their ability to mitigate fluctuations in wind power while preventing overcharging or over discharging. Similarly, Saxena et al. [172] harnessed fuzzy logic to minimize sustainable energy loss, feeder loss, voltage deviation, and overall power costs.

A different strategy to attain hybrid goals involves framing the issue as a multi-objective optimization. In contrast to a single-objective problem where a global optimum must be found, a multi-objective issue offers multiple Pareto optimal solutions. This allows the battery to enhance one performance criterion without negatively affecting others. Employing intelligent optimization techniques like GA, PSO, and NSGA-II is common to implement Pareto multi-objective solutions. An example would be using NSGA-II to find Pareto fronts that simultaneously reduce electricity production costs and maximize the lifespan of lead-acid batteries [173]. Another instance involves using a parallel algorithm to balance economic gains from energy arbitrage and battery lifespan, showcasing a similar application of the Pareto optimum operation [174]. It's worth noting that in some research, such as [70, 175], artificial intelligence methods were directly employed without utilizing Pareto multi-objective optimization techniques. An approach to consolidate hybrid goals is multi-stage optimization, where each step focuses on achieving a specific goal. In a dual-tier optimization structure presented in Reference [176], the BESS was programmed in the upper tier to curtail operational expenses, while in the lower tier, it aimed to mitigate predictive uncertainties and power variations by minimizing power perturbations.

Furthermore, methods like rule-based management can also be employed to address battery operations and hybrid system goals. Hybrid optimization objectives are prioritized and addressed accordingly. In Ref. [177], the BESS energy management strategy initially targeted stopping reverse power flow, followed by normalizing residual distribution network consumption and optimizing battery operation. "Residual distribution network demand" pertains to the variance between the energy needed and the renewable energy accessible within the grid system.

5 BESS Optimization Techniques

After establishing the dispatch objectives for the BESS, the subsequent pivotal step involves determining how to regulate the battery to fulfill these objectives or how to tackle the optimization challenge, given that the objectives and constraints are clearly defined. The technical solutions to BESS optimization are encapsulated within methods known as BESS optimization techniques. The initial step is to select an approach that proves effective in resolving the issue, considering certain methods might not be suitable for specific problem types due to their inherent limitations. This aspect will be further elaborated in the upcoming section.

The decision variables in optimization problems generally encompass either the power value of the battery at each time interval or the power patterns exhibited by the battery over a specific duration. Solving the optimization problem is essential to determine the power pattern for charging and discharging the battery storage. This process involves exploring potential solutions to pinpoint the best possible values for the decision variables, with the goal of attaining optimal outcomes for the specified objective.

A plethora of strategies have been employed in the pursuit of resolving the optimization challenge, spanning from simple rule-based systems to complex multi-stage optimizations. This section provides a summary of the approaches employed to tackle optimization challenges in managing BESS. These approaches can be categorized into methods centered on DSB, probabilistic approaches, and control strategies. A summarized visual representation in the shape of a schematic diagram outlines the discussed approaches and their classification in Fig. 4.

5.1 Direct Search Based (DSB) Methods

This section provides a summary of three distinct varieties of DSB approaches. These encompass the employment of analytical solvers, the utilization of dynamic programming, and the application of heuristic techniques. The working process of DSB method is illustrated in Fig. 5.

5.1.1 Mathematical Solvers

When dealing with optimization challenges that can be formally described as linear or NLP, both mixed-integer and not, traditional optimization techniques or mathematical solutions can be efficiently employed. When the constraints or objective functions exhibit non-linearity, a nonlinear programming issue arises. On the other hand, a mixed-integer problem arises when only a subset of the optimization problem involves integer decision variables, and a nonlinear programming problem is characterized by having both nonlinear constraints and objective functions. The Lagrange multiplier [156] is an established approach often utilized to find solutions to convex optimization problems.

The GAMS stands out as the most frequently employed platform for solving optimization problems, equipped with a range of integrated solvers. Historically, GAMS has effectively addressed MILP problems [89, 162], NLP [54] as well as nonlinear programming through linearization [87].

Furthermore, IBM ILOG CPLEX Optimization Studio (CPLEX) stands out as a widely employed software tool

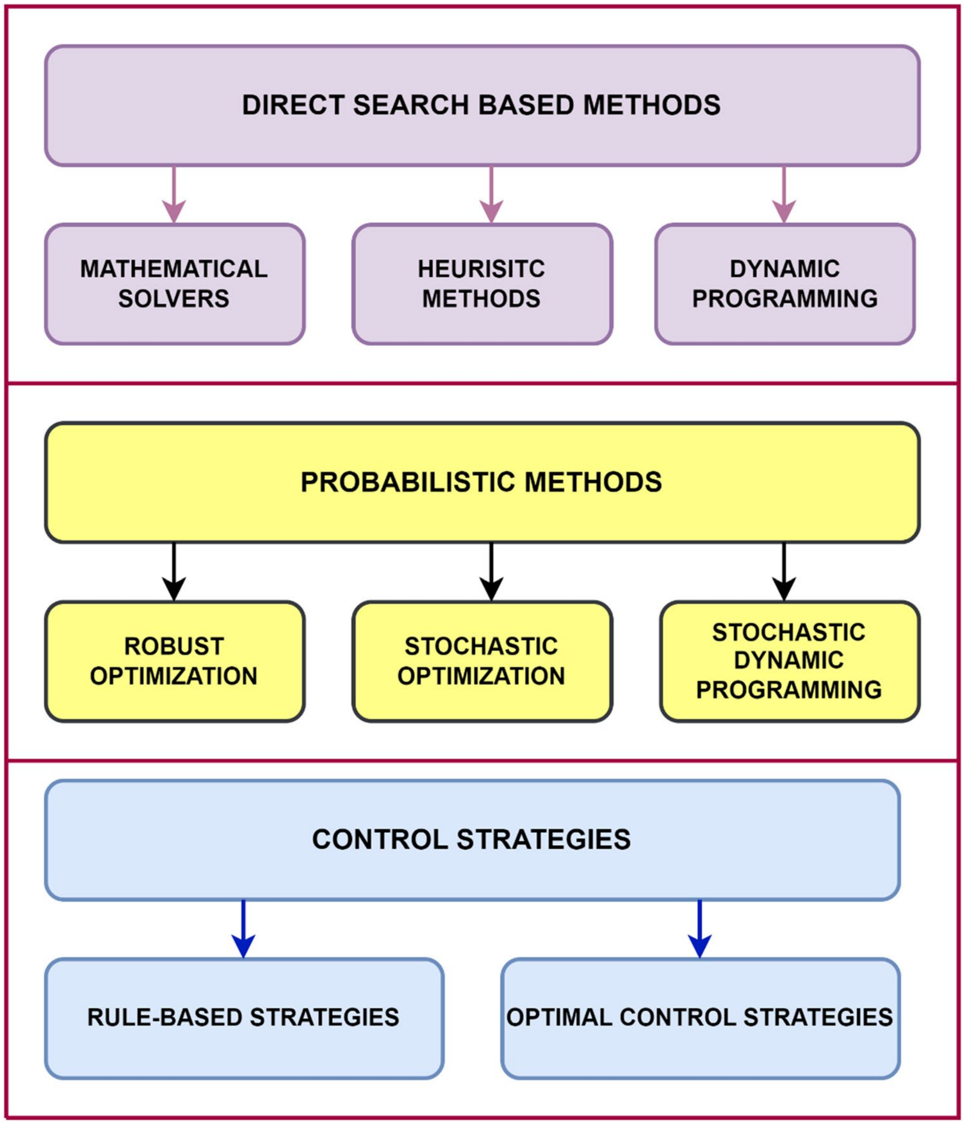


Fig. 4 Charge management approaches of BESS

for managing optimization challenges. CPLEX is adaptable to various platforms, including MATLAB and Python, rendering it extensively utilized. This solver is also integrated into the previously mentioned GAMS system, as seen in solving the optimization problem discussed in Reference [87] by combining GAMS and the CPLEX solver. The flexibility of the CPLEX solver enables it to tackle an array of optimization tasks, encompassing but not confined to IP, LP, and QP challenges. Instances of its application incorporate addressing a linear convex issue [110] and a MILP challenge [130] within the MATLAB environment.

Apart from the previously discussed CPLEX solver, alternative packages with varying solutions can be integrated into MATLAB. For instance, to address a two-stage problem's upper and lower layers, the interior point optimizer IPOPT [178] was utilized for NLP, while the solver Gurobi [179] handled QP. Both these tools were employed to address the issue at hand.

In some scenarios, the optimization problem may not be amenable to standard formulation, particularly when considering additional constraints related to battery energy management, such as battery degradation or operational logic. These constraints involve the battery's degradation process and other operational rules. Consequently, the designated problem solvers may not be suited for this specific application. The introduction of more variables to a problem not only amplifies the model's complexity but also increases its dimensions to accommodate supplementary information. This, in turn, leads to escalated memory requirements and challenges when employing mathematically oriented methods. For example, specific solvers, such as the open version of CPLEX, come with predefined constraints on

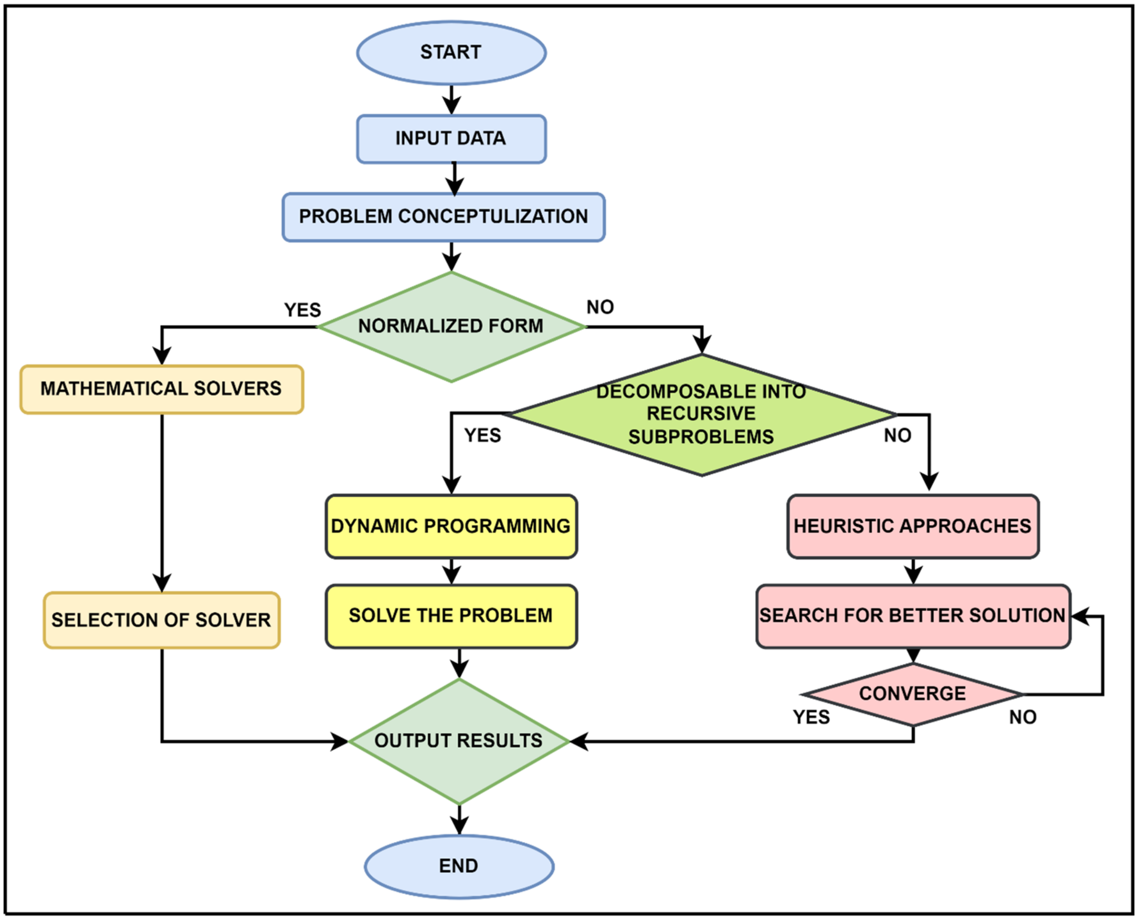


Fig. 5 Working process of direct search-based approaches

the quantity of decision variables. As a result, numerous researchers seeking viable approaches for resolving battery energy management-related optimization issues are exploring diverse search-based methodologies.

5.1.2 Dynamic Programming

In accordance with the principles of dynamic programming (DP) emphasized by Bellman [180], the decision-making process from an initial to a final position can be subdivided into multiple stages. The decisions at each stage can be framed based on the available data regarding the current system conditions. Additionally, complex problems can be deconstructed into a sequence of more manageable subproblems, allowing for iterative resolution of the original issue. The SOC of a battery serves as an indicator of how its previous condition influences its present state. Consequently, SOC can serve as a state variable, following the formal definition provided in Ref. [181].

Furthermore, SOC of the battery can be determined by employing determining factors such as the battery's power profile. Numerous studies have demonstrated the effectiveness of DP in addressing battery energy management challenges. For instance, a study comparing DP to a rule-based management strategy revealed DP algorithms achieving approximately a 13% improvement in platform gains [118]. Additionally, Ref. [85] employs a two-scale DP approach encompassing macro-scale and micro-scale DP techniques. This method leverages multi-scale forecasts of wind power output, utility pricing, and loads to optimize battery storage management. This integration significantly enhances system cost-effectiveness through enhanced precision.

5.1.3 Heuristic Methods

Heuristic techniques, including GA, PSO, NSGA-II, and others, are gaining prominence as effective strategies based on directed search. Synonyms such as artificial intelligence techniques or methods inspired by nature could also be present in scholarly works. Heuristic methods involve practical strategies, similar to the process of trial and error, searching for acceptable solutions. These approaches can be applied to various optimization problems, even if the problem's description isn't precise. While heuristic methods don't assure finding the global optimum, they exhibit notable flexibility and robustness.

GAs operates as a search heuristic, likening the fitness function to the natural selection process, favoring the fittest individuals (survivors for reproduction) across generations [182]. Similarly, PSO emerged from observations of collective animal behavior, like bird flocks and fish schools. In this analogy, individual solutions within a population act as particles evolving toward optimal solutions [183]. NSGA-II, rooted in GAs, is a popular choice for multi-objective optimization tasks.

The application of heuristic techniques to attain the best possible energy management for BESS is increasingly prevalent and is anticipated to continue. For instance, an innovative self-adjusting optimization approach employing PSO was developed with the aim of reducing overall operational costs of the grid [84]. Furthermore, a distributed network with integrated renewable energy was optimized through a multi-objective approach that combined fuzzification and PSO [172], both showcasing PSO's utility in battery optimization. GA is also employed for tasks like scheduling BESS to reduce line loss [97] and reducing daily net expenses in advance-market scenarios [111].

NSGA-II, proves to be a valuable tool for addressing multi-objective optimization challenges. It classifies populations based on Pareto ranking derived from fitness evaluations, thus sorting them into different non-dominated tiers. The application of NSGA-II extends to optimizing battery performance across diverse objectives, as evidenced by References [173, 175], which are also explored in Sect. 4.3. Furthermore, there exists a substantial array of newly developed heuristic approaches employed for optimizing BESS. An innovative HH algorithm, showcased in Reference [96], stands out for its application in seeking the optimal scheduling strategy for BESS.

Hyper-heuristic methodologies encompass search techniques and learning procedures aimed at selecting or generating heuristics tailored to specific optimization problems. This delineation is provided in the same reference [96], where hyper-heuristic algorithms were harnessed to discover the most suitable scheduling approach for BESS. Another distinct heuristic method, known as SFL optimization, was synergistically combined with PSO in Reference [184]. The intention of this combination was to achieve a worldwide enhancement of the membership function within a fuzzy logic controller. In contrast to GA, which focus solely on parent–child interactions, this approach accommodates the propagation of memes through interactive individuals, fostering enhanced information dissemination flexibility.

To ascertain the optimal performance of BESS, with the dual goals of maximizing revenues and upholding smart grid reliability, researchers in Reference [185] employed a methodology closely resembling it, labeled as the crow search technique. Moreover, a formulated model for a restricted stochastic shortest path was created, subsequently tackled via a recommended parallel technique featuring an iterative simultaneous search for the optimal Lagrange multiplier, as detailed in Reference [174]. Regarding battery energy management optimization, the methods centered on directed search, previously discussed, prove notably effective in seeking solutions. In contrast to probability-based and stochastic techniques, directed search-based (DSB) approaches lack assurance in securing the global optimal solution due to unpredictable variables like solar and wind resources, demand, and electricity price. Therefore, the subsequent section will demonstrate the advantages of probabilistic methods, considering the distribution of random variables across an extensive range of potential outcomes. These outcomes encompass extreme scenarios, which deterministic optimization methods may or may not encompass.

5.2 Probabilistic Methods

There are three distinct probabilistic methods utilized in battery energy management: robust optimization, stochastic optimization, and SDP. The working process of probabilistic method is illustrated in Fig. 6.

5.2.1 Robust Optimization

In robust optimization, ambiguity is introduced into the deterministic optimization process by aiming for the worst-case scenario. The foundation of robust optimization lies in analytical optimization, which extends the analytical method to optimization. Both stochastic optimization and this method have been widely employed in recent years to address unit commitment challenges [186, 187]. One straightforward and effective approach for robust optimization is formulating the issue in a problem with two stages focused on maximizing and minimizing. Here, the first step involves planning the battery storage system, as illustrated in [91], to minimize potential profits within the search space by introducing a few random variables to identify the worst possible outcome and determine the optimal solution. In the subsequent step, robust optimization is finalized by maximizing potential earnings under the worst-case scenario, maximizing the total number of potential profits. A similar instance of utilizing min–max-min robust optimization is exemplified in Reference [131], wherein wind turbine and PV power generation are treated as random variables, mirroring the case presented in Reference [131]. An alternative approach to address battery management optimization issues involves transforming a dual-stage maximum-minimum problem into an analogous single-level optimization

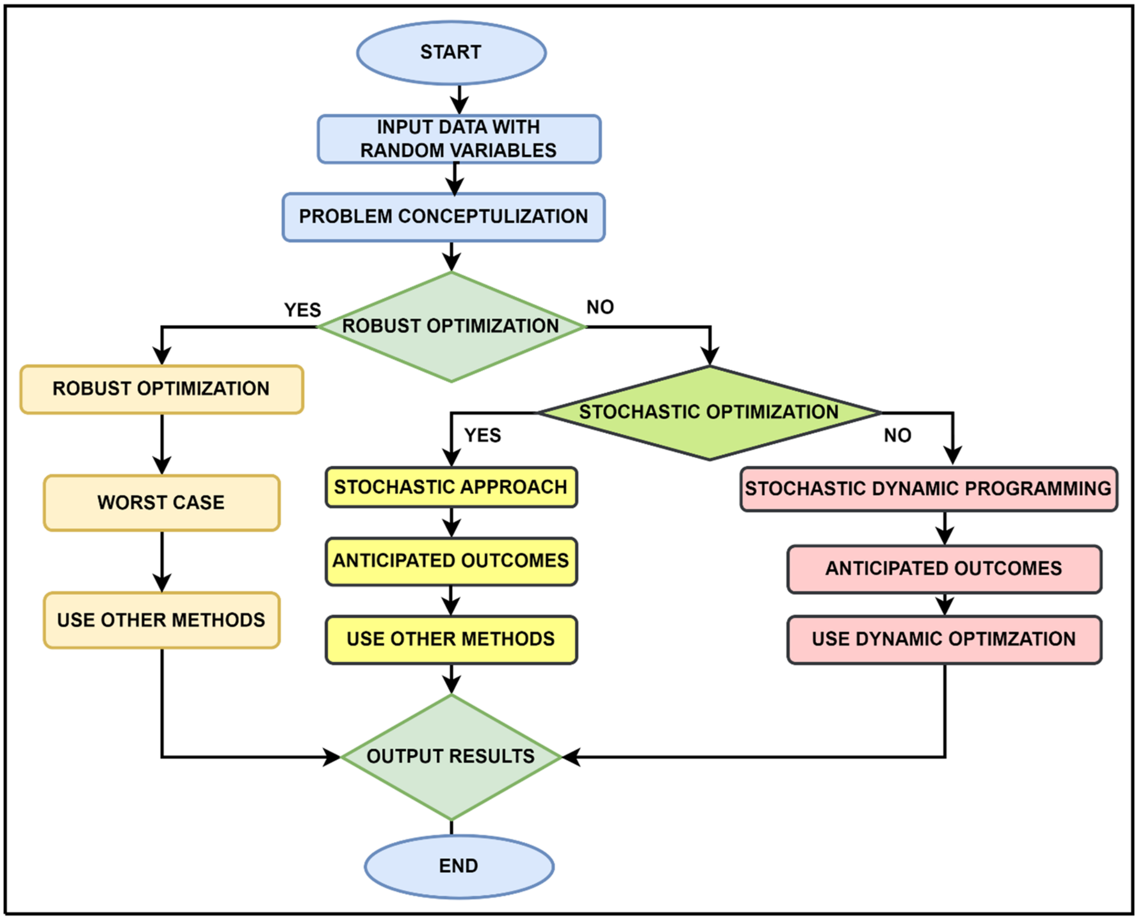


Fig. 6 Working process of probabilistic approaches

applying the Karush–Kuhn–Tucker optimality conditions, outlined in the reference [92].

5.2.2 Stochastic Optimization

Batteries are commonly optimized using a probabilistic technique called stochastic optimization. Stochastic optimization involves optimizing a mathematical or statistical function under conditions of input parameter uncertainty, aiming to either maximize or minimize its outcome. For instance, stochastic optimization can be applied to maximize profits in a virtual power plant scenario, considering the uncertain electricity generation from PV and wind sources as well as market electricity prices [95]. Another use is capitalizing on the unpredictability of wind power to optimize revenue from the sale of electricity in the marketplace [108].

5.2.3 Stochastic DP

Stochastic DP, a probabilistic approach, finds application in battery energy management. It closely resembles stochastic optimization, discussed in detail in Sect. 5.1.2. SDP can be envisioned as an extension of DP infused with random variables. An illustrative example of this approach is outlined in Ref. [86], where an energy storage system's operation over a horizon considers battery degradation, variable generation, demand, and electricity costs. Unlike deterministic scenarios aimed at minimizing total costs across the project, here, projected costs are minimized at each step.

SDP further incorporates a Markov chain process, demonstrated in References [170, 188]. An outer Markov chain generates uncertain hourly renewable power generation and consumption profiles, while an inner Markov chain produces unpredictable daily average renewable energy output and demand usage. Both chains employ the Markov model. Here, forecasted or assumed values are substituted with randomly generated variable values, distinguishing it from dynamic programming. Addressing energy storage scheduling under photovoltaic unpredictability, a solution combines DP and SDP. This involves treating the clarity index, a ratio of global irradiation to additional irradiation on a horizontal plane, as a random variable during daylight hours, transforming it into an SDP challenge. Conversely, during the night, this value is preset as 0, transforming the problem into a DP scenario [161].

5.3 Control Strategies for Battery Energy Management

In the upcoming section, we will explore research that categorizes control approaches for battery energy management into rule-based methods and optimal control strategies. These techniques will be elaborated upon in the following passages. In the domain of BESS applications, control methods play a significant role in enhancing the dynamic and transient behavior of the system, often operating within time scales ranging from milliseconds to seconds. In specific instances, control theory has also been employed for BESS implementation over longer time spans, spanning from minutes to hours. Such cases frequently rely on optimal control strategies, including MPC [90, 109], although exceptions exist. Rule-based approaches are typically explained through logical steps rather than equations, offering clarity. Conversely, when pursuing a solution through optimal control, the problem is expressed as a set of concise matrix equations. The working process of control strategies is illustrated in Fig. 7.

5.3.1 Rule-Based Strategies

Apart from the strategies involving explicit issue statements, alternative studies utilize precise flowcharts, executive rules, or processes to determine charging and discharging methods for the BESS. These approaches exist alongside the methods mentioned earlier and fall under the "rule-based" category. A straightforward illustration of rule-based approaches is using the battery to compensate for discrepancies in PV forecasts [99]. This involves a rule where the battery charges when the PV power output prediction is lower than actual and discharges when it's higher.

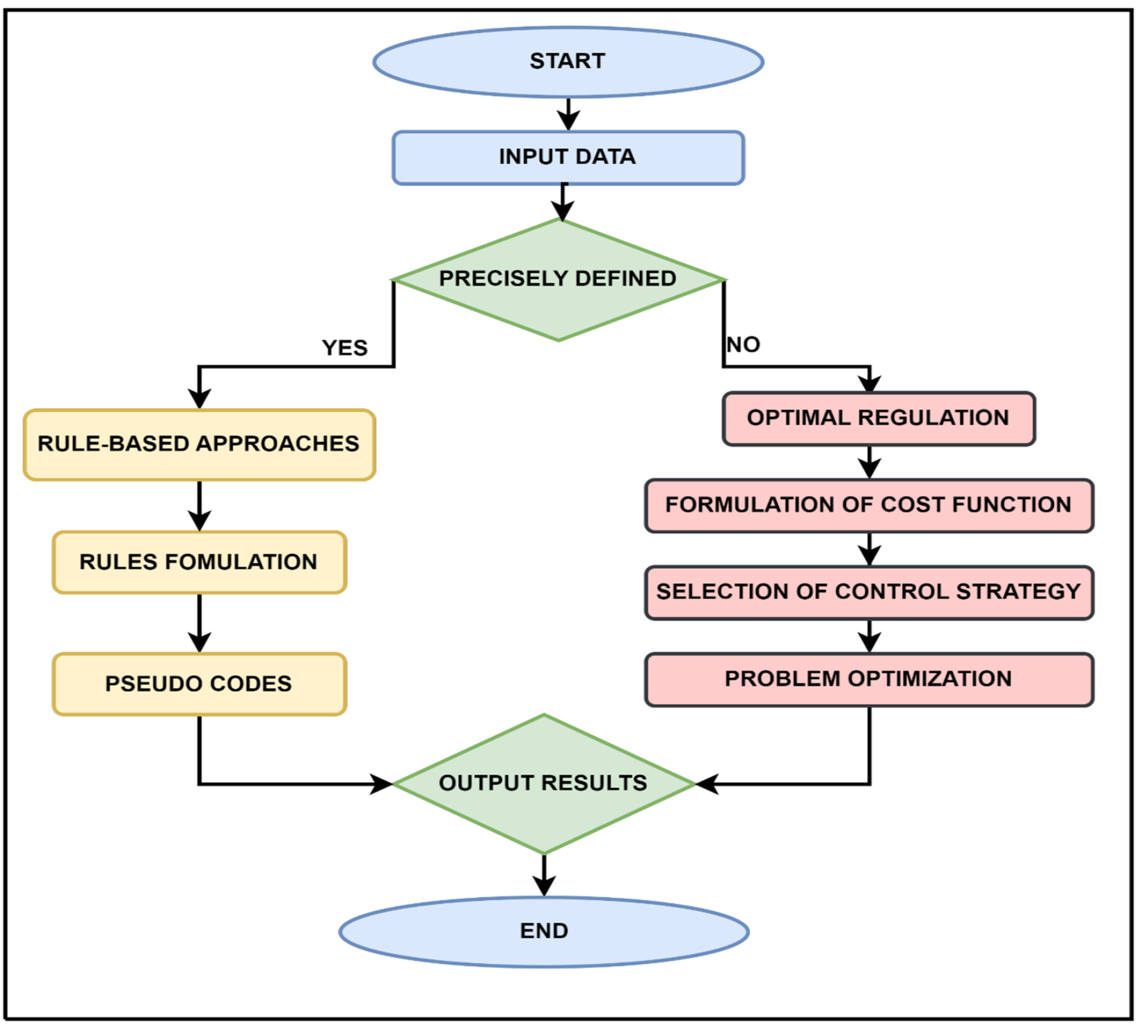


Fig. 7 Working process of control approaches

Rule-based methodologies can also incorporate prioritized criteria. For instance, in Reference [177], the authors establish three priorities: first, maximizing distributed renewable energy usage; second, efficient battery utilization; and third, demand management. Consequently, the battery system fulfills these priorities in the specified order. When photovoltaic panel generation exceeds load demand, a choice arises between charging the battery or sending excess energy to the grid, as exemplified in Reference [93]. This represents a rule-based system. Conversely, when there's an energy deficit and PV panels can't meet demand, a decision is needed on whether to source the deficit from the grid or the battery. Rule-based methodologies highlight the necessity of logical decisions for understanding battery operation. Typically, these decisions are depicted as flow diagrams or pseudocodes. For instance, in battery management, Zhang et al. [73] established two autonomous battery systems to enable independent charging and discharging processes. Similarly, in power grid regulation, rule-based approaches determine whether the battery should charge or discharge based on the deviation of frequency from the standard [66]. Decision criteria are also used for BESS control, with load dissatisfaction triggering action. The BESS charge or discharge power depends on the generation-to-requirement imbalance [126]. Rule-based strategies can also facilitate peak shaving. An illustration is found in Ref. [98], where a significant parameter, the demand constraint, serves as the peak shaving objective. This definition arises from profit-maximizing analytical optimization. When real demand exceeds the limit, the ESS discharges; conversely, it charges when demand is below the limit. Filters are essential for implementing method-based rules. Filters allow only specific frequency content, guiding unique procedures for each frequency set. For example, to segregate low and high-frequency components in primary tie-line power quality issues, two Butterworth filters were used. The BESS managed the low-frequency component, while electric heat pumps, considered as variable loads, addressed the high-frequency component [145].

5.3.2 Optimal Control Strategies

Compared to the primary control strategies that operate within milliseconds to seconds, the majority of optimal control approaches in battery dispatch are focused on medium to long-term regulation of BESS. These strategies operate on timescales ranging from several minutes to hours. Based on the structure of BESS, these control measures are categorized as secondary or tertiary levels, as detailed in Sect. 2. This segment of the study examines the most effective methods for managing battery energy. This emphasis is due to the research's primary focus on the utilization of battery energy management.

Considerable research is directed towards using BESS as an optimal control strategy to address the challenge of managing the unpredictability of renewable energy production. One widely adopted technique is SOC feedback control, which dispatches BESS to monitor designated power generation and ensure that the BESS's SOC remains within an acceptable operational range [147, 149]. MPC is a widely employed optimization approach for battery energy management. MPC divides the problem into discrete timeframes, considering both present and future timeframes. This facilitates optimization for the current timeframe while maintaining adaptability for shifting focus to different perspectives. An instance of MPC's practical application in battery optimal control can be found in Reference [109], where a novel decentralized financial MPC was used in a housing microgrid to optimize user benefits while accounting for energy losses. This represents a direct implementation of MPC in battery management. This showcases the versatility of the MPC framework. In the study by Miranda et al. [90], an MPC framework is adopted for rapid dispatching within a 4-h timeframe. Furthermore, Reference [88] introduces a Lyapunov optimization technique to simultaneously optimize load planning, energy flows, and storage control using a well-designed Lyapunov function. It's worth noting that coordinated control becomes essential when multiple BESS are integrated into renewable energy systems. One such coordinated control strategy is exemplified in Reference [55], where batteries are categorized as a master battery and multiple slave batteries. The master battery, typically the smallest among the BESS, takes precedence during interruptions. Should the master BESS's state of charge fall short, the remaining slave batteries are utilized as alternatives. This coordinated control strategy ensures efficient interaction among multiple BESS units.

Overall, the application of MPC and coordinated control mechanisms significantly enhances the management and optimization of battery energy systems.

6 Discussion

This section explores the relationships between optimization objectives and methodologies in battery energy management research. It discusses how optimization goals align with specific methodologies and highlights the trends in battery energy management objectives and methodologies. These discussions are drawn from research summaries that address battery energy management optimization targets and approaches.

6.1 Exploring the Interplay Between Optimization Objectives and Technique

The above summary clarifies that the selection of an optimization algorithm is closely linked not only to the objectives pursued by a BESS but also to how the optimization problem is formulated. The objectives can be effectively framed as optimization problems with constraints, incorporating control parameters within both the optimization problem and constraints. This applies to objectives that can be combined, such as costs, profits, energy consumption, or intangible "costs." Instances of such objectives encompass pricing and profits.

This category primarily covers financial objectives, certain technical objectives related to energy optimization, and hybrid objectives. For these scenarios, effective solutions can be attained through DSB methods, including mathematical solvers, dynamic programming, or heuristic approaches. For example, it's clear that a standard optimization form can be used to easily write down financial goals that involve a number of costs and gains that need to be taken into account. This highlights a discernible trend in research, as illustrated in Table 3, were frequently addressed using directed search methods for problem-solving. Additionally, for the utilization of mathematical solvers, the problem must initially be formulated in a precise standard optimization format, often requiring further mathematical analysis. Optimal solution discovery is most time-efficient with mathematical solvers. Conversely, heuristic methods necessitate minimal mathematical formulation, but they may sacrifice computation accuracy due to the potential of becoming trapped in local optima. Additionally, DP tends to be employed in scenarios where achieving a high level of computational accuracy is desired. Conversely, heuristic approaches are more suitable when the implementation is expected to be straightforward. The summary of various DSB techniques is depicted in Fig. 8, considering factors such as mathematical complexity, implementation feasibility, computational accuracy, and computational resource requirements.

This phenomenon indeed elucidates the utilization of heuristic methods across a wide array of objectives, regardless of the problem's clarity. Heuristic techniques have been applied to a diverse range of goals. In the context of technical objectives, DSB methodologies are commonly chosen as the optimization approach. This holds especially true when objectives can be defined within a conventional optimization framework, which includes a cost-based objective function and constraints articulated through decision variables [96, 97].

The prior-discussed research revolves around "energy optimization problem-solving," evident from the presentation of data in Table 4. Moreover, addressing these challenges often necessitates the implementation of control techniques in solution methods for managing battery usage to meet specific requirements [98, 99, 145], these issues often necessitate control techniques for solution methods. Rule-based methodologies and optimal control are frequently employed in these scenarios. The distinction between these two control approaches can also be attributed to how the problem is formulated. Optimal control often demands a

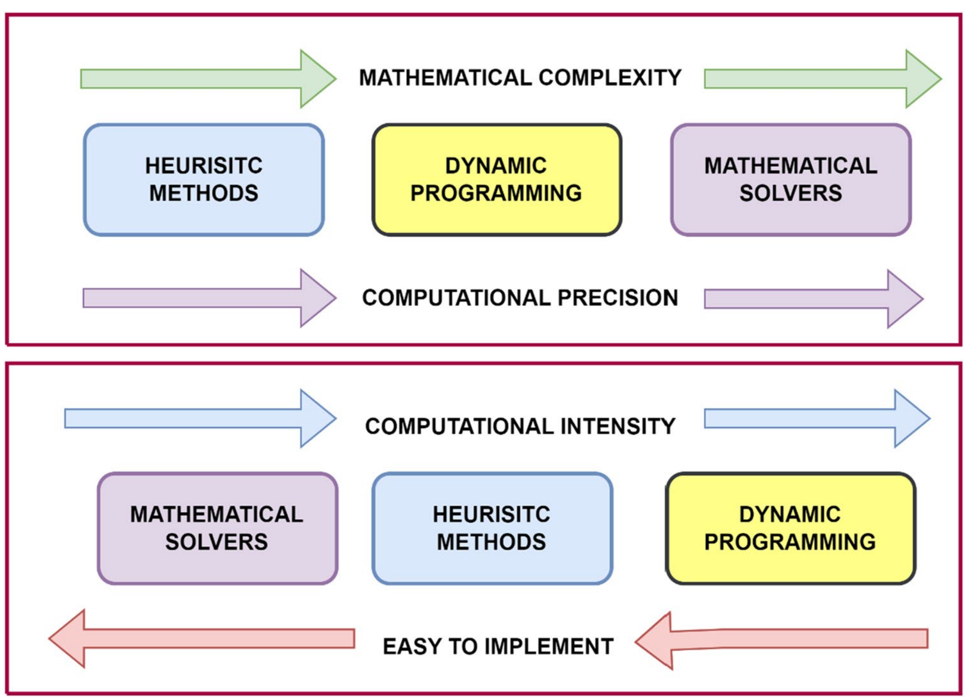


Fig. 8 Characteristics of techniques based on directed search

well-defined reference or the precise definition of a cost function. Conversely, rule-based solutions frequently involve flowcharts or "pseudo-codes" for problem-solving.

Another critical observation is the dependence of probabilistic methods on the consideration of random variable unpredictability. Specifically, this relates to whether incorporating uncertain factors like random photovoltaic and wind power generation, power consumption, and electricity prices into the formulation is beneficial.

When dealing with complex problems that account for the randomness and unpredictability of variables, leveraging stochastic and resilient optimization techniques becomes necessary. Conversely, deterministic optimization methods, which are grounded in directed search and control strategies, become prominent when the degree of randomness is lower. Utilizing predicted values for random variables, instead of extensive simulation studies, enhances the likelihood of obtaining optimal solutions. In a specific instance [85]), wind forecasts, electricity costs, and demand projections were employed to preemptively address optimization concerns, obviating the need for a probabilistic approach. From an alternative perspective, probabilistic techniques could be seen as DSB methods that encompass random variables. This arises because each deterministic scenario represents an optimization problem solvable through directed search approaches. As a result, compared to guided search-based methods, probabilistic approaches may present greater complexity in their application.

When incorporating random variables, various scenarios emerge, each of which can be regarded as a deterministic optimization problem solvable through the application of mathematical solvers in the context of stochastic and robust optimization. This streamlined approach significantly enhances the efficiency of resolving optimization challenges.

In the depicted diagram, it's evident that a majority of the financial objectives, along with certain technical and hybrid goals, primarily pertain to addressing issues through tertiary control. Here, different strategies might be suitable for resolving these challenges. Conversely, secondary control takes responsibility for managing other technical and hybrid objectives. Control techniques are typically employed to tackle such scenarios.

6.2 Exploring the Evolving Landscape of Battery Energy Management Goals

Upon reviewing the BESS dispatch objectives, it becomes evident that the administrator's intentions hold considerable sway over the established goals. If the BESS is managed by a non-profit power grid or corporate entity, its utilization is likely geared towards addressing system issues, such as maintaining system stability. Conversely, if the BESS falls under the control of a private investor, the battery's usage is more likely to be optimized for maximizing economic opportunities. In this scenario, the emphasis would be on enhancing technical quality.

In reality, both technological and financial objectives hold global significance, with prioritization stemming from the investment strategy. As a result, a prominent trend in battery energy management goals is the adoption of multi-objective optimization for BEM. This approach involves pursuing various and sometimes conflicting objectives for battery optimization, moving beyond single objectives or facility-centric approaches for the BESS. Consequently, this represents a significant trajectory in battery energy management objectives.

Besides multi-objective optimization, it's feasible that when defining one optimization goal, another objective can be achieved simultaneously without extra effort during the primary optimization process. This concept is referred to as simultaneous optimization. A prime example of this concept is demonstrated in the research study [118]. The study's main goal is to minimize total working capital, encompassing electricity costs and income from feed-in tariffs. The findings reveal the successful achievement of peak shaving while concurrently reducing power fluctuations within the grid. This case study serves as a robust illustration of simultaneous optimization, indicating a more rapid and effective deployment of BESS.

Another strategy involves mitigating the disparities between active power from the transformer and the standard power curve. Simultaneously, numerous supplementary performance objectives were effectively realized [142]. Though, it's essential to approach this cautiously, as conflicting optimization objectives could lead to reduced utility. This possibility necessitates careful consideration.

Emerging is the trend of establishing virtual power stations through peer-to-peer trading systems [115]. This research highlights the vital role of coordinated planning among a group of BESS to substantially reduce power generation costs for both producers and consumers. Household PV power and the dispatchability of household batteries hold significant potential for efficient energy market utilization. This setup benefits both consumers and companies by reducing monthly bills while enhancing grid capabilities simultaneously [189, 190].

6.3 Exploring Emerging Trends in Battery Energy Management Strategies

The comprehensive overview discussed in Sect. 5; a tabular comparison is presented in Table 6. From Table 6, it becomes evident that each chosen optimization approach comes with its own merits and drawbacks. No single strategy reigns supreme in addressing all BESS management optimization challenges. Therefore, this study not only

Table 6 Merits and demerits of battery optimization approaches

Optimization technique	Merits	Demerits
Mathematical solvers	Solvers featuring meticulous design, a diverse array of options for selection, and a guarantee of reaching the global optimum characterize the key attributes of our optimization approach. The thoughtful design of these solvers ensures a systematic and effective exploration of solution spaces. With a range of solvers at one's disposal, users have the flexibility to choose the most suitable method for their specific optimization requirements. The overarching objective is to secure the global ideal, emphasizing the importance of achieving optimal solutions across diverse problem domains	Limitations include confining the scope of variables considered in decision-making, the necessity of procuring licenses for the utilization of commercial solvers, and accessibility exclusively for problems that have been comprehensively defined
Dynamic programming	Irrespective of how the problem is formulated, the approach remains independent of its specific formulation, showcasing a high level of adaptability and robustness. The method exhibits a notable degree of toughness, demonstrating resilience and effectiveness across various problem formulations	Demanding significant computational resources, this process involves a high level of computational intensity
Heuristic methods	The implementation of this approach is characterized by its simplicity, offering a straightforward process. It exhibits a high degree of flexibility, allowing for versatile applications across different scenarios. Notably, the method demonstrates rapid convergence, ensuring efficient and timely outcomes. Moreover, the approach encompasses a comprehensive array of heuristic strategies, providing a diverse set of tools and techniques for problem-solving and optimization	The optimization process may converge towards a local optimum, indicating that the algorithm settles on a solution that is locally optimal within a specific region of the search space
Probabilistic methods	Taking uncertainties and extreme scenarios into account is crucial in decision-making processes. By acknowledging and factoring in these elements, the outcomes are more likely to yield safe and reliable results. This approach ensures a comprehensive consideration of potential variations and challenges, leading to a more robust and risk-aware decision-making framework	The computational demands of the process are significant, posing a challenge in locating the worst-case scenario. This complexity may lead to outcomes that err on the side of caution, potentially resulting in conservative results
Control strategies	The implementation is straightforward, utilizing simple and logical theories. There is valuable software support, making it user-friendly. Furthermore, it is adaptable for a wide range of timescales, enhancing its applicability across various contexts	Ensuring optimality cannot be guaranteed in this context

examines the advantages and limitations of each optimization strategy but also equips readers with insights into alternative viable strategies that can be employed based on specific needs.

Considering the discourse on the benefits and drawbacks of individual optimization techniques, a noteworthy advancement on the horizon is the integration or hybridization of methods. This fusion seeks to harness the strengths of different approaches and thereby surpass the efficacy of the original strategies. This exciting development marks a promising step in optimization techniques. The findings of this analysis reveal a considerable number of past research endeavors adopting multiple strategies for battery optimization. To illustrate the implementation of hybrid approaches, a logical breakdown of the issue into its constituent components or phases is recommended. Accordingly, suitable strategies can be allocated to specific stages based on the unique problem and the advantages they offer.

An instance of this hybrid methodology is demonstrated in a two-stage optimization framework discussed in Ref. [191]. Here, the active and reactive optimal power flow, treated as a MINLP problem, was divided into two stages. The upper stage was implemented in MATLAB using GA to tackle integer variables, while the lower stage was addressed as a NLP problem using GAMS. The framework was developed utilizing the GDXMRW platform, serving as an interface between GAMS and MATLAB. A similar approach employing a two-step strategic plan can be found in Reference [171]. The initial step of this approach aimed to identify the optimal SOC range, reducing excessive BESS overcharging and over discharging. The subsequent step aimed to stabilize wind speed fluctuations and manage SOC within the most favorable range. A two-step problem-solving strategy was employed: a fuzzy self-adjusting filter was applied to the first step, employing a low-pass filter to smoothen wind fluctuations and a fuzzy-logic filter to control the BESS's SOC in the optimized range. For the second step, fuzzy PSO was employed. Notably, PSO was also utilized to address the initial step of the two-step problem.

Additionally, battery energy management systems can benefit from various application-specific strategies to alleviate stress. Supplementary techniques like supercapacitors, demand response programs, and controllable loads such as electric vehicles and flexible equipment can play a role in energy conservation alongside the BESS, depending on the renewable power system's configuration [145]. Similarly, Reference [192] demonstrates the integration of a hydrogen storage system with the BESS, enabling an independent PV system's operation. Reference [193, 194] presented the techno-economic benefits of renewable energy in the presence of BESS.

6.4 Other Future Trends

An expanding body of research is focused on enhancing battery storage efficiency and its administration, in line with the previously mentioned battery energy management goals and approaches. Prospective studies stand to gain from advancements in battery management, driven by more precise modeling of battery characteristics and novel strides in battery technology. These endeavors aim to implement comparable techniques, minimize degradation, and prolong battery life. In the modern context of power grid management, the integration of AI and ML algorithms has become increasingly prevalent [195, 196]. These technologies are being harnessed in a multitude of significant ways. One such crucial application lies in the realm of comprehensive sensing, which entails the observance of electric equipment, forecasting renewable energy production, predicting energy demands, projecting electricity costs, and a host of other related tasks. This capability revolutionizes the grid's ability to respond dynamically to real-time conditions and fluctuations.

Moreover, AI and ML are playing a pivotal role in enhancing decision-making processes within the power grid landscape. This encompasses a wide array of functions, from strategic power system planning to rapid fault detection, and even extends to the optimization of demand-side management strategies. These technologies empower grid operators with unprecedented insights and tools to ensure the robustness and reliability of the power network. Furthermore, the influence of AI and ML is extending to the domain of battery operations and market-driven power pricing mechanisms. By leveraging advanced algorithms, energy storage systems can be optimized for efficiency, charging schedules, and discharge patterns. Additionally, these technologies are instrumental in the development of market models that respond intelligently to supply and demand dynamics, ultimately leading to more efficient and economically viable energy transactions. In sum, AI and ML technologies are reshaping the contemporary power grid landscape by enabling comprehensive sensing capabilities, enhancing decision-making processes, and influencing critical aspects such as battery operations and market-based pricing strategies. This integration marks a transformative shift towards a more adaptive, responsive, and efficient energy ecosystem.

Reinforcement learning techniques are also emerging for enhancing optimization models [197]. Furthermore, aggregated solar batteries are being employed as VPPs due to these battery activities. The energy stored in these batteries can power a sizable array of solar panels, offering controllable energy generation capabilities. Furthermore, the exchange of energy between home batteries and EVs through blockchain technology is capturing growing attention within the distribution system. It's possible that in the near future, power markets will become more dynamic, fostering increased interaction among individual consumers. This shift would necessitate the development of fresh strategies for utilizing battery power and innovative perspectives on its usage.

7 Conclusion

This study focuses on various techniques and approaches to integrate BESS with renewable energy sources. The implications of battery energy management are outlined, including modeling methodologies, chosen scheduling objectives, and implemented optimization strategies. Many of the examined studies used simplified charge and discharge mechanisms in their baseline battery models. A recurring observation is that BESS objectives are mainly grouped into three categories: economic, technological, and hybrid goals. Private individuals often pursue financial objectives to maximize profits, while system operators adopt technical objectives to improve system performance. Additionally, optimization strategies are divided into three main categories for this review.

In contrast, this evaluation provides a comprehensive overview of battery management methods, examining their research by correlating chosen optimization objectives with relevant algorithms. The efficacy of DSB approaches and control strategies for technical goals is found to outweigh their effectiveness in addressing financial objectives. The extent to which a problem can be mathematically defined significantly influences the applicable resolution strategies.

Moreover, algorithms inspired by natural phenomena and boasting high adaptability exhibit versatility across various scenarios, irrespective of whether the aims are financial, technological, or a fusion of both. In cases involving unknown variables, probabilistic approaches offer more comprehensive solutions by accounting for an array of possibilities. Comparative analysis of reported optimization techniques reveals the growing significance of hybrid approaches that amalgamate the strengths of multiple optimization methods.

Anticipated is the heightened stringency in evaluating the efficiency of BESS, as the trend toward increased integration of renewable energies continues. With the expanding spectrum of battery storage applications, it's evident that advanced optimization methods will be essential in achieving diverse objectives through battery storage.

Funding This research received no external funding.

Declarations

Conflict of interest The author declares no conflict of interest.

References

1. Suberu YM, Mustafa MW, Bashir N (2014) Energy storage systems for renewable energy power sector integration and mitigation of intermittency. Renew Sustain Energy Rev 35:499–514. https://doi.org/10.1016/j.rser.2014.04.009
2. Luo X, Wang J, Dooner M, Clarke J (2015) Overview of current development in electrical energy storage technologies and the application potential in power system operation. Appl Energy 137:511–536. https://doi.org/10.1016/j.apenergy.2014.09.081
3. Toledo OM, Oliveira Filho D, Diniz ASAC (2010) Distributed photovoltaic generation and energy storage systems: a review. Renew Sustain Energy Rev 14:506–511. https://doi.org/10.1016/j.rser.2009.08.007
4. Tan X, Li Q, Wang H (2013) Advances and trends of energy storage technology in Microgrid. Int J Electr Power Energy Syst 44:179–191. https://doi.org/10.1016/j.ijepes.2012.07.015
5. Mahto T, Mukherjee V (2015) Energy storage systems for mitigating the variability of isolated hybrid power system. Renew Sustain Energy Rev 51:1564–1577. https://doi.org/10.1016/j.rser.2015.07.012
6. Berrada A, Loudiyi K (2016) Operation, sizing, and economic evaluation of storage for solar and wind power plants. Renew Sustain Energy Rev 59:1117–1129
7. Divya KC, Østergaard J (2009) Battery energy storage technology for power systems—an overview. Electr Power Syst Res 79(3):511–520. https://doi.org/10.1016/j.epsr.2008.09.017
8. Das T, Krishnan V, McCalley JD (2015) Assessing the benefits and economics of bulk energy storage technologies in the power grid. Appl Energy 139:104–118. https://doi.org/10.1016/j.apenergy.2014.11.017
9. Del Rosso AD, Eckroad SW (2014) Energy storage for relief of transmission congestion. IEEE Trans Smart Grid 5(3):1138–1146. https://doi.org/10.1109/TSG.2013.2277411
10. Stephan A, Battke B, Beuse MD, Clausdeinken JH, Schmidt TS (2016) Limiting the public cost of stationary battery deployment by combining applications. Nat Energy 1:16079. https://doi.org/10.1038/nenergy.2016.79
11. Saxena V, Kumar N, Nangia U (2022) recent trends in the optimization of renewable distributed generation: a review. Ingen Invest 42(3):e97702. https://doi.org/10.15446/ing.investig.97702
12. Poullikkas A (2013) A comparative overview of large-scale battery systems for electricity storage. Renew Sustain Energy Rev 27:778–788. https://doi.org/10.1016/j.rser.2013.07.017
13. Lawder MT, Suthar B, Northrop PWC, De S, Hoff CM, Leitermann O et al (2014) Battery energy storage system (BESS) and battery management system (BMS) for grid-scale applications. Proc IEEE 102(6):1014–1030. https://doi.org/10.1109/JPROC.2014.2317451
14. Dai H, Jiang B, Hu X, Lin X, Wei X, Pecht M (2020) Advanced battery management strategies for a sustainable energy future: Multilayer design concepts and research trends. Renew Sustain Energy Rev. https://doi.org/10.1016/j.rser.2020.110480
15. Zakeri B, Syri S (2015) Electrical energy storage systems: a comparative life cycle cost analysis. Renew Sustain Energy Rev 42:569–596. https://doi.org/10.1016/j.rser.2014.10.011
16. Duffner F, Wentker M, Greenwood M, Leker J (2020) Battery cost modeling: a review and directions for future research. Renew Sustain Energy Rev 127:109872. https://doi.org/10.1016/j.rser.2020.109872
17. Sani SB, Celvakumaran P, Ramachandaramurthy VK, Walker S, Alrazi B, Jia Y et al (2020) Energy storage system policies: way forward and opportunities for emerging economies. J Energy Storage 32:101902. https://doi.org/10.1016/j.est.2020.101902

18. Díaz-González F, Sumper A, Gomis-Bellmunt O, Villafáfila-Robles R (2012) A review of energy storage technologies for wind power applications. Renew Sustain Energy Rev 16(4):2154–2171. https://doi.org/10.1016/j.rser.2012.01.029
19. Zhao H, Wu Q, Hu S, Xu H, Rasmussen CN (2015) Review of energy storage system for wind power integration support. Appl Energy 137:545–553. https://doi.org/10.1016/j.apenergy.2014.04.103
20. de Siqueira LMS, Peng W (2021) Control strategy to smooth wind power output using battery energy storage system: a review. J Energy Storage 35:102252. https://doi.org/10.1016/j.est.2021.102252
21. Barra PHA, de Carvalho WC, Menezes TS, Fernandes RAS, Coury DV (2021) A review on wind power smoothing using high-power energy storage systems. Renew Sustain Energy Rev 137:110455. https://doi.org/10.1016/j.rser.2020.110455
22. Lamsal D, Sreeram V, Mishra Y, Kumar D (2019) Output power smoothing control approaches for wind and photovoltaic generation systems: a review. Renew Sustain Energy Rev 113:109245. https://doi.org/10.1016/j.rser.2019.109245
23. Akram U, Nadarajah M, Shah R, Milano F (2020) A review on rapid responsive energy storage technologies for frequency regulation in modern power systems. Renew Sustain Energy Rev 120:109626. https://doi.org/10.1016/j.rser.2019.109626
24. Dai H, Jiang B, Hu X, Lin X, Wei X, Pecht M (2021) Advanced battery management strategies for a sustainable energy future: multilayer design concepts and research trends. Renew Sustain Energy Rev 138:110480. https://doi.org/10.1016/j.rser.2020.110480
25. Hoppmann J, Volland J, Schmidt TS, Hoffmann VH (2014) The economic viability of battery storage for residential solar photovoltaic systems—a review and a simulation model. Renew Sustain Energy Rev 39:1101–1118. https://doi.org/10.1016/j.rser.2014.07.068
26. Coppez G, Chowdhury S, Chowdhury SP (2010) Review of battery storage optimisation in distributed generation. In: 2010 Joint international conference on power electronics, drives and energy systems & 2010 power, India, pp 1–6. https://doi.org/10.1109/PEDES.2010.5712406
27. Hajiaghasi S, Salemnia A, Hamzeh M (2019) Hybrid energy storage system for microgrids applications: a review. J Energy Storage 21:543–570. https://doi.org/10.1016/j.est.2018.12.017
28. Zhang L, Hu X, Wang Z, Ruan J, Ma C, Song Z et al (2021) Hybrid electrochemical energy storage systems: an overview for smart grid and electrified vehicle applications. Renew Sustain Energy Rev 139:110581. https://doi.org/10.1016/j.rser.2020.110581
29. Naval N, Yusta JM (2021) Virtual power plant models and electricity markets—a review. Renew Sustain Energy Rev 149:111393. https://doi.org/10.1016/j.rser.2021.111393
30. Lee JW, Haram MHSM, Ramasamy G, Thiagarajah SP, Ngu EE, Lee YH (2021) Technical feasibility and economics of repurposed electric vehicles batteries for power peak shaving. J Energy Storage 40:102752. https://doi.org/10.1016/j.est.2021.102752
31. Zhang Z, Ding T, Zhou Q, Sun Y, Qu M, Zeng Z et al (2021) A review of technologies and applications on versatile energy storage systems. Renew Sustain Energy Rev 148:111263. https://doi.org/10.1016/j.rser.2021.111263
32. Tan KM, Babu TS, Ramachandaramurthy VK, Kasinathan P, Solanki SG, Raveendran SK (2021) Empowering smart grid: a comprehensive review of energy storage technology and application with renewable energy integration. J Energy Storage 39:102591. https://doi.org/10.1016/j.est.2021.102591
33. Bidram A, Davoudi A (2012) Hierarchical structure of microgrids control system. IEEE Trans Smart Grid 3:1963–1976. https://doi.org/10.1109/TSG.2012.2197425
34. Morstyn T, Hredzak B, Agelidis VG (2016) Control strategies for microgrids with distributed energy storage systems: an overview. IEEE Trans Smart Grid. https://doi.org/10.1109/TSG.2016.2637958
35. Dunn B, Kamath H, Tarascon J-M (2011) Electrical energy storage for the grid: a battery of choices. Science 334(80):928–935. https://doi.org/10.1126/science.1212741
36. Ferreira HL, Garde R, Fulli G, Kling W, Lopes JP (2013) Characterisation of electrical energy storage technologies. Energy 53:288–298. https://doi.org/10.1016/j.energy.2013.02.037
37. Jenkins DP, Fletcher J, Kane D (2008) Lifetime prediction and sizing of lead–acid batteries for microgeneration storage applications. IET Renew Power Gener 2:191–200. https://doi.org/10.1049/iet-rpg:20080021
38. Dogger JD, Roossien B, Nieuwenhout FDJ (2011) Characterization of Li-ion batteries for intelligent management of distributed grid-connected storage. IEEE Trans Energy Convers 26:256–263. https://doi.org/10.1109/TEC.2009.2032579
39. Hatta T (2012) Applications of sodium-sulfur batteries. In: Transmission and distribution conference and exposition (T&D), 2012 IEEE PES, pp 1–3. https://doi.org/10.1109/TDC.2012.6281442
40. Stan AI, Swierczynski M, Stroe DI, Teodorescu R, Andreasen SJ (2014) Lithium ion battery chemistries from renewable energy storage to automotive and back-up power applications: an overview. In: 2014 International conference on optimization of electrical and electronic equipment (OPTIM), pp 713–720. https://doi.org/10.1109/OPTIM.2014.6850936
41. Baccino F, Marinelli M, Nørgård P, Silvestro F (2014) Experimental testing procedures and dynamic model validation for vanadium redox flow battery storage system. J Power Sources 254:277–286. https://doi.org/10.1016/j.jpowsour.2013.12.078
42. Schreiber M, Harrer M, Whitehead A, Bucsich H, Dragschitz M, Seifert E et al (2012) Practical and commercial issues in the design and manufacture of vanadium flow batteries. J Power Sources 206:483–489. https://doi.org/10.1016/j.jpowsour.2010.12.032
43. Li Y, Sun L, Cao L, Bao J, Skyllas-Kazacos M (2021) Dynamic model based membrane permeability estimation for online SOC imbalances monitoring of vanadium redox flow batteries. J Energy Storage 39:102688. https://doi.org/10.1016/j.est.2021.102688
44. Liu W, Placke T, Chau KT (2022) Overview of batteries and battery management for electric vehicles. Energy Rep 8:4058–4084. https://doi.org/10.1016/j.egyr.2022.03.016
45. Zou C, Zhang L, Hu X, Wang Z, Wik T, Pecht M (2018) A review of fractional-order techniques applied to lithium-ion batteries, lead-acid batteries, and supercapacitors. J Power Sources 390:286–296. https://doi.org/10.1016/j.jpowsour.2018.04.033
46. Wang Y, Tian J, Sun Z, Wang L, Xu R, Li M et al (2020) A comprehensive review of battery modeling and state estimation approaches for advanced battery management systems. Renew Sustain Energy Rev 131:110015. https://doi.org/10.1016/j.rser.2020.110015
47. Shahjalal M, Shams T, Islam ME, Alam W, Modak M, Hossain SB et al (2021) A review of thermal management for Li-ion batteries: prospects, challenges, and issues. J Energy Storage 39:102518. https://doi.org/10.1016/j.est.2021.102518
48. Nguyen TA, Crow ML, Elmore AC (2015) Optimal sizing of a vanadium redox battery system for microgrid systems. IEEE Trans Sustain Energy 6:729–737. https://doi.org/10.1109/TSTE.2015.2404780
49. Cervone A, Carbone G, Santini E, Teodori S (2016) Optimization of the battery size for PV systems under regulatory rules using a Markov-Chains approach. Renew Energy 85:657–665. https://doi.org/10.1016/j.renene.2015.07.007

50. Rodrigues EMG, Osório GJ, Godina R, Bizuayehu AW, Lujano-Rojas JM, Matias JCO et al (2015) Modelling and sizing of NaS (sodium sulfur) battery energy storage system for extending wind power performance in Crete Island. Energy 90:1606–1617. https://doi.org/10.1016/j.energy.2015.06.116
51. Aaslid P, Geth F, Korpås M, Belsnes MM, Fosso OB (2020) Non-linear charge-based battery storage optimization model with bi-variate cubic spline constraints. J Energy Storage 32:101979. https://doi.org/10.1016/j.est.2020.101979
52. Li X (2012) Fuzzy adaptive Kalman filter for wind power output smoothing with battery energy storage system. IET Renew Power Gener 6:340–347. https://doi.org/10.1049/iet-rpg.2011.0177
53. Eghtedarpour N, Farjah E (2012) Control strategy for distributed integration of photovoltaic and energy storage systems in DC micro-grids. Renew Energy 45:96–110. https://doi.org/10.1016/j.renene.2012.02.017
54. Fares RL, Webber ME (2014) A flexible model for economic operational management of grid battery energy storage. Energy 78:768–776. https://doi.org/10.1016/j.energy.2014.10.072
55. Lee SJ, Kim JH, Kim CH, Kim SK, Kim ES, Kim DU et al (2016) Coordinated control algorithm for distributed battery energy storage systems for mitigating voltage and frequency deviations. IEEE Trans Smart Grid 7:1713–1722. https://doi.org/10.1109/TSG.2015.2429919
56. Sebastián R (2016) Application of a battery energy storage for frequency regulation and peak shaving in a wind diesel power system. IET Gener Transm Distrib 10:764–770. https://doi.org/10.1049/iet-gtd.2015.0435
57. Abdeltawab HH, Mohamed YARI (2015) Market-oriented energy management of a hybrid wind-battery energy storage system via model predictive control with constraint optimizer. IEEE Trans Ind Electron 62:6658–6670. https://doi.org/10.1109/TIE.2015.2435694
58. Tao L, Ma J, Cheng Y, Noktehdan A, Chong J, Lu C (2017) A review of stochastic battery models and health management. Renew Sustain Energy Rev 80:716–732. https://doi.org/10.1016/j.rser.2017.05.127
59. Xu B, Oudalov A, Ulbig A, Andersson G, Kirschen D (2016) Modeling of lithium-ion battery degradation for cell life assessment. IEEE Trans Smart Grid. https://doi.org/10.1109/TSG.2016.2578950
60. IRENA (2015) Battery storage for renewables: market status and technology outlook. http://www.irena.org/documentdownloads/publications/irena_battery_storage_report_2015.pdf
61. Sullivan JP, Fenton KR, Gabaly FEG, Harris TC, Hayden CC et al (2015) The science of battery degradation. Unlimited Release. Sandia National Laboratories, Albuquerque
62. Krieger EM, Cannarella J, Arnold CB (2013) A comparison of lead-acid and lithium-based battery behavior and capacity fade in off-grid renewable charging applications. Energy 60:492–500. https://doi.org/10.1016/j.energy.2013.08.029
63. Nuhic A, Terzimehic T, Soczka-Guth T, Buchholz M, Dietmayer K (2013) Health diagnosis and remaining useful life prognostics of lithium-ion batteries using data-driven methods. J Power Sources 239:680–688. https://doi.org/10.1016/j.jpowsour.2012.11.146
64. Cotton B (2012) VRLA battery lifetime fingerprints—Part 1. In: Intelec 2012. IEEE. https://doi.org/10.1109/INTLEC.2012.6374495
65. Ru Y, Kleissl J, Martinez S (2013) Storage size determination for grid-connected photovoltaic systems. IEEE Trans Sustain Energy 4:68–81. https://doi.org/10.1109/TSTE.2012.2199339
66. Stroe DI, Knap V, Swierczynski M, Stroe AI, Teodorescu R (2017) Operation of a grid-connected lithium-ion battery energy storage system for primary frequency regulation: a battery lifetime perspective. IEEE Trans Ind Appl 53:430–438. https://doi.org/10.1109/TIA.2016.2616319
67. Dragicevic T, Pandzic H, Skrlec D, Kuzle I, Guerrero JM, Kirschen DS (2014) Capacity optimization of renewable energy sources and battery storage in an autonomous telecommunication facility. IEEE Trans Sustain Energy 5:1367–1378. https://doi.org/10.1109/TSTE.2014.2316480
68. Li S, He H, Su C, Zhao P (2020) Data driven battery modeling and management method with aging. Appl Energy 275:115340. https://doi.org/10.1016/j.apenergy.2020.115340
69. Wang S, Guo D, Han X, Lu L, Sun K, Li W et al (2020) Impact of battery degradation models on energy management of a grid-connected DC microgrid. Energy 207:118228. https://doi.org/10.1016/j.energy.2020.118228
70. Lujano-Rojas JM, Dufo-López R, Atencio-Guerra JL, Rodrigues EMG, Bernal- Agustín JL, Catalão JPS (2016) Operating conditions of lead-acid batteries in the optimization of hybrid energy systems and microgrids. Appl Energy 179:590–600. https://doi.org/10.1016/j.apenergy.2016.07.018
71. Luo F, Meng K, Dong ZY, Zheng Y, Chen Y, Wong KP (2015) Coordinated operational planning for wind farm with battery energy storage system. IEEE Trans Sustain Energy 6:253–262. https://doi.org/10.1109/TSTE.2014.2367550
72. Yao DL, Choi SS, Tseng KJ, Lie TT (2012) Determination of short-term power dispatch schedule for a wind farm incorporated with dual-battery energy storage scheme. IEEE Trans Sustain Energy 3:74–84. https://doi.org/10.1109/TSTE.2011.2163092
73. Zhang X, Yuan Y, Hua L, Cao Y, Qian K (2017) On generation schedule tracking of wind farms with battery energy storage systems. IEEE Trans Sustain Energy 8:341–353. https://doi.org/10.1109/TSTE.2016.2598823
74. Barnes AK, Balda JC, Escobar-Mejia A (2015) A semi-markov model for control of energy storage in utility grids and microgrids with PV generation. IEEE Trans Sustain Energy 6:546–556. https://doi.org/10.1109/TSTE.2015.2393353
75. Wang G, Ciobotaru M, Agelidis VG (2014) Power smoothing of large solar PV plant using hybrid energy storage. IEEE Trans Sustain Energy 5:834–842. https://doi.org/10.1109/TSTE.2014.2305433
76. Zhang Z, Wang J, Wang X (2015) An improved charging/discharging strategy of lithium batteries considering depreciation cost in day-ahead microgrid scheduling. Energy Convers Manag 105:675–684. https://doi.org/10.1016/j.enconman.2015.07.079
77. Feng X, Gooi HB, Chen S (2015) Capacity fade-based energy management for lithium-ion batteries used in PV systems. Electr Power Syst Res 129:150–159. https://doi.org/10.1016/j.epsr.2015.08.011
78. Mazzola S, Vergara C, Astolfi M, Li V, Perez-Arriaga I, Macchi E (2017) Assessing the value of forecast-based dispatch in the operation of off-grid rural microgrids. Renew Energy 108:116–125. https://doi.org/10.1016/j.renene.2017.02.040
79. Comodi G, Giantomassi A, Severini M, Squartini S, Ferracuti F, Fonti A et al (2015) Multi-apartment residential microgrid with electrical and thermal storage devices: experimental analysis and simulation of energy management strategies. Appl Energy 137:854–866. https://doi.org/10.1016/j.apenergy.2014.07.068
80. Hanna R, Kleissl J, Nottrott A, Ferry M (2014) Energy dispatch schedule optimization for demand charge reduction using a photovoltaic-battery storage system with solar forecasting. Sol Energy 103:269–287. https://doi.org/10.1016/j.solener.2014.02.020
81. Teleke S, Baran ME, Bhattacharya S, Huang AQ (2010) Optimal control of battery energy storage for wind farm dispatching. IEEE Trans Energy Convers 25:787–794. https://doi.org/10.1109/TEC.2010.2041550

82. Yuan Y, Zhang X, Ju P, Qian K, Fu Z (2012) Applications of battery energy storage system for wind power dispatchability purpose. Electr Power Syst Res 93:54–60. https://doi.org/10.1016/j.epsr.2012.07.008
83. Jiang Q, Gong Y, Wang H (2013) A battery energy storage system dual-layer control strategy for mitigating wind farm fluctuations. IEEE Trans Power Syst 28:3263–3273. https://doi.org/10.1109/TPWRS.2013.2244925
84. Baziar A, Kavousi-Fard A (2013) Considering uncertainty in the optimal energy management of renewable micro-grids including storage devices. Renew Energy 59:158–166. https://doi.org/10.1016/j.renene.2013.03.026
85. Lei Z, Yaoyu L (2013) Optimal energy management of wind-battery hybrid power system with two-scale dynamic programming. IEEE Trans Sustain Energy 4:765–773. https://doi.org/10.1109/TSTE.2013.2246875
86. Abdulla K, De Hoog J, Muenzel V, Suits F, Steer K, Wirth A et al (2016) Optimal operation of energy storage systems considering forecasts and battery degradation. IEEE Trans Smart Grid. https://doi.org/10.1109/TSG.2016.2606490
87. Wang Y, Dvorkin Y, Fernandez-Blanco R, Xu B, Qiu T, Kirschen D (2017) Look-ahead bidding strategy for energy storage. IEEE Trans Sustain Energy. https://doi.org/10.1109/TSTE.2017.2656800
88. Li T, Dong M (2016) Real-time residential-side joint energy storage management and load scheduling with renewable integration. IEEE Trans Smart Grid. https://doi.org/10.1109/TSG.2016.2550500
89. Sigrist L, Lobato E, Rouco L (2013) Energy storage systems providing primary reserve and peak shaving in small isolated power systems: an economic assessment. Int J Electr Power Energy Syst 53:675–683. https://doi.org/10.1016/j.ijepes.2013.05.046
90. Miranda I, Silva N, Leite H (2016) A holistic approach to the integration of battery energy storage systems in island electric grids with high wind penetration. IEEE Trans Sustain Energy 7:775–785. https://doi.org/10.1109/TSTE.2015.2497003
91. Kazemi M, Zareipour H, Amjady N, Rosehart WD, Ehsan M (2017) Operation scheduling of battery storage systems in joint energy and ancillary services markets. IEEE Trans Sustain Energy. https://doi.org/10.1109/TSTE.2017.2706563
92. Kazemi M, Zareipour H (2017) Long-term scheduling of battery storage systems in energy and regulation markets considering battery's lifespan. IEEE Trans Smart Grid. https://doi.org/10.1109/TSG.2017.2724919
93. Riffonneau Y, Bacha S, Barruel F, Delaille A (2009) Energy flow management in grid connected PV systems with storage - a deterministic approach. In: 2009 IEEE international conference on industrial technology. IEEE, pp 1–6. https://doi.org/10.1109/ICIT.2009.4939609
94. Mariaud A, Acha S, Ekins-Daukes N, Shah N, Markides CN (2017) Integrated optimisation of photovoltaic and battery storage systems for UK commercial buildings. Appl Energy 199:466–478. https://doi.org/10.1016/j.apenergy.2017.04.067
95. Zhou B, Liu X, Cao Y, Li C, Chung CY, Chan KW (2016) Optimal scheduling of virtual power plant with battery degradation cost. IET Gener Transm Distrib 10:712–725. https://doi.org/10.1049/iet-gtd.2015.0103
96. Mallol-Poyato R, Salcedo-Sanz S, Jiménez-Fernández S, Díaz-Villar P (2015) Optimal discharge scheduling of energy storage systems in MicroGrids based on hyper-heuristics. Renew Energy 83:13–24. https://doi.org/10.1016/j.renene.2015.04.009
97. Jen-Hao T, Shang-Wen L, Dong-Jing L, Yong-Qing H (2013) Optimal charging/discharging scheduling of battery storage systems for distribution systems interconnected with sizeable PV generation systems. IEEE Trans Power Syst 28:1425–1433. https://doi.org/10.1109/TPWRS.2012.2230276
98. Zheng M, Meinrenken CJ, Lackner KS (2015) Smart households: dispatch strategies and economic analysis of distributed energy storage for residential peak shaving. Appl Energy 147:246–257. https://doi.org/10.1016/j.apenergy.2015.02.039
99. Brenna M, Foiadelli F, Longo M, Zaninelli D (2016) Energy storage control for dispatching photovoltaic power. IEEE Trans Smart Grid. https://doi.org/10.1109/TSG.2016.2611999
100. Alam MJE, Muttaqi KM, Sutanto D (2014) A novel approach for ramp-rate control of solar PV using energy storage to mitigate output fluctuations caused by cloud passing. IEEE Trans Energy Convers 29:507–518. https://doi.org/10.1109/TEC.2014.2304951
101. Abedlrazek SA, Kamalasadan S (2016) A weather based optimal storage management algorithm for PV capacity firming. IEEE Trans Ind Appl. https://doi.org/10.1109/TIA.2016.2598139
102. Hansang L, Byoung Yoon S, Sangchul H, Seyong J, Byungjun P, Gilsoo J (2012) Compensation for the power fluctuation of the large scale wind farm using hybrid energy storage applications. IEEE Trans Appl Supercond 22:5701904. https://doi.org/10.1109/TASC.2011.2180881
103. Teleke S, Baran ME, Bhattacharya S, Huang AQ (2010) Rule-based control of battery energy storage for dispatching intermittent renewable sources. IEEE Trans Sustain Energy 1(2):117–124. https://doi.org/10.1109/TSTE.2010.2061880
104. Bo L, Shahidehpour M (2005) Short-term scheduling of battery in a grid-connected PV/battery system. IEEE Trans Power Syst 20:1053–1061. https://doi.org/10.1109/TPWRS.2005.846060
105. Osório GJ, Rodrigues EMG, Lujano-Rojas JM, Matias JCO, Catalão JPS (2015) New control strategy for the weekly scheduling of insular power systems with a battery energy storage system. Appl Energy 154:459–470. https://doi.org/10.1016/j.apenergy.2015.05.048
106. Shuai H, Fang J, Ai X, Wen J, He H (2019) Optimal real-time operation strategy for microgrid: an ADP-based stochastic nonlinear optimization approach. IEEE Trans Sustain Energy 10:931–942. https://doi.org/10.1109/TSTE.2018.2855039
107. Wang B, Zhang C, Dong ZY (2020) Interval optimization based coordination of demand response and battery energy storage system considering SOC management in a microgrid. IEEE Trans Sustain Energy 11:2922–2931. https://doi.org/10.1109/TSTE.2020.2982205
108. Abu Abdullah M, Muttaqi KM, Sutanto D, Agalgaonkar AP (2015) An effective power dispatch control strategy to improve generation schedulability and supply reliability of a wind farm using a battery energy storage system. IEEE Trans Sustain Energy 6:1093–1102. https://doi.org/10.1109/TSTE.2014.2350980
109. Zhang X, Bao J, Wang R, Zheng C, Skyllas-Kazacos M (2016) Dissipativity based distributed economic model predictive control for residential microgrids with renewable energy generation and battery energy storage. Renew Energy. https://doi.org/10.1016/j.renene.2016.05.006
110. Sandgani MR, Sirouspour S (2017) Coordinated optimal dispatch of energy storage in a network of grid-connected microgrids. IEEE Trans Sustain Energy 8:1166–1176. https://doi.org/10.1109/TSTE.2017.2664666
111. Lujano-Rojas JM, Dufo-López R, Bernal-Agustín JL, Catalão JPS (2017) Optimizing daily operation of battery energy storage systems under real-time pricing schemes. IEEE Trans Smart Grid 8:316–330. https://doi.org/10.1109/TSG.2016.2602268
112. Al Essa MJM (2018) Management of charging cycles for grid-connected energy storage batteries. J Energy Storage 18:380–388. https://doi.org/10.1016/j.est.2018.05.019
113. Zhu Y, Zhao D, Li X, Wang D (2019) Control-limited adaptive dynamic programming for multi-battery energy storage

systems. IEEE Trans Smart Grid 10:4235–4244. https://doi.org/10.1109/TSG.2018.2854300
114. Zeynali S, Rostami N, Ahmadian A, Elkamel A (2020) Two-stage stochastic home energy management strategy considering electric vehicle and battery energy storage system: an ANN-based scenario generation methodology. Sustain Energy Technol Assess 39:100722. https://doi.org/10.1016/j.seta.2020.100722
115. Nguyen S, Peng W, Sokolowski P, Alahakoon D, Yu X (2020) Optimizing rooftop photovoltaic distributed generation with battery storage for peer-to-peer energy trading. Appl Energy 228:2567–2580. https://doi.org/10.1016/j.apenergy.2018.07.042
116. Zhang N, Leibowicz BD, Hanasusanto GA (2020) Optimal residential battery storage operations using robust data-driven dynamic programming. IEEE Trans Smart Grid 11:1771–1780. https://doi.org/10.1109/TSG.2019.2942932
117. Nath S, Wu J (2020) Online battery scheduling for grid-connected photo-voltaic systems. J Energy Storage 31:101713. https://doi.org/10.1016/j.est.2020.101713
118. Riffonneau Y, Bacha S, Barruel F, Ploix S (2011) Optimal power flow management for grid connected PV systems with batteries. IEEE Trans Sustain Energy 2:309–320. https://doi.org/10.1109/TSTE.2011.2114901
119. Sani Hassan A, Cipcigan L, Jenkins N (2017) Optimal battery storage operation for PV systems with tariff incentives. Appl Energy 203:422–441. https://doi.org/10.1016/j.apenergy.2017.06.043
120. Khalilpour R, Vassallo A (2016) Planning and operation scheduling of PV-battery systems: a novel methodology. Renew Sustain Energy Rev 53:194–208. https://doi.org/10.1016/j.rser.2015.08.015
121. Li T, Dong M (2015) Real-time energy storage management with renewable integration: finite-time horizon approach. IEEE J Sel Areas Commun 33:2524–2539. https://doi.org/10.1109/JSAC.2015.2481212
122. Yuan Y, Zhang X, Ju P, Li Q, Qian K, Fu Z (2014) Determination of economic dispatch of wind farm-battery energy storage system using Genetic Algorithm. Int Trans Electr Energy Syst 24:264–280. https://doi.org/10.1002/etep.1696
123. Correa-florez CA, Gerossier A, Michiorri A, Kariniotakis G (2018) Stochastic operation of home energy management systems including battery cycling. Appl Energy 225:1205–1218. https://doi.org/10.1016/j.apenergy.2018.04.130
124. Hossain A, Roy H, Squartini S, Zaman F (2019) Energy scheduling of community microgrid with battery cost using particle swarm optimization. Appl Energy 254:113723. https://doi.org/10.1016/j.apenergy.2019.113723
125. Cao J, Harrold D, Fan Z, Morstyn T, Healey D, Li K (2020) Deep reinforcement learning-based energy storage arbitrage with accurate lithium-ion battery degradation model. IEEE Trans Smart Grid 11:4513–4521. https://doi.org/10.1109/TSG.2020.2986333
126. Kim JS, Yang H, Choi SG (2017) Distributed real-time stochastic optimization based ESS management strategy for residential customers. In: 2017 19th International conference on advanced communication technology 2017, pp 321–325. https://doi.org/10.23919/ICACT.2017.7890107
127. Maheshwari A, Paterakis NG, Santarelli M, Gibescu M (2020) Optimizing the operation of energy storage using a non-linear lithium-ion battery degradation model. Appl Energy 261:114360. https://doi.org/10.1016/j.apenergy.2019.114360
128. Arteaga J, Zareipour H (2019) A price-maker/price-taker model for the operation of battery storage systems in electricity markets. IEEE Trans Smart Grid 10:6912–6920. https://doi.org/10.1109/TSG.2019.2913818
129. Zhang YJ, Zhao C, Tang W, Low SH (2016) Profit maximizing planning and control of battery energy storage systems for primary frequency control. IEEE Trans Smart Grid. https://doi.org/10.1109/TSG.2016.2562672
130. Bitaraf H, Rahman S (2017) Reducing curtailed wind energy through energy storage and demand response. IEEE Trans Sustain Energy. https://doi.org/10.1109/TSTE.2017.2724546
131. Zhang C, Xu Y, Dong ZY, Ma J (2016) Robust operation of microgrids via two-stage coordinated energy storage and direct load control. IEEE Trans Power Syst. https://doi.org/10.1109/TPWRS.2016.2627583
132. Barsali S, Giglioli R, Lutzemberger G, Poli D, Valenti G (2017) Optimised operation of storage systems integrated with MV photovoltaic plants, considering the impact on the battery lifetime. J Energy Storage 12:178–185. https://doi.org/10.1016/j.est.2017.05.003
133. He G, Chen Q, Kang C, Xia Q, Poolla K (2017) Cooperation of wind power and battery storage to provide frequency regulation in power markets. IEEE Trans Power Syst 32:3559–3568. https://doi.org/10.1109/TPWRS.2016.2644642
134. Zafar R, Ravishankar J, Fletcher JE, Pota HR (2020) Multi-timescale voltage stability-constrained Volt/VAR optimization with battery storage system in distribution grids. IEEE Trans Sustain Energy 11:868–878. https://doi.org/10.1109/TSTE.2019.2910726
135. Darcovich K, Kenney B, MacNeil DD, Armstrong MM (2015) Control strategies and cycling demands for Li-ion storage batteries in residential micro-cogeneration systems. Appl Energy 141:32–41. https://doi.org/10.1016/j.apenergy.2014.11.079
136. Leadbetter J, Swan L (2012) Battery storage system for residential electricity peak demand shaving. Energy Build 55:685–692. https://doi.org/10.1016/j.enbuild.2012.09.035
137. Teki VK, Maharana MK, Panigrahi CK (2020) Study on home energy management system with battery storage for peak load shaving. Mater Today Proc. https://doi.org/10.1016/j.matpr.2020.08.377
138. Uddin M, Romlie MF, Abdullah MF, Tan C, Sha GM, Bakar AHA (2020) A novel peak shaving algorithm for islanded microgrid using battery energy storage system. Energy 196:1–13. https://doi.org/10.1016/j.energy.2020.117084
139. Samanta H, Bhattacharjee A, Pramanik M, Das A (2020) Internet of Things based smart energy management in a vanadium redox flow battery storage integrated bio-solar microgrid. J Energy Storage 32:101967. https://doi.org/10.1016/j.est.2020.101967
140. Taylor Z, Akhavan-Hejazi H, Cortez E, Alvarez L, Ula S, Barth M et al (2019) Customer-side SCADA-assisted large battery operation optimization for distribution feeder peak load shaving. IEEE Trans Smart Grid 10:992–1004. https://doi.org/10.1109/TSG.2017.2757007
141. Cai Z, Bussar C, Stöcker P, Moraes L, Magnor D, Leuthold M et al (2015) Application of battery storage for compensation of forecast errors of wind power generation in 2050. Energy Proc 73:208–17. https://doi.org/10.1016/j.egypro.2015.07.673
142. Reihani E, Sepasi S, Roose LR, Matsuura M (2016) Energy management at the distribution grid using a battery energy storage system (BESS). Int J Electr Power Energy Syst 77:337–344. https://doi.org/10.1016/j.ijepes.2015.11.035
143. Kou P, Gao F, Guan X (2015) Stochastic predictive control of battery energy storage for wind farm dispatching: using probabilistic wind power forecasts. Renew Energy 80:286–300. https://doi.org/10.1016/j.renene.2015.02.001
144. Abbey C, Strunz K, Joos G (2009) A knowledge-based approach for control of two-level energy storage for wind energy systems. IEEE Trans Energy Convers 24:539–547. https://doi.org/10.1109/TEC.2008.2001453
145. Dan W, Shaoyun G, Hongjie J, Chengshan W, Yue Z, Ning L et al (2014) A demand response and battery storage coordination algorithm for providing microgrid tie-line smoothing

services. IEEE Trans Sustain Energy 5:476–486. https://doi.org/10.1109/TSTE.2013.2293772
146. Jae Woong S, Youngho C, Seog-Joo K, Sang Won M, Kyeon H (2013) Synergistic control of SMES and battery energy storage for enabling dispatchability of renewable energy sources. IEEE Trans Appl Supercond 23:5701205. https://doi.org/10.1109/TASC.2013.2241385
147. Jannati M, Hosseinian SH, Vahidi B, Li G (2016) ADALINE (ADAptive Linear NEuron)-based coordinated control for wind power fluctuations smoothing with reduced BESS (battery energy storage system) capacity. Energy 101:1–8. https://doi.org/10.1016/j.energy.2016.01.100
148. Dicorato M, Forte G, Pisani M, Trovato M (2012) Planning and operating combined wind-storage system in electricity market. IEEE Trans Sustain Energy 3:209–217. https://doi.org/10.1109/TSTE.2011.2179953
149. Teleke S, Baran ME, Huang AQ, Bhattacharya S, Anderson L (2009) Control strategies for battery energy storage for wind farm dispatching. IEEE Trans Energy Convers 24:725–732. https://doi.org/10.1109/TEC.2009.2016000
150. Teleke S, Baran ME, Bhattacharya S, Huang AQ (2010) Rule-based control of battery energy storage for dispatching intermittent renewable sources. IEEE Trans Sustain Energy 1:117–124. https://doi.org/10.1109/TSTE.2010.2061880
151. Arifujjaman M (2015) A comprehensive power loss, efficiency, reliability and cost calculation of a 1 MW/500 kWh battery based energy storage system for frequency regulation application. Renew Energy 74:158–169. https://doi.org/10.1016/j.renene.2014.07.046
152. Liu W, Liu Y (2020) Hierarchical model predictive control of wind farm with energy storage system for frequency regulation during black-start. Electr Power Energy Syst 119:105893. https://doi.org/10.1016/j.ijepes.2020.105893
153. Boyle J, Littler T, Foley A (2020) Battery energy storage system state-of-charge management to ensure availability of frequency regulating services from wind farms. Renew Energy 160:1119–1135. https://doi.org/10.1016/j.renene.2020.06.025
154. Engels J, Claessens B, Deconinck G (2020) Optimal combination of frequency control and peak shaving with battery storage systems. IEEE Trans Smart Grid 11:3270–3279. https://doi.org/10.1109/TSG.2019.2963098
155. Krata J, Saha TK (2019) Real-time coordinated voltage support with battery energy storage in a distribution grid equipped with medium-scale PV generation. IEEE Trans Smart Grid 10:3486–3497. https://doi.org/10.1109/TSG.2018.2828991
156. Xu Y, Hu J, Gu W, Su W, Liu W (2016) Real-time distributed control of battery energy storage systems for security constrained DC-OPF. IEEE Trans Smart Grid. https://doi.org/10.1109/TSG.2016.2593911
157. Zhu Y, Liu C, Sun K, Shi D, Wang Z (2019) Optimization of battery energy storage to improve power system oscillation damping. IEEE Trans Sustain Energy 10(2):1015–1024. https://doi.org/10.1109/TSTE.2018.2858262
158. Shayeghi H, Monfaredi F, Dejamkhooy A, Sha M, Catalão JPS (2021) Assessing hybrid supercapacitor-battery energy storage for active power management in a wind-diesel system. Electr Power Energy Syst. https://doi.org/10.1016/j.ijepes.2020.106391
159. Georgiou GS, Christodoulides P, Kalogirou SA (2020) Optimizing the energy storage schedule of a battery in a PV grid-connected nZEB using linear programming. Energy 208:118177. https://doi.org/10.1016/j.energy.2020.118177
160. Mégel O, Mathieu JL, Andersson G (2015) Scheduling distributed energy storage units to provide multiple services under forecast error. Int J Electr Power Energy Syst 72:48–57. https://doi.org/10.1016/j.ijepes.2015.02.010
161. Grillo S, Pievatolo A, Tironi E (2016) Optimal storage scheduling using Markov decision processes. IEEE Transactions on Sustainable Energy 7(2):755–764. https://doi.org/10.1109/TSTE.2015.2497718
162. Böcker B, Kippelt S, Weber C, Rehtanz C (2017) Storage valuation in congested grids. IEEE Trans Smart Grid. https://doi.org/10.1109/TSG.2017.2721982
163. Malysz P, Sirouspour S, Emadi A (2014) An optimal energy storage control strategy for grid-connected microgrids. IEEE Trans Smart Grid 5:1785–1796. https://doi.org/10.1109/TSG.2014.2302396
164. Moradi H, Esfahanian M, Abtahi A, Zilouchian A (2018) Optimization and energy management of a standalone hybrid microgrid in the presence of a battery storage system: Battery State of Charge Distributed Energy resources. Energy 147:226–238. https://doi.org/10.1016/j.energy.2018.01.016
165. Engels J, Claessens B, Deconinck G (2019) Combined stochastic optimization of frequency control and self-consumption with a battery. IEEE Trans Smart Grid 10:1971–1981. https://doi.org/10.1109/TSG.2017.2785040
166. Olivella-Rosell P, Rullan F, Lloret-Gallego P, Prieto-Araujo E, Ferrer-San-José R, Barja-Martinez S et al (2020) Centralized and distributed optimization for aggregated flexibility services provision. IEEE Trans Smart Grid 11:3257–3269. https://doi.org/10.1109/TSG.2019.2962269
167. Liang Z, Chen H, Wang X, Chen S, Zhang C (2020) Risk-based uncertainty set optimization method for energy management of hybrid AC/DC microgrids with uncertain renewable generation. IEEE Trans Smart Grid 11:1526–1542. https://doi.org/10.1109/TSG.2019.2939817
168. Kusakana K (2020) Optimal peer-to-peer energy management between grid-connected prosumers with battery storage and photovoltaic systems. J Energy Storage 32:101717. https://doi.org/10.1016/j.est.2020.101717
169. Xu X, Hu W, Cao D, Huang Q, Liu Z, Liu W et al (2020) Scheduling of wind-battery hybrid system in the electricity market using distributionally robust optimization. Renew Energy 156:47–56. https://doi.org/10.1016/j.renene.2020.04.057
170. Duong T, Khambadkone AM (2013) Energy management for lifetime extension of energy storage system in micro-grid applications. IEEE Trans Smart Grid 4:1289–1296. https://doi.org/10.1109/TSG.2013.2272835
171. Zou J, Peng C, Shi J, Xin X, Zhang Z (2015) State-of-charge optimising control approach of battery energy storage system for wind farm. IET Renew Power Gener 9:647–652. https://doi.org/10.1049/iet-rpg.2014.0202
172. Saxena V, Kumar N, Nangia U (2023) An extensive data-based assessment of optimization techniques for distributed generation allocation: conventional to modern. Arch Comput Methods Eng 30:675–701. https://doi.org/10.1007/s11831-022-09812-w
173. Bo Z, Xuesong Z, Jian C, Caisheng W, Li G (2013) Operation optimization of standalone microgrids considering lifetime characteristics of battery energy storage system. IEEE Trans Sustain Energy 4:934–943. https://doi.org/10.1109/TSTE.2013.2248400
174. Tan X, Wu Y, Tsang DHK (2016) Pareto optimal operation of distributed battery energy storage systems for energy arbitrage under dynamic pricing. IEEE Trans Parallel Distrib Syst 27:2103–2115. https://doi.org/10.1109/TPDS.2015.2478785
175. Zhang F, Wang G, Meng K, Zhao J, Xu Z, Dong ZY et al (2016) Improved cycle control and sizing scheme for wind energy storage system based on multi-objective optimization. IEEE Trans Sustain Energy. https://doi.org/10.1109/TSTE.2016.2636878
176. Ju C, Wang P, Goel L, Xu Y (2017) A two-layer energy management system for microgrids with hybrid energy storage considering degradation costs. IEEE Trans Smart Grid. https://doi.org/10.1109/TSG.2017.2703126

177. Purvins A, Sumner M (2013) Optimal management of stationary lithium-ion battery system in electricity distribution grids. J Power Sources 242:742–755. https://doi.org/10.1016/j.jpowsour.2013.05.097
178. Wächter A, Biegler LT (2006) On the implementation of an interior-point filter line-search algorithm for large-scale nonlinear programming. Math Program 106:25–57. https://doi.org/10.1007/s10107-004-0559-y
179. Gurobi optimizer reference manual (n.d.) http://www.gurobi.com/. Accessed 23 Mar 2018
180. Bellman R (1952) The theory of dynamic programming. Proc Natl Acad Sci USA 60:503–515
181. Firoozian R (2009) State variable feedback control theory. In: Firoozian R (ed) Servo motors and industrial control theory. Springer, Boston, pp 43–58. https://doi.org/10.1007/978-0-387-85460-1_3
182. Sadeghi J, Sadeghi S, Niaki STA (2014) Optimizing a hybrid vendor-managed inventory and transportation problem with fuzzy demand: an improved particle swarm optimization algorithm. Inf Sci 272:126–144. https://doi.org/10.1016/j.ins.2014.02.075
183. Bonyadi MR, Michalewicz Z (2017) Particle swarm optimization for single objective continuous space problems: a review. Evol Comput 25:1–54. https://doi.org/10.1162/EVCO_r_00180
184. Athari MH, Ardehali MM (2016) Operational performance of energy storage as function of electricity prices for on-grid hybrid renewable energy system by optimized fuzzy logic controller. Renew Energy 85:890–902. https://doi.org/10.1016/j.renene.2015.07.055
185. Afzali P, Anjom N, Rashidinejad M, Bakhshai A (2020) Techno-economic study driven based on available efficiency index for optimal operation of a smart grid in the presence of energy storage system. J Energy Storage 32:101853. https://doi.org/10.1016/j.est.2020.101853
186. Zheng QP, Wang J, Liu AL (2015) Stochastic optimization for unit commitment: a review. IEEE Trans Power Syst 30:1913–1924. https://doi.org/10.1109/TPWRS.2014.2355204
187. Bhardwaj A, Vikram Kumar K, Vijay Kumar S, Singh B, Khurana P (2012) Unit commitment in electrical power system-a literature review. In: 2012 IEEE international power engineering and optimization conference, Malaysia, pp 275–280. https://doi.org/10.1109/PEOCO.2012.6230874
188. Tran D, Zhou H, Khambadkone AM (2010) Energy management and dynamic control in Composite Energy Storage System for micro-grid applications. In: IECON 2010—36th annual conference of the IEEE Industrial Electronics Society, pp 1818–1824. https://doi.org/10.1109/IECON.2010.5675399
189. Saxena V, Kumar N, Nangia U (2022) An impact assessment of distributed generation in distribution network. In: Pandit M, Gaur MK, Rana PS, Tiwari A (eds) Artificial Intelligence and Sustainable Computing. Algorithms for Intelligent Systems. Springer, Singapore. https://doi.org/10.1007/978-981-19-1653-3_26
190. Saxena V, Kumar N, Nangia U (2021) Analysis of smart electricity grid framework unified with renewably distributed generation. In: Agrawal R, Kishore Singh C, Goyal A (eds) Advances in Smart Communication and Imaging Systems, vol 721. Lecture Notes in Electrical Engineering. Springer, Singapore. https://doi.org/10.1007/978-981-15-9938-5_68
191. Gabash A, Pu L (2013) Flexible optimal operation of battery storage systems for energy supply networks. IEEE Trans Power Syst 28:2788–2797. https://doi.org/10.1109/TPWRS.2012.2230277
192. Avril S, Arnaud G, Florentin A, Vinard M (2010) Multi-objective optimization of batteries and hydrogen storage technologies for remote photovoltaic systems. Energy 35:5300–5308. https://doi.org/10.1016/j.energy.2010.07.033
193. Kumar M, Diwania S, Sen S et al (2023) Emission-averse techno-economical study for an isolated microgrid system with solar energy and battery storage. Electr Eng 105:1883–1896. https://doi.org/10.1007/s00202-023-01785-8
194. Kumar M, Sen S, Jain H, Diwania S (2022) Optimal planning for building integrated microgrid system (BIMGS) for economic feasibility with renewable energy support. In: 2022 IEEE 10th Power India international conference (PIICON), New Delhi, India, pp 1–6. https://doi.org/10.1109/PIICON56320.2022.10045284
195. Kumbhar A, Dhawale PG, Kumbhar S, Patil U, Magdum P (2021) A comprehensive review: machine learning and its application in integrated power system. Energy Rep 7:5467–5474. https://doi.org/10.1016/j.egyr.2021.08.133
196. Saxena V, Kumar N, Nangia U (2022) An impact assessment of distributed generation in distribution network. In: Artificial intelligence and sustainable computing. algorithms for intelligent systems. Springer, Singapore. https://doi.org/10.1007/978-981-19-1653-3_26
197. Al-Saffar M, Musilek P (2020) Reinforcement learning-based distributed BESS management for mitigating overvoltage issues in systems with high PV penetration. IEEE Trans Smart Grid 11:2980–2994. https://doi.org/10.1109/TSG.2020.2972208