An Extensive Assessment of the Energy Management and Design of Battery Energy Storage in Renewable Energy Systems

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Abstract: - Many benefits are derivable when renewable energy systems (RES) are integrated with battery energy storage systems (BESS). However, appropriate energy management techniques should be adopted to realize optimal benefits. Many BESS operations' optimization approaches are available in RES with various techno-economic, environmental, and dispatch-related outputs. BESS operations are optimized using different methods. Past studies have mainly concentrated on certain renewable energy systems designed for specific purposes, such as distributed generation or large-scale. This paper thoroughly examines and analyzes various battery management systems by considering the relationship between the optimization methodology and the intended application. This strategy enables the identification of connections between favored optimization approaches and specific optimization goals. Some approaches are more effective in solving economic goal optimizations, whereas others are commonly used for technical goal optimizations. The selection of the solution methodology is also demonstrated to be highly contingent upon the degree of mathematical formulation of the problem. An analysis is conducted to assess the strengths and limitations of the described optimization techniques. The conclusion is that hybrid approaches, which combine the benefits of multiple techniques, will significantly impact the creation of future operating strategies. This paper provides a comprehensive analysis of optimization approaches and battery applications, aiming to assist researchers in efficiently identifying appropriate optimization strategies for emerging applications in the new generation.

Key-Words: - Battery energy management, Control approaches, Hybrid goals, Optimization algorithms, Renewable energy systems, Smart Grid, Technical goals, Economic goals.

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1 Introduction

In modern power systems, battery energy storage systems (BESS) are crucial due to their contribution to smart grid development, provision of technical support to power systems, and effectively tackling the problems of renewable energy intermittency, [1]. Researchers have examined BESS in various ways to improve its integration into renewable energy systems (RES). These systems include distributed renewable systems, renewable energy power plants, microgrids, and hybrid renewable energy systems (HRES). Other significant uses of battery storage in power systems that have gained attention include frequency and voltage management, transmission network expansions and improvements, and alleviating congestion in transmission networks, [2].

Although batteries have been recognized as a highly efficient solution for dealing with the sporadic nature of renewable energy, the significant upfront expense of BESS continues to hinder their broad adoption, [3].

Another important consideration is the duration for which the battery remains functional, making maximizing its usage throughout its lifespan a crucial worry for most applications. Some authors have extensively discussed the search for the most efficient battery size in a recent article, [4]. This evaluation complements the sizing assessment by examining devices with a fixed battery capacity. An essential factor is that the implementation of the BESS (i.e. which specific goals have been given priority) significantly influences the intended functioning of the BESS, indicating that the choice of the BESS's application goal is crucial. Hence, this study scrutinizes a substantial body of research on battery optimization, explicitly emphasizing the anticipated functionalities that batteries must fulfill and exploring the most effective methods for battery management.

Many reviews and research on energy storage systems (ESSs) have been published in recent years, with a specific emphasis on various facets. Several of these sources include comprehensive explanations of BESS technology for energy storage regulations [5], battery cost modeling [6], life cycle cost analysis [7], battery management systems [8], and large-scale applications [9], [10]. Prior analyses on battery optimization focused on individual renewable energy systems, where battery storage played a crucial role. These include distributed energy systems, microgrids, and large-scale wind power plants or solar energy. A thorough examination was conducted on several ESSs to improve wind power utilization. This includes addressing oscillation damping, voltage regulation, and fluctuation suppression, [11]. Authors in [12], similarly examined the use of ESSs for integrating wind power. It not only discusses the appropriate ESS technology but also covers ESS control, operation, and design, specifically for wind power facilities. Additionally, some studies focus on specific services, such as managing power output smoothing in solar PV and wind power plants, [13], and using batteries for frequency regulation in contemporary power systems, [14]. These articles, which concentrate on specific themes, provide the benefit of delivering a more precise overview within a narrower scope. Nevertheless, it cannot offer a comprehensive perspective on BESS's extensive array of uses. It is important to note that studies specifically focus on battery management systems, [15]. These reviews aim to enhance the management and control of battery cells at a more fundamental level, which is not the main emphasis of this study. Furthermore, the evaluations have encompassed large-scale applications and applications inside distributed energy systems. Authors in [16], provide a comprehensive analysis of the use of BESS in home Photovoltaic (PV) systems. The evaluation emphasizes the economic feasibility of using BESS in this application.

Furthermore, several studies have provided a concise overview of the applications of ESS in distributed PV generation, explicitly highlighting the significance of BESS technologies, as well as optimization strategies, [17], [18]. In addition, hybrid energy storage systems (HESS), namely the integration of super-capacitor and BESS, have garnered considerable interest due to their mutually beneficial characteristics. Extensive research has been conducted on utilizing HESS in microgrids, [19], [20], [21]. A further evaluation is conducted on HESS and its suitability for use in smart grid systems and other applications involving electric vehicles (EVs), [22]. Additionally, more recent articles specifically concentrate on EV batteries and the enhancement of virtual power plants (VPPs), [23]. While this analysis includes specific approaches and optimization goals for efficiently running VPPs and HESS, it does not primarily focus on the particular factors related to the operation of EV batteries, VPPs, and HESS. A prevalent characteristic in the studies above is their concentration on a particular energy system or a specific utilization of BESS or ESS. Nevertheless, there are still inquiries regarding the primary goal of integrating a battery into RESs and the rationale for selecting a particular approach or model to enhance the battery's performance. This study seeks to address these inquiries by compiling the operational goals and methodologies of battery research. This research highlights the primary relationships between the BESS modeling methods, specific optimization goals, and the appropriate approaches to solve the problems. The choice of the BESS modeling approach is dependent on its intended purpose and application complexity. Also, the integration of battery degradation modeling is related to its application objectives and operation duration. Another essential portion considered in this assessment is the connection between the recommended approaches and the selected optimization goals for BESS optimization. Particular optimization approaches are suitable for solving specific problems. In addition, analysis of BEM strategies and goals is essential for pattern identifications of BESS application goals and optimization methods, enabling researchers to examine fundamental concepts of running BESS in different RESs. This includes the analysis of BESS methodologies, operational goals, and modeling. These principles, derived from a comprehensive literature review, can serve as a reference for future implementations of BESS in any RES.

Furthermore, new papers specifically concentrate on the broader uses of BESS. A comprehensive analysis was carried out to examine the utilization of adaptable ESSs for integrating renewable energy (RE). The analysis categorized the different types of energy storage technologies, including gas, biomass, magnetic, compressed air, pumped, and batteries, [24], [25]. This configuration facilitates the comparison of various technologies but hinders the solutions in ESS applications and the identification of shared objectives. A compelling synopsis of the integration of BESS was offered, employing bibliometric analysis. Examining data using a survey-based method may be challenging in uncovering the underlying insights, but it provides valuable information. The study in [26], comprehensively summarized technologies integrating RE to support the power system. However, the crucial solution strategies for battery optimization were not mentioned. This study provides a comprehensive overview of various applications of BESS. The analysis is organized based on the methodologies employed to solve optimization challenges, the objectives of the applications, and the modeling methods. Furthermore, this analysis provides a concise discussion of the fundamental connections between the current developments in battery energy management, the BESS optimization approaches, and aims. This review focuses on the RE systems' operations of ESS and BESS with specific capacities.

This study contributes to the body of knowledge in the following ways:

- Analyse crucial optimization techniques and algorithms to demonstrate their strengths in BEM design.
- Evaluate optimization strategies to identify appropriate, efficient approaches for different battery applications.
- An in-depth assessment of the optimization methodology used and the intended application was conducted in this review to identify the connections between favored optimization approaches and specific optimization goals.

The demonstration of the selection of solution methodology is highly contingent upon the degree of mathematical formulation of the problems.

2 The BESS Operation Design

Various BESS operations aim to encompass battery power management and optimization for optimal economic outcomes, adherence to a reference target, and battery voltage and current control to ensure the stability of the RES's output. Additionally, the time frame for the battery's control and management goal window might vary from milliseconds to hours. Hence, it is crucial to distinguish between various techniques employed to manage and regulate batteries. A three-tier control hierarchy, commonly incorporating battery storage, has gained widespread utilization and acceptance in microgrid research, [27]. The three-layer control architecture consists of tertiary control at the top layer, prioritizing maximizing the microgrid's economic outcome. The secondary control acts as an intermediary between the primary and tertiary control layers, while the primary control, at the lowest layer, is primarily concerned with the fundamental control of converters. This paper presents a comparable notion built on a three-layer control hierarchy for a microgrid. Figure 1 illustrates the three-layer control architecture utilized for battery control and management.

The primary goals of each layer are depicted with solid lines, while dotted lines indicate the information and power flows. A BESS converter controller's primary function is to govern the power transfer from AC to DC and DC to AC while charging and discharging, respectively, similar to the fundamental control in a microgrid. The controller operates with a temporal precision ranging from milliseconds to seconds. Simultaneously, the controller also aims to track the provided reference from secondary control to uphold the RES's stability. The secondary control, which operates at a temporal resolution ranging from seconds to minutes, is responsible for enhancing the dynamic properties of the HRES, similar to the secondary control in a microgrid. When a disturbance, such as a fluctuation in RE, occurs in the system, the system controller will work to prevent any changes in frequency and voltage through primary control. This ensures that the power quality of the renewable energy system is maintained.

Furthermore, BESS will be controlled in an ideal manner to track any reference provided by tertiary control. Tertiary control, which operates at a time resolution of minutes to hours, involves the energy management center acting as a steady-state system optimizer to determine the best operational strategy for the RES.

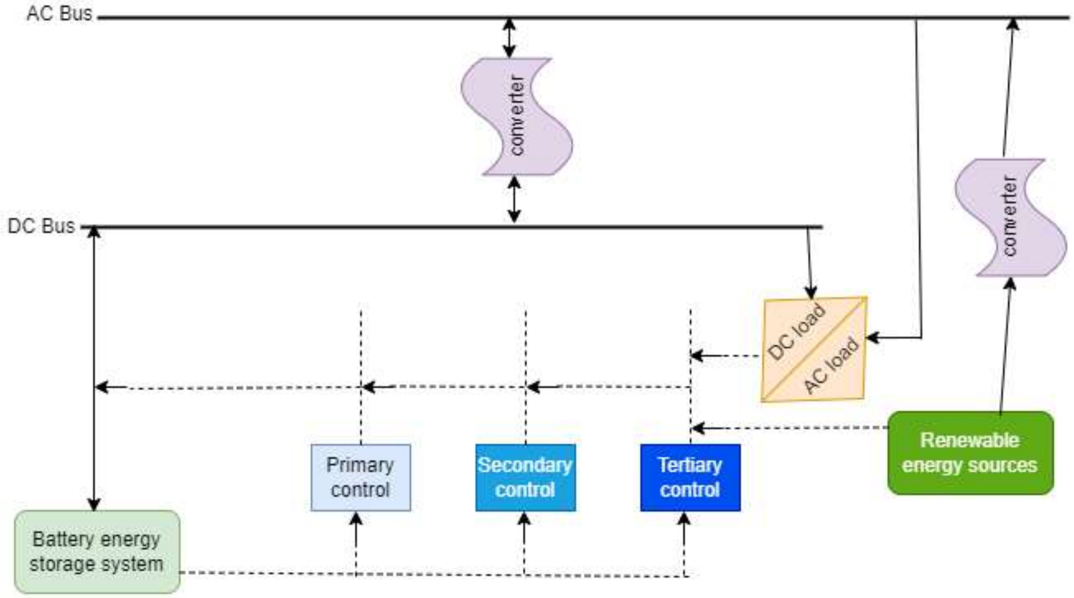

Fig. 1: BESS and the control hierarchy

Both economic and steady-state technical criteria can be utilized to optimize the performance of the RES. Energy management activities may be accomplished using practical dimensions, including arbitrage, peak-shaving, reducing operational costs, optimizing overall profits, and more. Please be aware that this evaluation specifically examines the anticipated functionalities of batteries in a RES and the methodologies employed to accomplish these functionalities. The functions often examine durations ranging from minutes to hours or the entire duration of the project. These timings are categorized as secondary and tertiary controls. Thus, this review provides a concise overview of the uses of BESS, with particular emphasis on research about BESS functioning for secondary and tertiary control purposes.

3 Battery Energy Management and Modeling

A BESS, composed of battery cells, is interconnected in series and parallel arrangements with converters to enable charging and discharging operations. Various battery technologies, including redox flow batteries, lithium-ion batteries, NaS batteries, and lead-acid batteries, [28], show promise for usage in grid or renewable energy systems (RES). This review does not thoroughly analyze the effects of materials-physics models on battery energy management systems (BEMS). However, it is essential to acknowledge that the physics of various battery technologies will affect the operational approaches and results of battery storage, particularly in terms of degradation profile, round-trip efficiency, and state of charge (SoC) restrictions, among others, [29]. BESS modeling uses mathematical formulae to illustrate the behaviors of the batteries. Modeling the Battery Energy Storage System (BESS) is crucial to controlling and managing BESS. BESS models were built at varied levels of sophistication and detail to cater to various BESS management needs. Using simplistic models for overall energy management issues and employing more precise models for intricate control challenges is a rational approach; for instance, in research aimed at comparing the results of utilizing various battery technologies, a fundamental and universal battery model was employed, with distinct characteristics assigned to each battery type, [30].

Regarding simulation settings and modeling methodologies, BESS models may be categorized into fundamental and dynamic models, including analogous circuit models. The fundamental model is commonly used for modeling energy management in steady-state conditions at minute/hour resolution. Dynamic models offer extra benefits when performing transient state dynamic control simulations. This section also reviews the modeling of BESS for battery deterioration, which is another critical component of BESS functioning. The primary emphasis of this part is on using BESS modeling to optimize battery energy in RES. The main goals of battery energy optimization are technical advancement and improved economic outcomes for RESs. This view is different from battery management, which aims to optimize the life cycle and particular battery performance, such as the research on temperature management, SoC forecasting, fractional order models, [31] and so on. The outcomes of battery management research can serve as inputs for battery energy optimization. These inputs could include the degradation profile, resistance-capacitance model parameters, SoC's upper and lower limits, and round-trip efficiency.

3.1 Battery Fundamental Models

More details on the generally used BEM models, i.e., the fundamental models that track BESS SoC variations due to the battery's charging and discharging operations. The SoC is a standard index for measuring a battery's energy level. SoCs range from 0% to 100%, with 0% representing a discharged battery and 100% representing a fully charged battery. The quantity of stored charge concerning the total capacity of a battery is referred to as its SoC. Suppose we assume that the voltage of the battery remains constant. In that case, the SoC may be defined as the amount of energy stored in the battery compared to its total energy capacity.

Moreover, the variations in battery condition over specific time intervals may be characterized as a time series comprising discrete values of SoC. An increase in SoC signifies the batteries are being charged, while a decrease in SoC means they are being discharged. The mathematical representation of this technique, which considers the efficiencies of discharging and charging, denoted as ηd and ηc, is summarized by equations (1) and (2), respectively, [32].

$$SoC\left(t+\Delta t\right)=SoC\left(t\right)+\frac{P_{BESS}\left(t\right)\Delta t}{\eta_d EC_{BESS}}, \quad \text{when discharging} \tag{1}$$

$$SoC\left(t+\Delta t\right)=SoC\left(t\right)+\frac{P_{BESS}\left(t\right)\eta_c\Delta t}{EC_{BESS}}, \quad \text{when charging} \tag{2}$$

where PBESS represents the power at which the BESS is either discharging or charging. A positive value of PBESS indicates that the battery is charging, while a negative value indicates that the battery is draining. This occurs over a specific period, Δt. ECBESS stands for Energy Capacity of BESS. The fundamental approach is often applied since it focuses on BESS applications without specifying the specific BESS/ESS technology type. This allows for examining the impact of energy storage properties on the entire system and identifying the best suitable technologies for the specific application based on the revealed required properties using the fundamental model. To streamline the intricacy, several research examined in this work assume that η_c and η_d are constant variables. The values are contingent upon the battery technology and operating parameters like temperature, voltage, and current. Therefore, alternative research has employed more intricate methodologies to calculate these efficiencies, such as employing curve-fitting techniques for estimation or utilizing parameters derived from empirical findings, [33].

3.2 Battery Dynamic Model

While the fundamental model effectively elucidates the correlation between the power of charging and discharging and the SoC of the battery, it presupposes that alterations in SoC resulting from an excess or shortfall of energy are consistently attainable. It is presumed that any current or voltage alteration or magnitude may be attained to accommodate the anticipated variation in SoC. Dynamic models can be used to accurately represent the voltage and current characteristics, including transients of the BESS when controlling them is crucial, [34]. Equivalent circuits are a frequently employed dynamic model technique. Various dynamic models are often employed in the literature, including simple and first- and second-order models. Figure 2 displays a basic dynamic model for batteries. The system comprises a voltage source equal to the open-circuit voltage V_{OC} and an internal battery resistance R_0, linked in series.

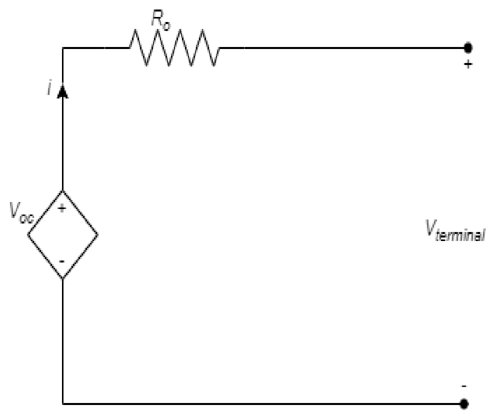

Fig. 2: The battery's basic dynamic model

The governing equation describes the battery's basic dynamic model, Eq. (3), which is advantageous when the transitory characteristic of the system may be disregarded.

$$v_{terminal} = v_{oc} - iR_o \tag{3}$$

To capture transient effects, first and second-order dynamic models contain resistor-capacitor (RC) networks, [35], as illustrated in Figure 3. Applying Kirchhoff's rules to the circuit enables the construction of a system of differential equations that describes the time-dependent behavior of voltage.

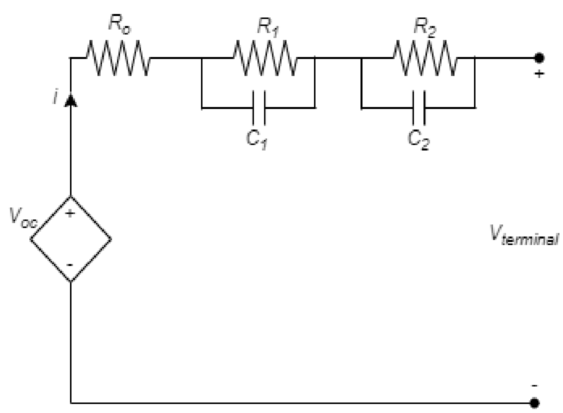

Fig. 3: The battery's second-order model

Utilizing battery models of second-order or first-equivalent circuits enables users to comprehend the intricate dynamic process of battery functioning via differential equations' solutions. State-space models are a commonly employed dynamic method in which differential equations are condensed into a concise matrix equation by selecting an appropriate state variable to determine solutions. The broad availability of commercial software that rapidly simulates very adaptive and complicated circuits, such as PSCAD and MATLAB, has made these techniques popular, [36], [37].

3.3 Models for the Deterioration of Batteries

The deterioration of battery performance is mainly attributed to chemical processes in the electrolyte, cathode, and anode, resulting in changes over time, [35], [38]. Battery deterioration encompasses both cycle and calendar deterioration. Calendar deterioration refers to the natural deterioration of a battery over time, regardless of whether it is used or not. The SoC and the temperature of the battery influence the pace of deterioration. Conversely, cycling deterioration occurs whenever the battery is charged and drained and is influenced by the extent of discharge, the average SoC of each cycle, and the average temperature of the cell. Regular cycles of discharging and charging, as well as deeper cycles (often defined as discharging below 20% of SoC, which may vary depending on the battery type), may decrease the battery's lifespan, particularly for lithium-ion and lead-acid batteries. One significant consequence of battery deterioration on system modeling is the reduction in storage capacity, referred to as capacity fade, [39]. In the battery manufacturing sector, it is commonly acknowledged that a battery, such as a lead acid or lithium-ion battery, has reached the end of its useful lifespan and should be replaced when its usable capacity falls below 80% of its initial value. It is crucial to include deterioration in the energy management process when dealing with long-term projects, particularly during long-term simulations. A measure different from SoC, which is valuable for evaluating battery deterioration, is the battery's state of health (SoH), [40]. The SoH is often determined based on the reduction in the rated capability, and it is expressed as [35]:

$$SoH = \frac{C_{act} - C_{EOL}}{C_{nom} - C_{EOL}} \cdot 100\%, C_{act} \geq C_{EOL} \tag{4}$$

$$C_{EOL} = 0 \cdot 8C_{nom} \tag{5}$$

in which it is observed that when the battery is in a pristine condition, the true battery capacity, denoted as C_{act}, is equivalent to the nominal capacity, denoted as C_{nom}, ($C_{act} = C_{nom}$), resulting in a *SoH* of 100%. The *SoH* is 0% when the capacity of C_{act} has achieved its end-of-life (C_{EOL}) capacity, shown by $C_{act} = C_{EOL}$. Subsequently, the capacity losses will be assessed by utilizing experimental data that quantifies the influence of analogous cycles on the reduction in capacity. As previously mentioned, the point at which 80% of the initial capacity of a fresh battery is reached is often regarded as the end of its lifespan, as indicated by the equation (5). On the other hand, the operational battery capacity can indicate deterioration, which is the discrepancy between the loss of capacity and the nominal capacity of a fresh battery. As previously mentioned, the battery's deterioration process involves cycle and calendar deterioration, with the former being the primary factor in battery deterioration and more challenging to evaluate. Consequently, several methodologies have been devised to assess the deterioration of BESS caused by cycling. The machine learning technique, [41], is a method that is regularly employed for counting cycles over a certain period. This methodology is frequently utilized in power electronic systems. By employing this technique, the SoC profiles may be transformed into cycles of equal value.

Furthermore, Wiener process models are employed to assess battery deterioration. Research with similar objectives has been carried out to evaluate these models for optimizing the BESS in a microgrid linked to the primary power grid, [42]. Additionally, several expenses associated with the decline in battery performance have been employed, including wear, usage, depreciation, and lifespan costs, [43], [44]. Other research concentrates on reducing battery deterioration by preventing overcharging and deep discharging, [45]. The primary objective is to minimize battery deterioration by implementing optimized charge and discharge methods, which drives the advancement of BEMS. Another approach that is gaining more attention is the utilization of HESS, which involves the integration of ultracapacitors (UCs) to prolong the battery's lifespan by handling high-frequency events, [46].

4 The Goals of BEMS

The BESSs are crucial in the functioning of RESs, providing many benefits such as regulating grid frequency, smoothing power output, enabling peak shaving, and improving overall system profitability. The capabilities of the available BESS and the operational demands of the RESs heavily influence the anticipated roles of the BESS in a particular system. This section provides a comprehensive assessment of research focused on BEMS, explicitly targeting the management of BESS regarding its techno-economic and hybrid goals.

4.1 Technical Goals

The BESS has been adopted to enhance the technical performance of RESs, optimize RE outputs, and reduce distribution networks' power loss. Table 1 in Appendix outlines the relevant literature on BEMS for accomplishing the technical goals. Generally, the applications executing technical goals focus on secondary and tertiary controls. These two control levels are based on the BESS operating architecture. Regarding BESS management, these applications' aims may be categorized into three main areas: i) improving overall performance, ii) enhancing power profile, and iii) optimizing energy usage.

The optimization of tertiary control goals, such as battery scheduling for the daily or hourly performance of RESs, is mainly accomplished through long-term horizon optimization. Energy optimization may be classified as a tertiary control target, with the accumulated energy measured in MWh or kWh units as the primary indicator. For instance, the dispatched battery in [60], was to reduce the loss of power in the distribution lines, and in [61], was to reduce the amount of energy consumed by the utility. Line loss refers to the total amount of reactive and actual power lost in a distribution or transmission power network over a specific period. This indication is crucial for demonstrating the effectiveness of network operations. Indicators based on accumulated energy diverge from financial goals as they do not incorporate power pricing. In addition to stored energy, maintaining energy balance is a crucial objective for BESS in RESs. For instance, in [62], the battery balances power demand and supply inside a microgrid.

Another crucial category of technical indicators in the optimization process is the characteristics of the power profile, measured in megawatts (MW) or kilowatts (kW). These qualities encompass mitigation of variations, accurate monitoring of desired task execution, and peak load reduction, [63]. Another widely employed purpose of utilizing the BESS is to control and monitor the intended allocation of resources. The forecasts frequently define the desired dispatch. In these applications, the BESS is used to adhere to the power target, minimize discrepancies between the intended and actual wind power generation, or mitigate forecasting mistakes, [64].

Furthermore, several studies are dedicated to utilizing the BESS to mitigate the intermittent behavior of renewable energy-producing systems caused by the unpredictable nature of the resources. These studies primarily focus on solar PV and wind farm variability, [65]. In addition to the technical goals that have longer timeframes in tertiary control layers, such as daily or hourly resolutions, some significant technical measures, such as voltage and frequency regulation, will be included in the scope of secondary control. In traditional power systems, thermal generators in the network or the spinning reserves are activated to regulate the frequency. At the same time, other technologies, such as static var compensation (SVC), can be employed to regulate the voltage by compensating for reactive power, [66]. By employing sophisticated power electronic techniques, the battery may assist both reactive and active power, enabling it to regulate voltage and frequency, [67]. Table 1 (Appendix) provides more comprehensive research on battery energy management, explicitly addressing technological objectives.

4.2 Economic Goals

Given the significance of economic performance, many researchers have used economic factors to optimize their batteries. In addition, various indicators are employed as economic goals in battery optimization, including maximizing the long-term value generated by the ESSs, maximizing the operational profits of the system, and minimizing the overall operational cost, [68], among others. Table 2 (Appendix) provides a comprehensive overview of several variables related to BEMS, focusing on economic goals, as summarized from a selection of literature.

Table 2 (Appendix) shows that the most commonly used aim among the numeric indicators is maximizing the operation profits, equivalent to minimizing the overall operation expenses. However, several studies have differing definitions of operating expenses, particularly the components that make up these costs. As an illustration, the process of reducing the overall expense of a microgrid involved considering the cost associated with shutting down or starting up the power sources inside the microgrid, the cost of power exchange between the utility and the microgrid, and the cost of fuel for diesel generators. Thus, Table 2 (Appendix) illustrates each research's optimization goals, relying on the specific components of the established indicators. The precise components within the objectives can be identified in this matter. These studies consider several factors relevant to battery applications, resulting in varied approaches. One possible cause is the variation in the components used in the simulated system. For instance, including conventional generators in the microgrid might significantly impact the overall cost structure. The microgrid analyzed in [69], incorporated fuel cells and micro-turbines, taking into account the expenses related to fuel, as well as the costs associated with starting up and shutting down the units.

Conversely, the microgrid examined in [70], only relied on photovoltaic (PV) power generation, focusing on the expenses incurred due to battery deterioration and the financial gains from the electricity market. Another consideration is that researchers select specific indicators in their studies due to various systems with distinct operational procedures. An instance of this is if the functioning of hybrid systems includes involvement in the energy market since this will directly determine whether the inclusion of profit/cost trading in the electricity market is necessary. Table 2 (Appendix) demonstrates that most of the research focused on the power profits/costs due to the simulated system's connection to the utility. Nevertheless, in self-contained HRES, BESS does not consider the profit or cost associated with power. Including specific indicators is necessary to reach other specialized aims for the RES or to meet a predetermined optimization goal for the BESS. An instance of a specialized objective is using the BESS to engage in the regulation and reserve market, [71]. The objective of including this ambition in the economic goals for BESS management is to enhance profits by active involvement in the energy regulation and reserve market. When considering specific objectives, the feed-in tariff was included to minimize the overall cost of delivering the load, [72], as this energy system requires. In addition, there are additional specific objectives, such as the expenses associated with greenhouse gas emissions [73], unserved demand [74] and renewable curtailment [75]. These components become extra profits/costs to be added to the target due to the specific emphasis on the associated factors. Furthermore, recent research has shown a heightened focus on battery deterioration. These studies incorporate the expense of battery deterioration as an additional factor in the overall profit/cost analysis, [76].

4.3 Hybrid Goals

While those above technical and economic goals for BEMS encompass a significant portion of research in this area, there is a rising body of recent studies that concentrate on utilizing the battery to simultaneously achieve both technical and economic goals, referred to as hybrid goals. This is logical since the technical and economic goals are frequently interconnected, mainly when the enhancements from technical viewpoints may be measured in terms of economic values. Hybrid goals, which consist of many objectives, typically use multi-objective optimization approaches. Table 3 (Appendix) is a compilation of publications focused on BEMS using hybrid goals.

A practical approach to implementing hybrid goals involves combining various objectives using a set of weights to form a unified optimization problem. If the weights are equal to the unit costs of the objectives, the sum of the costs for individual objectives will equal the overall cost. Table 2 (Appendix) displays several research pieces that encompass technical and economic goals, categorized by profits and costs. These extra technical aspects have been acknowledged as regularly used to assess profitability. Many studies encompassing technical and economic goals and involving a range of profit/cost elements can be classified as having hybrid goals through economic aggregation. For instance in [88], the authors used BESS to conduct research that employed control approaches to reduce PV curtailment and financial loss. An alternative approach to accomplish hybrid objectives is to frame the problem as a multi-objective optimization.

In contrast to the single-objective problem that requires finding a single optimal solution, the multi-objective problem entails identifying a collection of Pareto optimal options. This implies that the battery will have the capability to enhance one performance indication without compromising the others. Pareto multi-objective solutions are commonly used with artificial intelligence optimization technologies, such as genetic particle swarm optimization (PSO) and genetic algorithms (GA). An example of a multi-objective problem is minimizing the cost of power generation and life cycle emissions using HRES and BESS, [89]. An additional comparable instance of employing Pareto optimum operation involves balancing economic gains by minimizing CO_2 emissions and operation costs, [90].

Furthermore, it is noteworthy that several studies have used artificial intelligence approaches directly without relying on Pareto multi-objective optimization solutions, [91]. The hybrid goals can also be combined through multi-stage optimization, where a single target is a primary outcome at each step. A two-layer optimization methodology was employed in the given scenario, as described in [92]. The top layer focused on minimizing the operational cost of the BESS, while the bottom layer aimed to minimize power variations and forecast uncertainty. Furthermore, alternative methods can be employed to regulate the battery for hybrid purposes, including implementing rule-based control. The hybrid optimization objectives are addressed in a prioritized manner. In [93], the BEMS prioritized the efficient battery utilization. The second priority was smoothing the residual distribution grid demand, and the third priority was the peak shaving.

5 Optimization Approaches for the BESS

After selecting the goals for deploying the BESS, the subsequent crucial task is determining the method of controlling the battery to accomplish those goals. This involves solving the optimization issue, provided the goals and constraints have been clearly defined. BESS optimization approaches refer to the technological solutions that address BESS optimization challenges. Choosing an appropriate methodology to address the issue is a crucial stage. Some issues may need to be compatible with specific approaches due to constraints. An optimization issue needs to be better defined; mathematical solutions cannot be used.

Further elaboration on this topic will be provided in the next section. In the optimization problem, the power profile of the battery over a specific period is typically included as part of the decision variable(s). To solve the optimization problem, one must find the optimal values for the decision variables to achieve the highest performance for the specified objective among the available solutions. This process will determine the battery storage's discharging and charging power profile. Various approaches have been used to solve the optimization problems, from straightforward rule-based techniques to more intricate multi-stage optimizations. This section overviews the strategies used to solve BESS optimum management problems.

5.1 The Adaptive Model Predictive Control (AMPC) Method

The adaptive model predictive control (AMPC) is a control algorithm that regulates parameters based on real-time feedback to optimize system performance. The AMPC applies conventional concepts to solve intricate micro-grid problems and employs systematic structures in a well-organized manner. The adaptive controller ensures power synchronization throughout the network, enabling efficient power supply production from each microgrid unit. AMPC provides a solution by creating an ideal energy storage configuration, energy consumption, and power generation for each optimization sample case. The subsequent sample instance presents a novel optimization solution by utilizing the result of the previous solution as the new input. The feedback mechanism theoretically produces an ideal design that effectively addresses the microgrid's disturbances. The primary factors contributing to disruptions and uncertainty in the micro-grid system are the energy generated by RESs (affected by variations in solar irradiation and wind speed) and the energy demand. The traditional model predictive controller (MPC) cannot handle the fluctuations in RESs; thus, the advanced model predictive controller (AMPC) is better suited for this task. This functions by incorporating updates to the system based on alterations to its internal working circumstances. Figure 4 displays the AMPC algorithm flowchart. The state-space expressions often employed for AMPC modeling are represented by [32]:

$$x(t+1) = Ax(t) + Bu(t) \tag{6}$$

$$y(t) = Cx(t) \tag{7}$$

where *x(t), u(t),* and *y(t)* represent the charging state of the BESS, the vector variables of the producing units, and the output vector of the system's current condition, respectively.

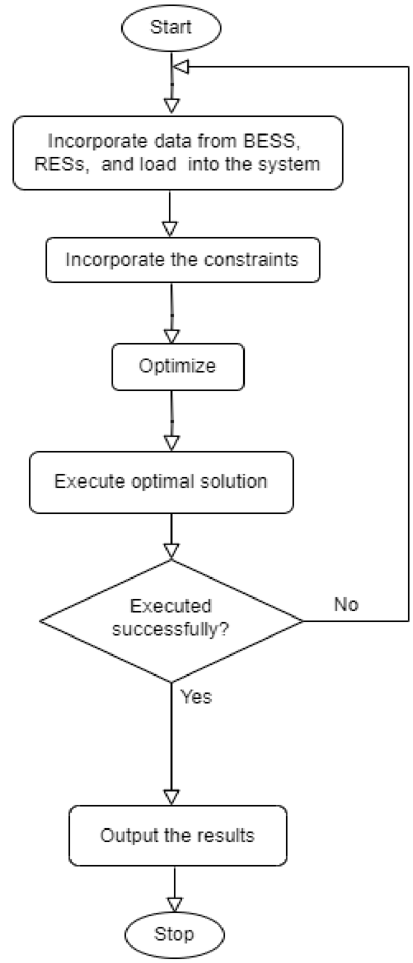

Fig. 4: Algorithm flowchart for AMPC

5.2 Artificial Bee Colony (ABC) Method

The artificial bee colony (ABC) algorithm is a nature-inspired computational technique introduced in 2005, [105]. It is an optimization approach that emulates the behavior of bees in their quest for food using mathematical algorithms. The bee colony comprises three distinct types of bees. The initial group is referred to as the employed bees (B_{em}); they randomly explore the search region to discover potential nectar locations (potential solutions). Upon discovering a nectar position (NP), the bees commit the specifics of this location (nectar quantity) to memory and communicate the NP information to the rest of the colony through a dance performed within the hive. The dance length indicates the level of nectar quality (fitness value). The second kind of bee is referred to as the observer bee (B_{on}). These bees observe the dance the working bees perform before selecting a new NP. A wealthy NP garners a more significant number of observer bees compared to an impoverished NP. The third kind of bee is referred to as scout bees. These bees are worker bees whose nest sites are discarded due to their low quality after a specific number of attempts. Observer bees have the potential to transition into worker bees if they come upon a novel food source. During this search procedure, exploitation and exploration co-occur. The ABC optimization technique assigns an equal number of spectator bees and employed bees. The quantity of potential NPs is equivalent to the quantity of bees now working. Scout bees mostly conduct the scouting process, consisting of three critical phases in each iteration: (1) Conduct a search for different NPs and gather information on the quality of each NP. (2) Onlooker bees pick an NP based on the information provided by the employed bees. (3) Employed bees with inferior NPs are reassigned as scout bees and sent to explore new NPs.

During the initialization step, a random distribution of the initial population of solutions x_i (i = 1, 2, . . ., B_{em}) is formed, where i represents the size of the population and B_{em} is the number of hired bees. Each solution is associated with a dimension, denoted as D_n, which represents the number of parameters that need to be optimized. Following initialization, the solutions' population undergoes successive cycles (C = 1, 2, . . ., MCN) of the search process for the three categories of bees, with MCN being the maximum cycle number. During each cycle, the hired bees alter the NP by considering the local information (visible content) and the quantity of nectar available. When the quantity of nectar at the new location surpasses that of the prior one, the bee stores it in memory and disregards the previous solution. Otherwise, it maintains the previous position. Once all the industrious bees have completed the exploration process, they disseminate the acquired knowledge among the observing bees within the hive. The observer bees choose a specific NP by assessing the shared nectar information. The likelihood of choosing an NP is correlated with the quantity of honey. The roulette wheel selection approach allows for the evaluation of the likelihood of picking a specific NP. The likelihood of choosing a particular NP is expressed as [105]:

$$P_i = \frac{fitness_i}{\sum_{i=1}^{B_{em}} fitness_i} \quad (8)$$

where fitness represents solution i's fitness value.

It is worth mentioning that a wealthy NP will attract a more significant number of observer bees compared to a less affluent NP. Before the observer bees choosing another NP, they assess the fitness value of the position i in comparison to i + 1. This process continues until all observer bees are scattered. Should the solution's fitness fail to improve within a set threshold, the employed bees will relinquish this solution and transition into scout bees. The cycle recommences upon selecting a new place until the ultimate criteria are fulfilled. The ABC algorithm employs the following methods to ascertain the neighboring NP about the present NP:

$$x_{ijnew} = x_{ijold} + rand\left[0,1\right]\left(x_{ijold} - x_{kj}\right) \quad (9)$$

where $k \in (1, 2, . . ., B_{em})$, $k \neq i$, and $j \in (1, 2, . . ., D_n)$. During each cycle, the scout bees generate a novel solution, provided by:

$$x_{inew}^{j} = x_{i\min}^{j} + rand\left[0,1\right]\left(x_{i\max}^{j} - x_{i\min}^{j}\right) \quad (10)$$

The ABC algorithm is characterized by three control parameters: the maximum cycle number, the limit value, and the colony size, [105]. Figure 5 displays the flowchart of the algorithm.

5.3 Backtracking Search Optimization (BSO) Method

BSO has similarities to various evolutionary algorithms. The BSO consists of five sequential phases. The five stages involved in the process are initialization of the population, selection I of the population, mutation of the population, crossover of the population, and selection II of the population, [106].

(1) Initialization of the population

BSO is insensitive to the beginning value of the population, allowing for random generation of the initial population value.

$$Pop_{i,j} \sim U\left(low_j, up_j\right) \quad (11)$$

where $\boldsymbol{Pop}$, is the population, $i \in [1, 2, ..., N]$, N represents the total number of elements in the population. $j \in [1, 2, ...,]$, D represents the population dimension. low and up represent the lower and upper bounds of the search interval, respectively. U refers to a function that generates values from a uniform random distribution.

(2) First (1st) selection of the population

BSO chooses new historical populations, referred to as *OPops*, during each evolution generation. The concept involves randomly choosing one individual from a preceding population, ensuring that each individual has an equal chance of being selected. A random sample is selected from either the parent population (***Pop***) or the historical population (***OPop***) using two random integers. The algorithm that is being suggested is outlined as:

$$OPop = \begin{cases} Pop, a \prec b \\ OPop, a \geq b \end{cases} \tag{12}$$

(3) Mutation of the population

The generation of a new population occurs through the process of mutation, which is outlined as:

$$M = Pop + F \cdot (OPop - Pop) \tag{13}$$

The coefficient F is the scale factor that satisfies:

$$F_i = 3 \cdot rand, i \in [1, 2, ..., N] \tag{14}$$

where $rand$ is a randomly generated number within the range of 0 to 1.

(4) Crossover of the population

Population crossover refers to the process in which genetic information is exchanged between individuals in a population during the reproduction phase of a genetic algorithm. The control of the number of crossing particles in the population is achieved by manipulating the percentage parameters using the BSOA method, as described by:

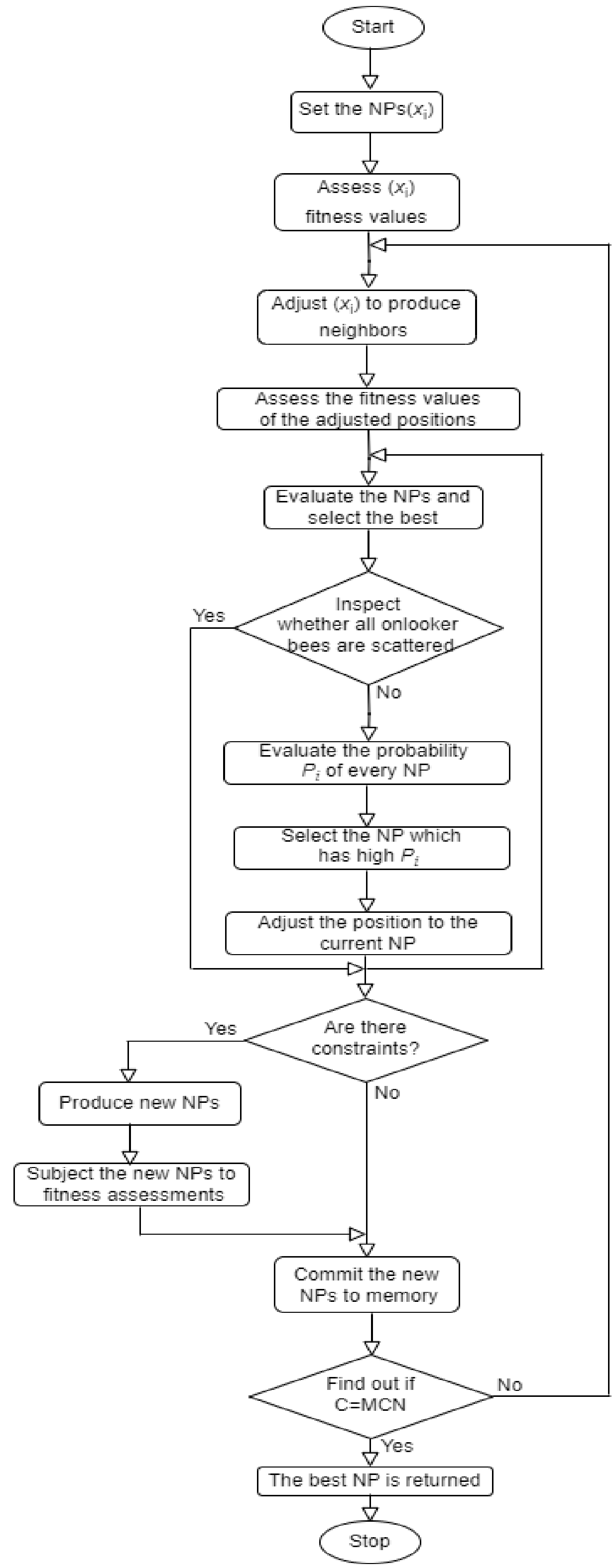

Fig. 5: Algorithm flowchart for ABC optimization

$$T_{i,j} = \begin{cases} M_{i,j}, map_{i,j} = 1 \\ Pop_{i,j}, map_{i,j} = 0 \end{cases} \quad (15)$$

where $\boldsymbol{map}$ is a binary integer matrix with dimensions $N \times D$. The first assignment is 1. The expression is:

$$\begin{cases} map_{i,u(1:\lfloor mr \cdot rand(D) \rfloor)} = 0, a \prec b \\ map_{i,rand(D)} = 0, a \geq b \end{cases} \quad (16)$$

where $rand$ (D) is a randomly generated number within the range of [0, D]. The parameter, mr represents the mixing ratio. r, a, and b are random integers chosen uniformly from the interval [0,1]. $\boldsymbol{u}$ is an arbitrary integer vector consisting of the numbers [1, 2, ..., D]. The BSO algorithm regulates the size of the new population $\boldsymbol{T}$ using Equation (16) in the crossover process described above. Once the new population $\boldsymbol{T}$ is created, the border regulates the elements within the population. If the element surpasses the search border, a new population is formed based on Equation (17).

(5) Second (2nd) selection of the population
The fitness values of the individuals at corresponding positions in the new population $\boldsymbol{Pop}$ and the population $\boldsymbol{T}$ are compared. If the fitness of the *ith* individual in $\boldsymbol{T}$ is lower than the fitness of $\boldsymbol{Pop}_i$, then $\boldsymbol{T}_i$ replaces $\boldsymbol{Pop}_i$ and updates the contemporaneous population $\boldsymbol{Pop}$ and expressed as:

$$Pop_i = \begin{cases} T_i, \, fitness(T_i) \prec fitness(Pop_i) \\ Pop_i, \, fitness(T_i) \geq fitness(Pop_i) \end{cases} \quad (17)$$

The population $\boldsymbol{Pop}$ has been upgraded and is now entering the next iteration cycle. The algorithm iterates the aforementioned procedure until it reaches the maximum number of iterations or the fitness value satisfies the predefined requirements. The BSO algorithm produces the most efficient solution. The BSO algorithm is shown in Figure 6.

5.4 Lighting Search Algorithm (LSA) Method

The LSA algorithm is shown in Figure 7. In 2005, a sophisticated metaheuristic optimization technique known as LSA was developed, [107]. The phenomenon of lightning is utilized in the creation of LSA. The search techniques of LSA for attaining optimum solutions rely on step leader propagation. The particles of LSA are referred to as projectiles, which resemble the terms "swarm" or "particle" used in other optimization approaches. The projectiles represent the original population and are organized in a binary tree formation. The projectiles might also be arranged in a synchronous configuration with two leaders at fork locations instead of the typical method of utilizing a step leader. When a projectile moves through the atmosphere and collides with molecules and atoms, there is a dissipation of kinetic energy. The mathematical representations of the kinetic energy (E_p) and velocity (v_p) of a bullet are given by:

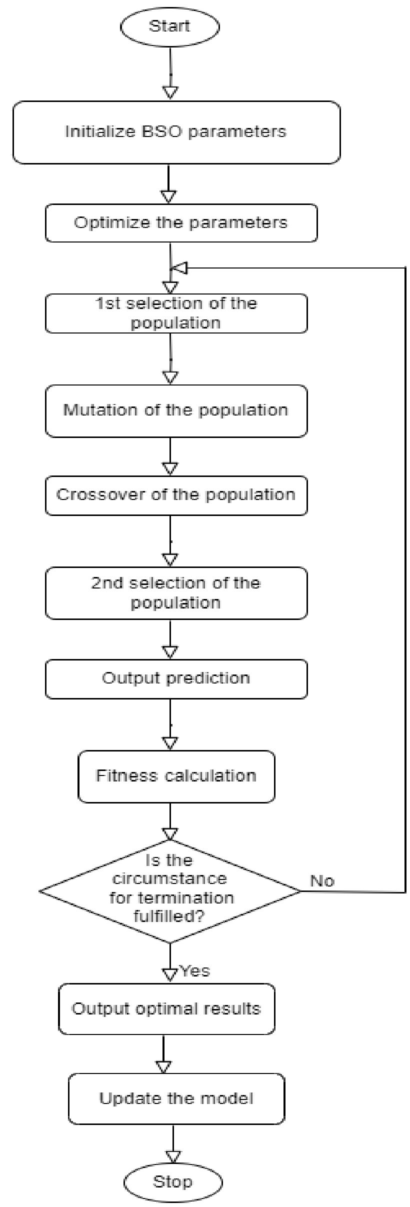

Fig. 6: Algorithm flowchart for BSO

$$E_p = \left(\left(\frac{1}{\sqrt{1 - \left(\frac{v_p}{c} \right)^2}} \right) - 1 \right) mc^2 \tag{18}$$

$$v_p = \left[1 - \left(\frac{1}{\sqrt{1 - \left(\frac{v_o}{c} \right)^2}} - \frac{sF_i}{mc^2} \right)^{-2} \right]^{-\frac{1}{2}} \tag{19}$$

where v_p and v_0 indicate the current velocity and starting velocity of the projectile, respectively. F_i is the ionization constant rate, c is the speed of light, m is the mass of the bullet, and s is the route length that the projectile traverses. Equations (18) and (19) demonstrate that a projectile's kinetic energy and velocity are significantly influenced by the position of the leader tip and the projectile's mass. If a projectile has minimal mass and has to go a long distance, it will lack the energy to ionize or explore the desired distance. Under those circumstances, the missile is limited to going just a short distance for ionization or exploitation. Hence, the step leaders' comparative energies determine the LSA's ability to exploit and explore.

6 Discussion

This section discusses the correlations between optimization objectives and approaches and the trends in battery energy management targets and techniques based on an analysis of BEM studies focusing on optimization techniques and targets.

6.1 Exploration of the Connections between Optimization Targets and Approaches

Based on the preceding analysis, it is evident that the choice of optimization approach is closely linked to the goals of a BESS and the formulation of the issue to be optimized. When dealing with targets that may be combined, such as energy consumption, profits, expenses, or the costs of non-physical entities, the goals can be effectively expressed as an objective function, considering necessary constraints. This formulation includes the choice factors in both the objective function and the constraints. This category encompasses most technical and economic goals related to energy optimization and specific components of hybrid goals. All the sampled optimization techniques (from the proceeding section) can be effectively employed to tackle these issues. For instance, economic goals and a range of revenues and expenses to be considered may be easily expressed in a conventional optimization format. Thus, it is evident that many researchers have utilized these strategies to address their challenges, [32], [108], [109], [110]. The selection of an approach heavily depends on the formulation of the optimization issue. When the problem is defined correctly, it will reduce computing complexity and increase optimization accuracy. Some approaches are more suitable for straightforward implementations, while others are desirable when a high level of computational accuracy is desired.

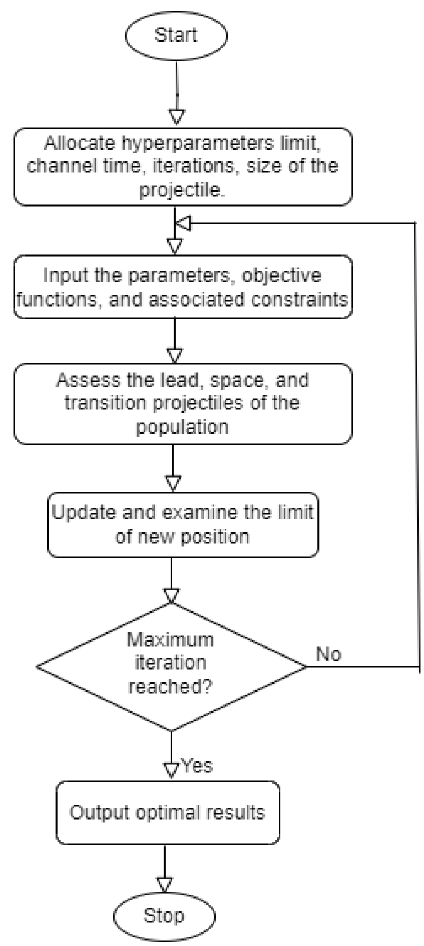

Fig. 7: Algorithm flowchart for LSA

6.2 Discussion on Trends of BEM Targets

Analysis of BEM targets reveals that the goals selected are contingent upon the expectations of the BESS operator/owner. When a private owner operates the BESS, there is a greater likelihood that the battery will be managed to maximize its economic potential. Alternatively, suppose the power network or a non-profit corporation manages BESS. In that case, it is more probable that the BESS will address system issues, such as maintaining system stability. However, in the latter scenario, greater emphasis will be placed on enhancing technical performance. Technical and economic goals hold universal significance, and the investing approach determines any preference for one over the other. Therefore, a significant trend in BEM aims will involve the application of multi-objective optimization for BEM. This means considering numerous, perhaps conflicting, purposes for battery optimization rather than focusing on a single service or goal for the BESS to accomplish. A growing body of research has employed several goals in their battery optimization studies, with a comprehensive list of such studies included in Table 3 (Appendix). In addition to multi-objective optimization, while pursuing one optimization goal, another target can be accomplished simultaneously without any additional work during the optimization process of the first goal. As such, the efficiency of deploying the BESS is significantly enhanced.

6.3 Analysis of BEM Strategies Trends

A comparative assessment of the benefits and drawbacks of battery optimization strategies is necessary before choosing the optimization approach for a particular problem. Each optimization strategy possesses distinct advantages and disadvantages, indicating the absence of a universally superior strategy for solving all BESS management optimization challenges. By examining the merits and drawbacks of each optimization method, it is evident that a significant advancement in optimization strategies is integrating several methods to leverage their respective benefits and surpass the effectiveness of the original approaches. As emphasized in this review, several studies have been conducted that have integrated multiple techniques for battery optimization. The elementary use of hybrid approaches involves partitioning the problem into several phases or segments to assign appropriate strategies to certain phases based on the unique problem and the benefits of the selected methodologies.

6.4 Additional Anticipated Developments

In addition to the BEM goals and methods stated above, a growing body of research focuses on enhancing the control and performance of battery systems. Future research is expected to benefit from advancements in battery technology and improved battery management. This includes more precise modeling of battery properties and reduced battery deterioration. The modern power grid has included artificial intelligence algorithms and machine learning. One of the primary uses is for complete perception, including forecasting power prices, predicting demand, forecasting renewable energy, and monitoring electric equipment. In addition, intelligent decision-making is crucial in several applications, such as demand-side management, defect detection, and power system planning. Furthermore, these algorithms are progressing in battery operation and bidding inside power markets. The battery operations will encompass aggregated solar batteries functioning as virtual power plants (VPP). A VPP is a network of interconnected household batteries that may be operated and synchronized collectively as a single power plant. The combined energy extracted from each battery can supply a substantial reservoir of manageable solar energy.

Furthermore, the use of blockchain technology in the distribution network has garnered increased interest due to its ability to facilitate peer-to-peer trade of home batteries and Electric Vehicles (EVs). With increased user engagement, future power markets are expected to become more dynamic. Consequently, there will be a need to create more complex concepts and approaches for BEMs.

7 Conclusion

The primary focus of this analysis has been on the strategies and methodologies for integrating BESS into RESs. The applications of BEMs have been summarized based on the utilized optimization strategies, selected scheduling objectives, and modeling methodologies. Based on the evaluated research, most of them utilized a standardized model for their battery systems. This model employed simplified charge and discharge processes to depict the connection between the SoC and the power going into and out of the battery. In addition, the primary goals of implementing the BESS can be classified into technical, economic, and hybrid goals. Economic goals are more likely pursued by private owners seeking more significant profits, while system operators prioritize technical goals to enhance system performance. Hybrid methods (combining both technical and economic goals), which leverage the distinct strengths and limitations of diverse techniques, are expected to play a crucial role in the advancement of optimization strategies in the future, thereby having a system that is technically sound and economically reasonable for both consumers and utilities alike. Prior reviews have concentrated on particular RESs, such as distributed generation or large-scale renewable energy plants. In contrast, this review offers a thorough overview of battery management approaches and examines the connection between the chosen optimization targets and the preferred optimization techniques used in these studies. The selection of problem-solving methods is heavily contingent upon the degree to which the problem is mathematically stated. Moreover, it is evident that algorithms, which possess remarkable adaptability, may be applied and used in many situations, irrespective of whether they pertain to technical, economic, or hybrid goals. The study compares the benefits and drawbacks of the optimization strategies mentioned. It concludes that hybrid approaches, which combine the advantages of multiple techniques, will significantly impact future operation plan development. Although a comprehensive review and analysis have been conducted in this study, its limitation is that no simulation or experimental studies were performed. As the shift towards further incorporation of renewable energy progresses, greater demands are expected to be placed on the efficiency of the BESSs. The growing prevalence of battery storage applications indicates that future studies should explore developing more sophisticated optimization strategies for managing battery storage to achieve numerous objectives.

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APPENDIX

Table 1. Specific research on BEMS for technical goals

Ref	Techniques	Goals	ESSs	RESs
[47]	Battery and Supercapacitor Control Systems	Minimizing the fluctuations of RESs	BESS, Supercapacitor	Wind Turbine (WT), PV
[48]	BESS Optimization and scheduling controller	Minimizing carbon emission problems	BESS	Microgrids
[49]	Building optimization model	Power balance	Lead-acid batteries, flow batteries, and hot water tank	PV
[50]	Particle swarm optimization (PSO),	Peak shaving	BESS	PV
[51]	Degradation costs and constraints	Battery degradation control	BESS	Generic
[52]	Primal-dual optimization	Power Scheduling	community energy storage (CES)	Generic
[53]	Monte Carlo simulation (MCS)	Power Scheduling	BESS	Electric vehicle (EV)
[54]	Scheduling procedure and control algorithm	Peak load shaving and load leveling	Generic	Generic
[55]	Mixed-integer linear programming (MILP)	Energy Stability and network energy loss reduction	Generic	WT, EVs, PV
[56]	Lexicographic and robust ordering optimization	Power Scheduling	Generic	WT, PV EV
[57]	modified IEEE 123 bus system simulation	Day-ahead scheduling	BESSs	WTs, PVs,
[58]	Mixed integer quadratically constrained programming (MIQCP)	Shift some loads from high-price to low-price Periods (load scheduling)	Generic	WT, PV
[59]	CPLEX in general algebraic modeling system (GAMS)	Power Scheduling	Virtual energy storage systems (VESS), thermal energy storage (TES), hydrogen storage systems (HSS)	EVs

Table 2. Specific research on BEMS for economic goals

Ref	Techniques	Goals	ESSs	RESs
[77]	MILP, model predictive control (MPC)	Modeling of degradation cost for battery's optimal scheduling.	BESS	Generic
[78]	Quantile nearest neighbor (QNN), Artificial neural networks (ANN), genetic algorithm (GA)	Reducing microgrid's total cost by Improving the system's power/voltage profile	Generic	PV
[79]	Non-dominated sorting genetic algorithm II (NSGA-II)	Minimization of operating cost	HESS	WT, PV
[80]	Reinforcement learning.	Minimizing ESS's life-cycle cost	Generic	Generic
[81]	Reinforcement learning	Reducing the cost of energy of a railway system	Generic	Generic
[82]	PSO	Reducing BESS operating costs	BESS	WT, PV
[83]	Converged barnacles mating optimizer (CBMO),	Cost reduction of microgrid's operation	Generic	PV
[84]	Load shifting mechanism	Reducing the energy cost of microgrid	BESS	WT, PV
[85]	Deterministic optimization, Rainflow-counting algorithm.	Minimizing battery degradation cost	BESS	Generic
[86]	Slime mold algorithm (SMA)	Minimizing microgrid's operation costs	BESS	Plug-in hybrid electric vehicles (PHEV)
[87]	Generalized reduced gradient (GRG)	Investigating the economic feasibility of EVs for vehicle-to-grid (V2G) services.	BESS	EV

Table 3. Specific research on BEMS for hybrid goals

Ref	Techniques	Goals	ESSs	RESs
[94]	Comprehensive review	Optimal scheduling, improving environmental effects, reducing costs	Generic	Generic
[95]	Improved grasshopper optimization algorithm (IGOA)	Minimizing the total net present cost (TNPC) and the loss of energy	BESS	WT, PV
[96]	artificial electric field algorithm (AEFA)	Minimizing the cost of system lifespan, designing an optimal framework for microgrid	BESS	WT, PV
[97]	Cost optimisation	Minimizing MGs environmental impact. and operating costs	BESS	PV
[98]	Comprehensive review	extending battery life, regulating grid load, and reducing energy refueling duration	BESS	EV
[99]	pseudo-two-dimensional (P2D)	Investigating size variation on BESS degradation and energy generation costs	BESS	WT, PV
[100]	MILP	Investigating the effects of battery degradation on carbon emission and cost of energy	BESS	EV, PV
[101]	water/ethanol hybrid (WEH) electrolyte	High safety, high power density, environmental friendliness, and low cost	BESS	Generic
[102]	Multi-objective optimization	Environmental, economic, and technical assessments	Generic	WT, PV
[103]	Principles of materials breakdown and cell fabrication	Boosting the energy density of the battery pack and reducing the production cost of an electric vehicle	BESS	EV
[104]	Generic optimization	Investigating the impacts of tariffs, electricity prices, load profiles, and costs	BESS	PV

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Conflict of Interest

The authors have no conflict of interest to declare.

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