



Battery energy-storage system: A review of technologies, optimization objectives, constraints, approaches, and outstanding issues

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ABSTRACT

Due to urbanization and the rapid growth of population, carbon emission is increasing, which leads to climate change and global warming. With an increased level of fossil fuel burning and scarcity of fossil fuel, the power industry is moving to alternative energy resources such as photovoltaic power (PV), wind power (WP), and battery energy-storage systems (BESS), among others. BESS has some advantages over conventional energy sources, which include fast and steady response, adaptability, controllability, environmental friendliness, and geographical independence, and it is considered as a potential solution to the global warming problem. This paper provides a comprehensive review of the battery energy-storage system concerning optimal sizing objectives, the system constraint, various optimization models, and approaches along with their advantages and weakness. Furthermore, for better understanding, the optimization objectives and methods have been classified into different categories. This paper also provides a detailed discussion on the BESS applications and explores the shortages of existing optimal BESS sizing algorithms to identify the gaps for future research. The issues and challenges are also highlighted to provide a clear idea to the researchers in the field of BESS. Overall, this paper conveys some significant recommendations that would be useful to the researchers and policymakers to structure a productive, powerful, efficient, and robust battery energy-storage system toward a future with a sustainable environment.

1. Introduction

The energy concepts are evolving all around the world due to increasing technological advancements, decarbonization initiatives, the establishment of the smart grid concept, and the rapid growth in the use of renewable resources. In the past, fossil fuels are critical resources for generating electrical power. Due to global warming and greenhouse gas (GHG) emissions resulting from the widespread use of diesel, petrol, and other fossil fuels, which emits tons of CO₂, the world is now approaching toward decarbonization through low-carbon emission while expanding the utilization of sustainable power sources [1]. As a result, the electrical power infrastructures are facing significant challenges such as the dispersed nature of making power, the requirement for autonomous microgrids to guarantee reliability, the need of reducing GHG

discharges, and the ability to suit blended energy resources to meet innovative and unpredictable demands of providing consistent power supply [2,3]. To address these issues, the usage of the renewable energy-storage system (RESS) has increased tremendous consideration and has become an appealing option for researchers due to its promising features in decreasing GHG. However, the wide assortment of alternatives and complex performance matrices can make it hard to assess an Energy Storage System (ESS) technology for a specific application [4,5].

The principle highlight of RESS is to consolidate at least two renewable energy sources (PV, wind), which can address outflows, reliability, efficiency, and economic impediment of a single renewable power source [6]. However, a typical disadvantage to PV and wind is that both are dependent on climatic changes and weather, both have high initial costs, and both would need to be larger than average to make

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their independent frameworks robust for the occasions when neither one of the systems is delivering enough electric capacity to fulfill the load [7]. The BESS can be applied to RESS frameworks to expand the effectiveness and evacuate the deficiencies. Truth be told, when the wind speed or solar radiation diminishes, or a peak demand happens, the presence of these capacity units gets essential.

The design optimization aided by an efficient sizing of BESS is essential to expand the exhibition and reliability, which may satisfy the external load demand, lessen the energy cost and net present cost (NPC), and limit the ozone harming substance emanations [7]. The optimal sizing of an effective BESS system is a tedious job, which involves factors such as aging, cost efficiency, optimal charging and discharging, carbon emission, power oscillations, abrupt load changes, and interruptions of transmission or distribution systems that needed to be considered [6,7]. Thus, the interest in developing a competent and reliable BESS is increasing among the researchers. Many researchers have developed different optimization algorithm to find out the best possible outcome from the traditional BES system considering the low cost, high lifetime, reliability, and lower environmental impact.

Until now, a couple of significant BESS survey papers have been distributed, as described in Table 1. A detailed description of different energy-storage systems has provided in [8]. In [8], energy-storage (ES) technologies have been classified into five categories, namely, mechanical, electromechanical, electrical, chemical, and thermal energy-storage technologies. A comparative analysis of different ESS technologies along with different ESS applications is mentioned, and the suitable technology for each application is provided. However, the challenges of different technologies and the BESS optimization methods were not described extensively in the research.

The sizing of BESS in the RES is mainly focused in [9]. The application of BESS sizing has been categorized into four sectors, namely, BESS sizing in microgrids, distributed renewable energy systems, standalone hybrid renewable energy systems (HRES), and renewable energy power plant. However, the study did not include BESS sizing methods and optimization techniques in detail. Details about microgrids and the technologies integrated with microgrids are discussed in [10], but detail about BESS sizing and optimization is missing in the literature. A comprehensive review on battery and non-BESS from a distributed energy perspective is given in [11].

The chemical formulation and differences of various types of lead-acid batteries have been presented in [1]. A comparative study on BESS and non-battery energy-storage systems in terms of life, cycles, efficiency, and installation cost has been described. Multi-criteria decision-making-based approaches in ESS, including ESS evolution, criteria-based decision-making approaches, performance analysis, and stockholder's interest and involvement in the criteria-based analysis, have been mentioned in [12]. Nevertheless, BESS sizing and optimization techniques have not been discussed in detail. A detailed discussion on ESS sizing methods toward achieving decarbonization in the microgrid (MG) application is presented in [13]. The optimization methods and algorithms for ESS sizing are divided into two modes, namely, grid-connected and isolated mode, and a brief comparative study is also presented considering decarbonization. Olabi et al. in [14] have divided the ESS into four major categories, i.e., mechanical, electromechanical, chemical, and thermal ES systems. Detailed construction and application of each category are described followed by future challenges. The detailed discussion of ESS sizing and optimization techniques along with system constraints is absent in the manuscript. Only the ESS technology development and application are being focused on.

To bridge these research gaps, this review provides a brief discussion on BESS sizing technologies and optimization methods. Moreover, a brief comparative study on BES technology, recent sizing, and optimization methods, and outstanding issues of BESS sizing strategies are presented. The main objective of the study is to develop a comprehensible analysis of the existing research for a critical research question and identify the research gap. The key objectives of this study are

Table 1

Discussion on a recently published review article in the field of BESS.

Ref.	Year	Focused topics	Research gaps
[8]	2016	A detailed discussion on ES technologies and applications has been provided.	The challenges and issues of different BESS and their optimization techniques were also not provided extensively.
[9]	2017	Presented BESS sizing in renewable energy system (RES). The sizing techniques have been categorized into four methods, namely, probabilistic methods, analytical methods, direct search based, and hybrid methods.	The clarification of BESS sizing optimization was constrained to only a few methods.
[10]	2017	Provided details about microgrid definition, characteristics, classification, challenges, combining technology with microgrids, and future scope.	Theoretical analysis of microgrid integrated technologies has been given, but discussion about the sizing and optimization methods is missing.
[1]	2018	Described the lead-acid batteries principles, cell construction, durability limiting factors, application in different countries, and sustainability.	Focused only on lead-acid batteries. The energy sizing and optimization techniques have not been discussed.
[11]	2018	A comprehensive literature review of ESS sizing, smart charging and discharging, and mitigation possibilities of power quality issues by ESS placement are provided.	The execution process of BESS sizing optimization algorithms was not described extensively.
[12]	2019	Multi-criteria decision-making-based approaches in ESS are described. Moreover, criteria for ESS evolution, performances, comparative studies among criteria, uncertainty analysis, and stockholder's involvement and interests are provided.	BESS sizing and optimization methods and implementation factors were not involved in the literature.
[13]	2020	Discussion on ES sizing methods toward achieving decarbonization in MG application is presented based on grid-connected and isolated mode of operation. The comparative study, including advantages, limitations, and outcome, is presented.	The constraints of the BESS system have not been clarified and described clearly.
[14]	2021	According to the manuscript, mechanical, electromechanical, chemical, and thermal energy-storage systems are the four main divisions of the ESS. Each category is outlined in-depth, including its construction and implementation, as well as potential challenges.	The manuscript lacks a thorough discussion of ESS sizing and optimization methods, as well as system constraints.

summarized as follows:

- To deliver researchers a clearer image of the cutting-edge electrochemical advances available and where they would be appropriate for integration into a power generation and distribution framework
- To study the different BESS technologies, constraints, and applications
- To classify various optimization strategies according to their approaches, technologies, advantages, and disadvantages
- To discuss various optimization methods' problems and concerns
- To provide some valuable guidelines for potential system development

2. Surveying methodology

In terms of recent research, there has been a developing enthusiasm

to create compelling and dependable BESS frameworks. To discover the present state of scientific research in the field of “battery energy-storage system,” a brief search in Google Scholar, Web of Science, and Scopus database has been done to find articles published in journals indexed in these databases within the year 2005–2020. The keywords that were selected to search for the publication include *energy storage, battery energy storage, sizing, and optimization*. Various articles were found, but appropriate articles were recognized by assessing the title, abstracts, focus, and contributions of the manuscript. The outcome of the selection process is categorized into four stages. Firstly, the different BESS optimization objectives, alongside system constraints, were broadly explored. Secondly, an extensive survey on BESS modeling and development approaches, intelligent systems, strengths, weaknesses, and key findings were reviewed. Thirdly, the BESS application in a real-life scenario, including the issues and challenges regarding BES system development, was analyzed and described. Finally, the survey provides some significant proposals for the further development of the battery ES system to achieve clean energy and sustainable environmental goal. Fig. 1 summarizes the selection process and the review outcome.

2.1. Selection process

- Following the primary process, a total of 496 papers were selected.
- The first evaluation and screening were done utilizing the proper catchphrases, title, theoretical, and article content, and 298 articles were recognized through this refining process.
- The second assessment and screening were conducted, utilizing the articles’ impact factor, review procedure, and citation.
- Finally, a sum of 173 papers from journals and scientific conference proceedings were chosen for the review stage.

2.2. Research outcome

- BESS optimization objectives and system constraints toward achieving clean energy were comprehensively reviewed.
- A comprehensive survey on BESS modeling and development approaches, objective functions, advantages, disadvantages, and key findings were given in detail.
- The real-time BESS applications, issues, and challenges while developing a robust and efficient BESS optimization method were also broadly described.
- Few selective and significant proposals for further improvement of BESS, including the improvement of power quality, battery lifetime, cost reduction, and carbon emission, were provided.

3. BESS market trend

The 2015 United Nations Climate Change Conference in Paris set the structure for a quick worldwide move to an economical energy framework to avoid the danger of disastrous environmental change [15]. Energy storage has been a key part of empowering the outstanding transition as it depends more on renewables and less on fossil fuels. Among various ES technologies, BESS follows with the most potential [16]. According to BloombergNEF (BNEF), battery prices have dropped to 87% from the year 2010 to 2019 [17]. Fig. 2 shows the lithium-ion (Li-ion) battery pack price. As shown in Fig. 2, the prices in 2010 were above 1100 \$/kWh and reduced gradually and 156 \$/kWh in 2019. Besides, the battery market is also proliferating due to the rapid reduction of cell pack prices and better value for money while installing new ES systems. The annual lithium-ion battery market worth will increase from \$28 billion to \$116 billion from the 2020 to 2030 [17].

According to Deb [18], \$1 billion has been given by the world bank to accelerate the investments in BESS. This will allow the developing and middle-income countries to overcome the obstacles toward the next generation of power technology, expand energy access, and set the stage

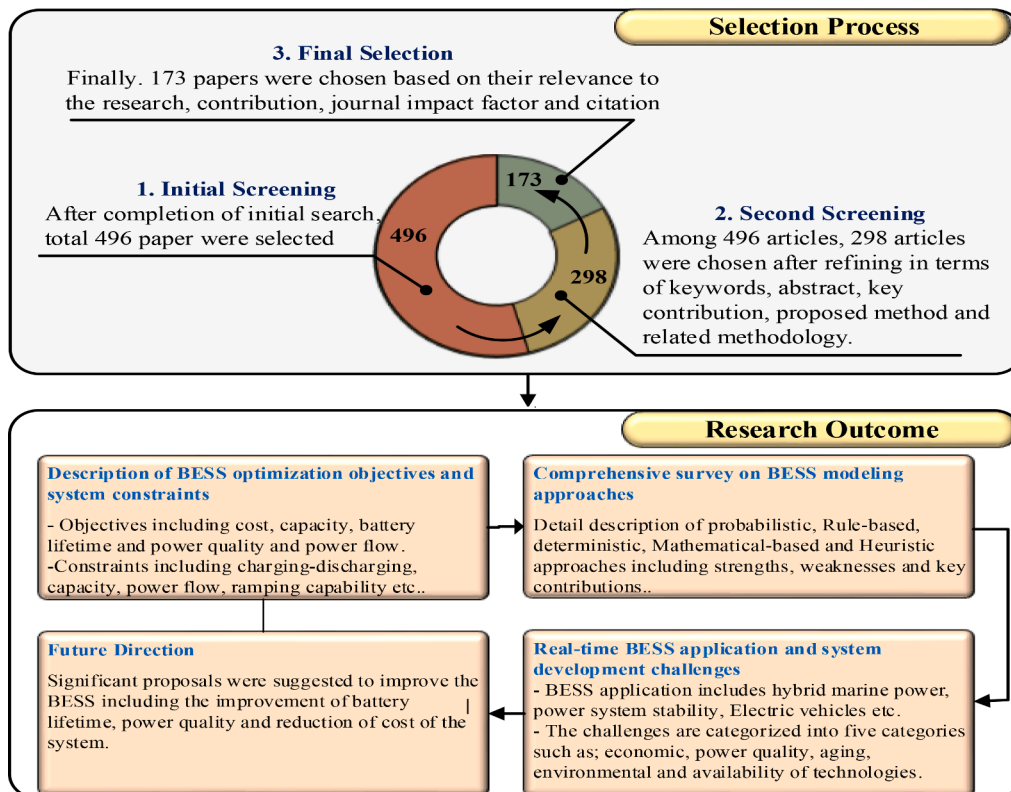


Fig. 1. Schematic diagram of the entire surveying methodology of the literature.

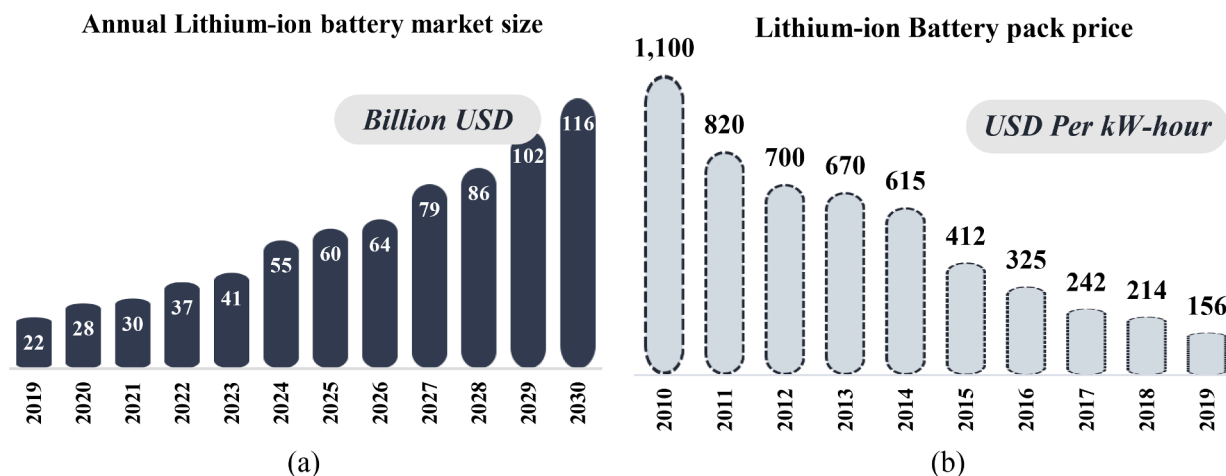


Fig. 2. (a) Annual lithium-ion battery market size (b) Lithium-ion battery pack price from the year 2010 to 2019.

for cleaner and more stable energy systems. According to [19], the growth of the battery market in Malaysia is expected to be over 6.6% during 2020–2025, and lead–acid battery is expected to dominate the market. A detailed discussion on Malaysian electricity tariff and methods of grid-tied potential sources (PV and BESS) to mitigate the peak demand shaving is presented in [20].

4. Overview of battery ES technologies

Clean energy sources which use renewable resources and the battery storage system can be an innovative and environmentally friendly solution to be implemented due to the ongoing and unsurprising energy crisis and fundamental concern. As previously discussed, BESS is a supporting system with a rapid response time, high reliability, and low self-discharge rate and is highly potential under the circumstances [21]. BESS can also be a great alternative in mitigating peak shaving instead of using liquid-based generation [22]. Every storage type has specific attributes, namely, capacity, energy, and power output, charging/discharging rates, efficiency, life cycle, and cost, which need to be taken into consideration for possible applications. The diverse ESS technologies display differing confinements relying upon the materials and power electronic interfacing. Table 2 presents a comparative summary of different battery ES technologies considering life cycle, efficiency, power and energy density, advantages, limitation, and applications [1, 10–12, 23–27].

As presented in Table 2, an electric double-layer capacitor (EDLC) or supercapacitor has the highest life cycle and energy density but the lowest specific energy. Among all the storage options, the supercapacitor has a wide variety of applications such as bus, rail, and electric vehicles (EV) and backup power applications. Supercapacitors show significantly less sensitivity to temperature than Li-ion batteries with potential working temperatures in the scope of -40 – 65°C [28]. Hydrogen batteries have the highest specific energy compared to other storage systems and have a high life cycle as well. Though hydrogen batteries are environmentally friendly and have a long life cycle, it has a high initial cost. On the other hand, flow batteries are safe as they are nonflammable and demonstrated a long battery life, and it is not dependent on the depth of discharge. Flow batteries are mainly used in EVs and for load balancing along with solar and wind. There are different types of flow batteries, including Fe–Cr, Fe/V (vanadium redox), zinc bromide (Zn–Br), and zinc chloride (ZnCl₂). Among them, vanadium redox is the most common type of storage option. Vanadium redox flow battery (VRFB) has a larger energy capacity than other technologies, and it can be left discharged for extended periods with no harmful impacts. However, the main disadvantage is that the VRFB has poor energy-to-volume ratio and a poor round trip

efficiency [29].

Lead–acid is the oldest rechargeable battery technology. Lead–acid batteries have a moderate life cycle and efficiency, and the most common applications are in emergency lighting and electric motor. Regardless of having a meager energy-to-weight ratio and a low energy-to-volume ratio, its capacity to supply high surge current implies that the cells have a moderately substantial power-to-weight ratio. These features, alongside their ease, make them appealing for use in motor vehicles to give the high current required by starter engines [1].

The most common battery energy technology is lithium-ion batteries. There are different types of lithium-ion batteries, including lithium cobalt oxide (LiCoO₂), lithium iron phosphate (LiFePO₄), lithium-ion manganese oxide batteries (Li₂MnO₄, Li₂MnO₃, LMO), and lithium nickel manganese cobalt oxide (LiNiMnCoO₂). The main advantages of lithium-ion batteries are portability, high energy density, and fast response time; however, the main drawbacks considered are its high cost and limited capacity. Different types of lithium-ion batteries have different applications. LiMnO₂ is used in mobile phones, laptops, and cameras, among others, because it is safe and can deliver high power. LiNiMnCoO₂ and Li₂MnO₄ are mainly used in medical instruments. Among all storage options, Li-ion presents a relatively high cycle efficiency, superior power, and energy density.

5. Optimization objectives and constraints in BESS

In this review, objective function of the optimization and constraint i.e. limitations on the optimization of BESS have been explained detail. The BESS optimization requires the process of optimizing the derivatives of the objective functions with respect to some variables in presence of constraints. Detail objective functions and optimization constraints of BESS are demonstrated in the following section.

5.1. Optimization objectives in BESS

BESS optimization refers to the sizing and placement of the BESS in such a way which become more popular among consumers on the cost-effectiveness, energy cut and demand expenses. Nowadays, due to the constant increase of fossil fuel burning, carbon emission, and scarcity of fuel sources, BESS is becoming a promising alternative source for fast response, adaptability, controllability, environmental friendliness, and geographical independence. Researchers show great interest in developing an efficient BESS system. Fig. 3 shows the basic construction of the BESS sizing optimization problem.

Researchers have used several methods to improve various parameters. The most common goals in different papers are to determine the cost, capacity, lifetime and power quality, and load flow. The most

Table 2
Overview of different battery ES technologies considering life cycle, efficiency, power and energy density, advantages, limitation, and applications [1,10–12,23–27].

Technology	Life cycle at 80% depth of discharge (DoD)	Efficiency (%)	Specific energy(Wh/L)	Energy density (W/L)	Advantages	Limitations	Applications
Lead-acid	300–3000	70–90	35–40	80–90	- Cheap - Available	- Low-energy density - Restricted cycling ability - High environmental impact	- Emergency lighting - Electric motors - Diesel-electric submarines
NiCd	3000	80	40–60	50–150	- Good life cycle - Improved low-temperature performance	- High self-discharge rate - High environmental impact - Memory effect	- Low-cost rechargeable batteries - Battery manufacturing companies
NiMH	2000	66–92	60–120	140–300	- High tolerance level - Improved low-temperature performance - Availability and high energy density	- Highly expensive - Damage may happen due to full discharge mode	- Low-cost rechargeable batteries - Battery manufacturing companies
Li-ion	3000	75–90	100–265	250–693	- High energy density - Fast response time - High efficiency and low self-discharge rate - No memory effect	- High initial expense - Safety issue depending on the type	- Portable devices like mobile phones, laptops, etc. - Thermometers, remote car locks, laser pointers, MP3 players, hearing aids, etc. - Electric vehicles (EV)
LiCoO ₂	500–1000	95.7–98.4	150–200	2710	- High detailed energy - Secured market share	Expensive, limited power, no longer relevant	Mobile phones, tablets, laptops, cameras
LiMn ₂ O ₄	300–700	80	100–150	2310	- High power - Safer than LiCoO ₂ .	Less capacity, need to combine with NMC to improve efficiency	Power tools, medical devices, electric powertrains
LiNiMnCoO ₂	1000–2000	-	150–220	-	- High capacity and high power - Leading system	- Highly expensive - Complex monitoring and control	E-bikes, medical instruments, EVs, industry application
LiFePO ₄	2000>	-	90–120	1932	- Safe - Stable voltage discharge	Low capacity, used for preliminary energy storage	Portable and stationary application where high load current is needed
LiNiCoAlO ₂	500	-	200–260	-	- High specific energy and stability - Works as an energy cell	Expensive, limited power capacity	Medical application, industry, and power train
Li ₂ TiO ₃	3000–7000	-	50–80	-	- High life cycle - Fast charging and safer technology - Wide thermal range	Expensive, low specific energy	uninterruptible power supply (UPS), solar-powered street lighting
Flow batteries	2000–20000	65–85	40	-	- Nearly unlimited longevity - Scalability	High maintenance - An extra electrolyte tank is needed - Complex monitoring and control	- UPS - Can be used alongside solar and wind for load balancing - EV
NaS	4500	89	150–300	10000	- High efficiency - High life cycle	- High maintenance - High operating temperatures	- Load balancing - Secondary UPS - EV
NaNiCl ₂	1500–3000	85–95	90–120	150	- Long life cycle - High energy density	- High thermal management is needed	- Load leveling - EV
Electric double-layer capacitor (EDLC)	1000000	95	<8	10000–20000	- High power density - Long life cycle - Fast response time - Lower thermal management required	- Low specific energy - Complex water and thermal control - High initial cost - Low efficiency	- Hybrid bus, rail, and EV - Backup power applications - Standalone or hybrid technology with battery for ES system
Hydrogen	20000	20–66	500–3000	500<	- Less environmental impact - Long life cycle	-	- Electrical energy in satellite - Space probes

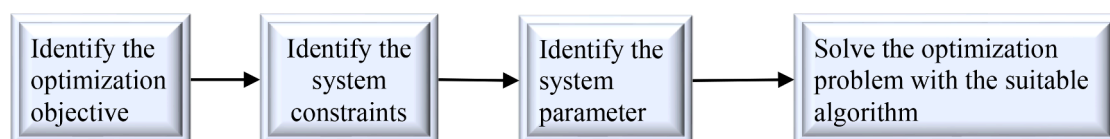


Fig. 3. Overall system flowchart of the BESS optimization technique.

notable objective functions in the BESS optimization are discussed below.

5.1.1. BESS cost optimization

Another very widely recognized optimization is cost optimization, which is conducted to minimize the cost and achieve the highest possible outcome with minimum cost (including installing and operation cost). In most of the literature, the best possible outcome in the most cost-effective way has been considered. In [7,30–40], and [41], cost function is used as an optimization parameter. In [30], BESS scheduling is solved through mixed-integer linear programming (MILP) where the cost function is defined as follows:

$$\sum_{i=1}^N \sum_{j=T^*}^T \left\{ u_{i,j}^{T^*} \cdot (FC_i) \cdot \Delta T + u_{i,j}^{T^*} \cdot (1 - u_{i,j}^{T^*}) \cdot SC_i \right\} \quad (1)$$

where $T^* = T^{pre}$ is for the previous day and $T^* = T^{cu}$ is for the current day, ΔT is the unit time, and $u_{i,j}^{T^*}$ is the activator for the thermal generator i at time j (0: stop; 1: start). The system constraints are categorized in three categories, namely, constraints of thermal power generator, constraints of BESS, and constraints of forecast update. The thermal power generator output constraints include maximum and minimum power limit, upward reverse capacity, and load frequency control, whereas the BESS constraints include charging–discharging and the stored energy of the primary and end state. The result shows that the determination of charging–discharging of BESS with respect the actual PV power outcome can reduce the energy shortfall of the overall system and improve the system reliability and reduce the overall cost.

In [36], two objective functions have been considered, namely, total cost and loss of load expectation. The cost objective function is defined as follows:

$$\text{Min } \phi_1 = IC + OC \quad (2)$$

$$IC = \sum_{j \in n} \left\{ ICP_B P_B^R j + ICE_B C_B^{\max} j \right\} \quad (3)$$

$$\begin{aligned} OC &= \sum_{s=1}^{NS} \rho_s \sum_{t=1}^{NT} \sum_{h=1}^{NH} \times \sum_{j \in n} \left[\lambda_{th} \times P_{sun}^{s, j_{th}} \right] \\ &+ \sum_{s=1}^{NS} \rho_s \sum_{t=1}^{NT} \sum_{h=1}^{NH} \times \sum_{j \in n} \left(a_j P_{DG}^{s, j_{th}} + b_j P_{DG}^{s, j_{th}} + c_j \times u_{j_{th}}^s \right) \\ &+ \sum_{s=1}^{NS} \rho_s \sum_{t=1}^{NT} \sum_{h=1}^{NH} \times \sum_{j \in n} \left\{ SUC_{j_{th}}^s \times \left(u_{j_{th}}^s - u_{j_{th}(t-1)h}^s \right) \right\} \end{aligned} \quad (4)$$

where IC and OC are the installment cost and operation cost, respectively. NH , NT , and NS are the number of days, hours, and scenarios, respectively, whereas ρ_s is the scenario possibility. $P_{DG}^{s, j_{th}}$, $SUC_{j_{th}}^s$, and $u_{j_{th}}^s$ are the generation, startup cost and on/off condition of the DG units in bus j at time t in day h . ICP_B and ICE_B are the installation cost of ESS and C_B^{\max} is the maximum battery capacity at bus j . The two main constraints are power flow limitation and total generation cost of DG. Optimal sizing of BESS with and without demand response program (DRP) is shown here, and the obtained result has revealed that the total cost of microgrids considering the DRP is 13.34% less than the reasonable condition. In [41], the techno-economic analysis is carried on using two key parameters, i.e., life cycle cost of storage (LCCOS) and the leveled cost of energy (LCOE), and the analysis is divided into three categories, i.e., short-, medium-, and long-term ESS. The result shows that for long-term, medium-term, and short-term analysis, pumped hydroelectric storage (PHS), NaS technology, and supercapacitor energy storage (SCES) technology have provided the lowest LCCOS and LCOE, respectively. In the context of cost optimization, the main constraints include but are not limited to fuel constraints, emissions constraints, and plant characteristics.

5.1.2. BESS capacity and lifetime optimization

Another key optimization factor is capacity optimization in BESS where the capacity of the power conversion system and the battery storage capacity are considered. In designing an efficient BESS, power rating and battery storage capacity are needed to be optimized accordingly. Several researchers proposed various methods to optimize the battery capacity and improve BES system performance and cast minimization [42–48]. In [42], the main goal of the BESS capacity optimization model is maximizing the equivalent uniform annual profit:

$$\text{maxobj} = C^{\text{sell}} - C^{\text{WP}} - C^{\text{PV}} - C^{\text{CSP}} - C^{\text{BESS}} - C^{\text{OM}} - C^{\text{tax}} \quad (5)$$

where, C^{sell} is the annual income, C^{WP} , C^{PV} , C^{CSP} , C^{BESS} , C^{OM} and C^{tax} are the equivalent uniform annual cost of wind, PV, concentrated solar power, BESS, operation and maintenance and annual tax respectively. Transmission line capacity, renewable energy annual curtailment rate, WP, PV, CSP, BESS operation, and state of charge (SoC) limitations are considered as the constraints. The capacity optimization is conducted on an hourly basis over a year, and the result concluded that the profit should be maximized, less than 5% of the annual curtailment rate is ensured, and 99MW/254MWh battery will be disposed from the project. Moreover, 0.09\$/kWh is the threshold level of the profit margin from the project. An optimal method for BESS sizing is proposed in [49], where the capacity and annual charging and discharging are optimized to achieve the annual maximum reduction rate. A dynamic programming (DP)-based capacity degradation and cost modeling are computed in [48], where the BESS is optimized along with the wind turbine (WT). Five different system configurations are considered:

- WT output = Load; BESS is not required.
- WT output > Load; BESS can eradicate the excess power.
- WT output >> Load; BESS can no longer eradicate, so the excess power is discarded. In this scenario, the excess power can be sold to the grid to reduce the overall operating cost.
- WT output < Load; BESS delivers the stored energy to mitigate the demand.
- WT output + BESS < Load.

The capacity of BESS is optimized to reduce the overall system cost in [46] where the mixed-integer linear problem is expressed as follows:

$$c_{pv} \cdot K_{pv} + c_w \cdot K_w + c_{bat} \cdot K_{bat} + c_{fc} \cdot K_{fc} + H^{\text{cost}} n_{hyd} \quad (6)$$

where c_{pv} , c_w , c_{bat} , and c_{fc} are the PV, wind, BESS, and fuel cell capacity, respectively. The results show that replacement of the installed Li-ion batteries recurring on a frequent basis may trigger the uplift in overall cost for the systems having extended life span crossing the threshold of 14 years. Fig. 4 shows the flow chart of the proposed capacity optimization determination system in [50].

In the optimization process, ESS capacity, SoC, and output power are considered system constraints. The result shows that a BESS life span can be significantly improved by an optimal configuration of BESS and WT and with the discarded energy selling can effectively minimize the operating cost of the system.

The lifetime of a battery depends on its cell structure, operation procedure, and thermal environment along with charging and discharging cycle. Many researchers perform different techniques to analyze and optimize the lifetime, and sometimes the lifetime is integrated with cost function as well. The main idea in [43] is the allocation of battery capacity and power according to the current state of health (SoH). The rate of degradation, corrosion, cycle count, and SoH are considered as parameters for the battery management system (BMS). Multiuse application with UPS system is applied with BESS to increase lifetime through higher mean SoC, lower DoD, and lower nominal current rate per string. In [51], SoH estimation of Li-ion battery is completed based on self-adaptive differential evolution algorithm, which increases SoH estimation accuracy by adding a community of

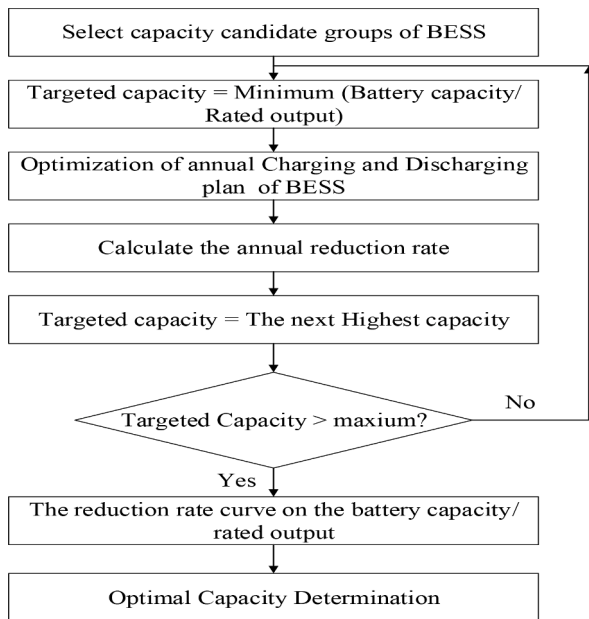


Fig. 4. Optimal method to determine BESS capacity.

poor learners. In [52], the two main objective functions include RMS battery power and overall cost, to reduce initial cost and battery life span. A hybrid particle swarm–Nelder–Mead algorithm involving multi-objective optimization is used for BESS sizing. Cycle counting-based battery life span assessment is used in [53], where DoD and SoC are the two key parameters used for the battery control algorithm. The battery lifetime estimation is formulated as follows:

$$L_{BESS} = \frac{T}{\sum_{i=1}^m \frac{N_i}{CF_i}} \quad (7)$$

where T is the simulation duration in years, N_i is the number of cycles at each DoD, and CF_i is the number of cycles to failure at the corresponding DoD. From the literature, it is concluded that the proposed method improves battery life and reduces battery degradation due to overuse. Battery cycle count and sizing are also done in [54–56]. A demand response program combined with BESS is presented in [57], where the cost function, internal power transfer, external power rating, load profile, and batter SoC characteristics are analyzed. To estimate and improve battery life span, thorough SoC optimization is also presented in [58–63]. A cloud-based optimal energy management system (EMS) based on DP is introduced in [64] to diminish the battery lifetime

degradation in China. The outcome shows significant improvements over the rule-based methods. A PV-BESS-based prototype is presented in [65]. The BESS of the prototype consists of three nickel–metal hydride (NiMH) batteries providing up to 3.24 kWh of storage capacity. Fig. 5 shows a block diagram of the prototype system.

The two key objectives are maximizing the delivered energy by PV framework and restraining the power drain from the distribution network. Table 3 presents the control strategy of the charging and discharging of the prototype system.

The battery lifetime is also dependent on temperature and humidity. If the temperature exceeds 25°C, a significant decrease in battery capacity is shown in [66]. The study shows that if the temperature changes from 25°C to 35°C, the cycle count of an LFP cell at 90% capacity is decreased from 2600 to 1450. The cycle count can reduce to 400 at 55°C. Therefore, at an increase of 30°C, the cycle count will decrease to 84.6%. Both the battery capacity and battery lifetime optimization are essential as it is directly related to the operational cost of the overall BES system.

5.1.3. Power quality and power flow optimization

An unoptimized BESS in the distribution network leads not only to the degradation of the power quality but also to the reduction of reliability, load controlling, voltage, and frequency regulation. A brief description of the importance and problems regarding power quality and frequency regulation in the smart power system is presented in [67–69]. Since the frequency regulation profoundly relies upon infusion and ingestion of real power inside a brief span, the different study applies different BESS technologies to achieve frequency stability. In [70] and [71], SMES-based ESS is applied, which showed promising results in damping out the power flow oscillation. Detailed overvoltage and undervoltage problems due to install rooftop PV are discussed in [72]. A PV inverter with reactive capability along with an ESS is proposed to minimize the problem. Voltage imbalance for rooftop PV is analyzed in [73], and a control method of distributed and localized SoC of the distributed ESS is proposed. A new approach for BESS sizing is

Table 3

Control strategy of battery charging and discharging by the PV system.

1. Start
2. Input: load active power P_{DC} and P_{AC}
3. If, load power $\neq 0$; $SOC_{min} < SOC < SOC_{max}$;
4. And, $P_{PV} > P_{PVmin}$;
5. Output: Battery will charge
6. If, $SOC \geq SOC_{max}$;
7. And, $P_{PV} \leq P_{PVmin}$;
8. Output: battery will discharge
9. End

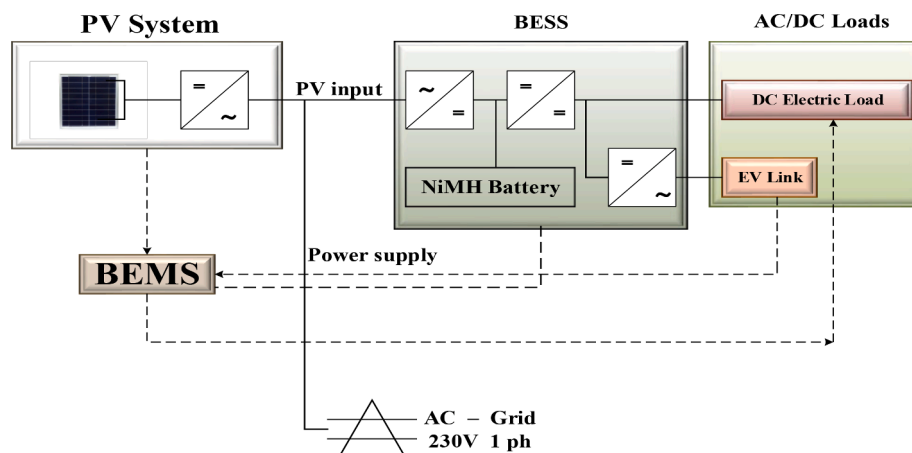


Fig. 5. Integration of BESS with the PV system [65].

introduced in [44], where second-order cone program (SOCP)-based optimal power flow (OPF) algorithm is used in a medium voltage distribution feeder. The two main objective functions are loss minimization and minimization of absolute active power flow at the substation. Optimal sizing of VRFB is done in [74], where the cost and frequency deviation are considered using a hybrid optimization model.

5.2. Constraints on BESS optimization

The constraints are the prohibitive criteria which must be considered in some arbitrary scenario. Nevertheless, defining the required scope of constraints in the optimization procedure may be difficult. The issues and difficulties can be diverse as far as climate conditions, area, population, and infrastructural conditions. An overall outline of the BESS sizing constraints, including the literature, is given in Fig. 6. The most notable constraints in the BESS sizing optimization are discussed below.

5.2.1. Charging and discharging constraint

The most common operational constraint while developing an efficient BESS optimization technique is the charging and discharging constraint or SoC constraint. While considering BESS optimization, the rate of degradation of battery and life span should be considered. Both are directly related to the SoC. BESS cost optimization considering SoC is presented in the following literature [37,75–78]. On the other hand, optimizing BESS capacity, power loss, power balance, control strategy, and battery lifetime, SoC constraints have been considered in [53] and [79–87]. In [86], the impact of battery constraints is analyzed for microgrid application. DP is used to optimize the cost and SoC, and battery capacity is considered as constraints. The defined conditions are as follows:

$$0.3 \leq SOC(k) \leq 0.9 \quad (8)$$

$$-6 \text{ kW} \leq P_b(k) \leq 6 \text{ kW} \quad (9)$$

The battery charging is done in a constant–current–constant–voltage (CCCV) manner for system safety. The grid energy cost with and without CCCV charging constraints are compared. MILP-based ESS optimization with flexible demand control is presented in [81]. The self-sufficiency index and the system self-consumption index are used to evaluate the system performance. The SoC is considered as a system constraint, and the maximum and minimum charging constant is defined as follows:

$$E_{min} = 0.2P_{stge}; E_{max} = 0.8P_{stge} \quad (10)$$

$$0 \leq P_{ch}^t \leq \delta_{ch}^t \cdot P_{stge} \text{ and } 0 \leq P_{dch}^t \leq \delta_{dch}^t \cdot P_{stge} \quad (11)$$

where the discharge time h is the maximum duration for which the system can discharge the rated power, P_{stge} , P_{ch}^t , and δ_{ch}^t are the ES

nominal power, charge power, and charge control, respectively. E_{max} and E_{min} are the maximum and minimum depth of discharge. In [53], the SoC constraints executed by battery and inverter conditions are defined as follows:

$$P^B(k) = \begin{cases} 0, SOC(k) = SOC^{min} & P^B(k) > 0 \\ 0, SOC(k) = SOC^{max} & P^B(k) < 0 \\ 0, SOC(k) < \eta'_d \cdot P^B(k) / 12 E_{rated} \\ 0, (SOC(k) - 1) > \eta_c \cdot P^B(k) / 12 E_{rated} \\ P^B_{rated}, P^B(k) > P^B_{rated} & SOC(k) \neq SOC^{min} \\ -P^B_{rated}, P^B(k) < -P^B_{rated} & SOC(k) \neq SOC^{max} \\ P^B(k), \text{ else} \end{cases} \quad (12)$$

where η_c and η'_d refers to the charging and discharging efficiency, P^B_{rated} and $P^B(k)$ are the BESS rated and output power, respectively. The condition implies that if, $SOC(k) = SOC^{min}$, battery power output = 0, and the battery will not charge if $SOC(k) = SOC^{max}$. The third limitation implies that the BESS cannot supply power to the grid if the demand power is greater than the remaining power of the battery. The fourth condition limits the overcharging of BESS as the charging cannot occur more than battery capacity. The fifth and sixth conditions state that the output and input power cannot exceed the rated power. Thus, providing different SoC conditions during the system development can improve the battery life span by limiting the overcharging of the battery.

5.2.2. Capacity constraint

Under certain predetermined conditions, the maximum amount of energy that can be extracted from a battery is known as the capacity of that battery. As the lifespan of a battery is dependent on the rate of degradation, the battery capacity consideration is very important while sizing a BESS. In [37], power and energy capacity is considered as BESS constraints which are defined as;

$$0 \leq P_i^{B,d} \leq S_{max}; 0 \leq P_i^{B,c} \leq S_{max} \forall i; \sum_{i=1}^{24} P_i^{B,d} \leq W_{max} \quad (13)$$

where, $P_i^{B,d}$ and $P_i^{B,c}$ are discharge and charge rates of BESS in i^{th} hour. In [84], battery capacity is considered as the main objective function where initial charging and discharging rate and capacity are considered as the main constraints. While considering BESS cost optimization, battery capacity is considered as constraint in [37,88,89,90].

5.2.3. System reliability constraints

To ensure the developed optimized model reliability, few battery

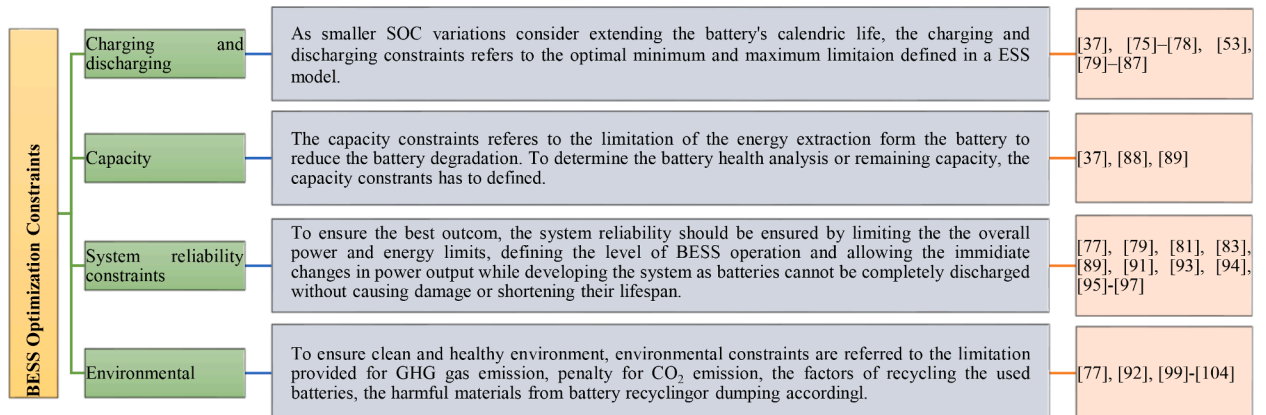


Fig. 6. The summary of the BESS optimization constraints.

parameters such as; maximum and minimum energy limit, power flow limitation, ramping capabilities has to predefined is known as system reliability constraints. To optimize cost, power and energy limit constraints is considered in [77,91]. As power flow determines the best possible operating level of the BESS, considering power flow as a system parameter is very crucial [92]. In [77,79,93,94], power flow is considered as a system constraint. In [77], the objective function cost and for the case study, IEEE 15 bus system is for system verification. The power flow constraint is stated as:

$$P_{Net, i}^k + P_{BESS, i}^{Dis, Max} \leq P_i(W^k) \leq P_{Net, i}^k + P_{BESS, i}^{Chr, Max} \quad (14)$$

$$Q_i(W^k) = -Q_{Net, i}^k \quad (15)$$

$$|I_{ij}^k| < I_{ij, max} \quad (16)$$

$$P_1(W^k) < S_{T, R}^{max} \quad (17)$$

where, $P_{Net, i}^k$, $P_{BESS, i}^{Chr, Max}$ and $P_{BESS, i}^{Dis, Max}$ are the net demand, power output while charging and power output whole discharging of BESS, respectively. $I_{ij, max}$ is the current limit of line ij. The power flow of the BESS can rapidly substitute from positive to negative or the other way around, by which the battery charging-discharging cycles are increased of a shallow DOD level [93].

Power and energy balancing among the demand and generation section is another important consideration for BESS sizing. In [77,79,81, 83,89,95–97] power and energy balance is considered as a constraint in the BESS optimization approach. In [79], the optimal sizing of BESS is done for microgrid operation, and the power balance constraints are stated as;

$$X_{T, k} + \sum_{i=1}^n X_{i, k} = P_{L, k} - \sum_{j=1}^m P_{j, k}; \forall k, k = k_i \dots k_f \quad (18)$$

where X_T is the tie flow from utility and P_L is the local load. k_i and k_f are the initial and final times, respectively. The main objective function is the capacity, and the experiment is conducted in Thailand.

Ramping up and down usually relates to the ability to change the power output of the system concerning the demands. For PV and wind, the rapid change in power output is dependent on weather conditions. A control strategy must apply to minimize the power fluctuation and smoothing the output curve [91]. In [98], a unique ramping control algorithm is presented where the ramping control algorithm is stated as;

$$P_{BAT}(t) = P_G(t) - P_{PV}(t) \quad (19)$$

where, $P_{PV}(t)$, $P_G(t)$, and $P_{BAT}(t)$ are the power of inverter, grid, and battery, respectively. The ramping condition is;

$$|\Delta P_{G,1, min}(t)| > T_{MAX} \quad (20)$$

Thus, the corresponding power excess or shortage is either taken from ($P_{BAT}(t) > 0$) or stored into ($P_{BAT}(t) < 0$) the battery for minimizing the ramping effect.

5.2.4. Environmental constraint

Due to the rapid increase in the price of fossil fuel and GHG emissions, an alternative environment-friendly energy solution is required. Integration of BESS in the RESS has a high potentiality in solving global warming problems. EV can be a great solution in terms of reducing GHG gas, and the impact of EV charging stations in a distributed network is significant [93,100–102]. A quantum-inspired particle swarm optimization (QPSO)-based optimization method is used in [103] to optimize the cost and the power consumption capacity. The economic dispatch (ED) model is the combination of BESS and wind power (WP) considering carbon emission, as described below.

$$F_{cost} = \sum_{i=1}^M C_{i,t}^P + \sum_{j=1}^N C_{j,t}^W + \sum_{i=1}^M C_{i,t}^e - \sum_{j=1}^N C_{j,t}^s + \sum_{j=1}^N E[C_{o,t}(W_{oe})] + \sum_{j=1}^N E[C_{u,t}(W_{ue})] + \sum_{i=1}^N C_{i,t}^{BESS} \quad (24)$$

$$C \sum_{i=1}^M \epsilon_{i,t} = C_{Tax} EM_i(p_i) \quad (25)$$

$$EM_i(p_i) = \epsilon f_i (f_i + g_i p_i + h_i p_i^2) \quad (26)$$

where, $EM_i(p_i)$ is the carbon emission of the thermal unit i and ϵf_i is the fuel emission factor of CO₂ and whereas C_{Tax} is the market carbon tax price. $C_{i,t}^P$, $C_{j,t}^W$, $C_{i,t}^e$ and $C_{j,t}^s$ are the cost of thermal generator, wind power, emission, and government subsidy, respectively. The result shows that the BESS integration with WP can reduce up to 20% of carbon emission, including the total cost. However, optimized plug-in hybrid electric vehicles (PHEVs) integration model considering the cost and environmental impact is presented in [104]. A multi-objective optimization approach is presented in [105], where the NPC and life cycle environmental impact are considered as the main objective functions. The HRES is optimized using genetic algorithm (GA) at the household level, and the results shows that PV is the most cost-efficient system to minimize the GHG emissions with reliable renewable supply. Table 4 presents a comprehensive summary of the reviewed literature considering different objectives and constraints of the BESS system.

From the above discussion, it can be summarized that the charging and discharging constraint has been considered by most of the researcher. A very few researchers consider environmental impact as a constraint which can be considered as a future suggestion in the field of BESS development and optimization.

6. Optimization approaches

Fast response time, improvement in power quality, minimizing voltage and frequency regulation, reduction of GHG emission, and adaptability are the main reasons why BESS is considered as an alternative to the existing energy sources. BESS needs to be optimized according to its size, capacity, cost, and lifetime. To achieve such a goal, many researchers focus on developing optimal BESS sizing methods. An outline of BESS sizing optimization approaches is described below.

6.1. Probabilistic approaches

The probabilistic method is considered one of the simplest methods for BESS sizing as only one or two system parameters can be optimized. The main advantage of probabilistic approaches is the requirement of limited data to achieve the output. Therefore, probabilistic approaches are perfect for circumstances with constrained information accessibility. The main drawback of such an approach is the limitation of the number of the considered parameter (one or two). To achieve optimal sizing of BESS, probabilistic approaches are mainly used to define the uncertainty parameter of the optimized method [85,107–112]. In [107], a probabilistic generation model is used to determine the cost of community ES (CES) installation and the number of units required. In [108], a probabilistic framework based on 2m point estimate method is proposed to identify the load forecasting error. The main advantage of the proposed model is the reliability of the cost function from the energy operation management point of view. A PV-BESS-based system is developed in [73], where probabilistic analysis is used to determine the PV generation over a year estimation.

Table 5.

Table 4
Overview of the research on the BES system’s optimization objectives and requirements.

Ref.	Year	Case Study	Optimization Objectives						Constraints	
			Cost	Capacity	Power Loss	Lifetime	Power flow	Reliability		Emissions
[103]	2015	Australia	✓	✓	×	×	×	×	✓	CDC, PEBC, PELC, EC
[79]	2016	Thailand	×	✓	×	×	×	×	×	P ELC, PEBC, PFC
[36]	2017	-	✓	×	✓	×	×	×	×	PFC
[84]	2017	-	×	✓	×	×	×	×	×	C DC, CC
[53]	2018	-	×	×	×	✓	×	×	×	C DC
[37]	2018	Rooftop PV generation	✓	×	×	×	×	×	×	CDC, CC
[77]	2018	IEEE 15-bus system	✓	×	×	×	×	×	×	CDC, PELC, PEBC, PFC
[76]	2018	-	✓	×	×	×	×	✓	✓	CDC, EC
[78]	2019	-	✓	×	×	×	×	×	×	CDC
[83]	2019	Illinois Institute of Technology	✓	✓	×	×	×	×	×	C DC, PELC, PEBC
[81]	2019	-	✓	×	✓	×	×	×	×	CDC, PELC, PEBC
[92]	2019	-	✓	✓	×	×	×	×	×	P ELC, RCC
[80]	2020	Fujian, China	✓	✓	×	×	×	×	×	C DC
[105]	2020	-	✓	×	×	×	×	×	✓	CDC, EC
[106]	2021	-	✓	✓	×	×	×	×	×	C DC, PELC

CDC, charging and discharging constraint; CC, capacity constraint; PELC, power and energy limit constraint; PEBC, power and energy balance constraint; PFC, power flow constraint; RCC, ramping capability constraint; EC, environmental constraint

6.2. Rule-based optimization (RBO) approaches

Another popular optimization approach is the RBO approach, consisting of a set of rules to identify an expected solution. The most prominent RBO approach in BESS sizing is fuzzy logic [31,36,82, 113–115]. The main advantage of using a fuzzy optimizer is that the number of uncertainty parameters or any change in parameter number has almost no effect on the size of the optimization problem [116]. In [113], fuzzy linear programming (FLP) is used for BESS price forecasting to ensure computational tractability. The fuzzy optimization model is described as follows:

$$\text{Maximize, } \lambda = \min \{ \mu_{TP}, \mu_{\sigma^E}, \mu_{\sigma^D}, \mu_{\sigma^R}, \mu_{\sigma^E} \} \tag{27}$$

The fuzzy constraints are as follows:

$$\lambda * \overline{TP} \leq TP \tag{28}$$

$$\lambda * (\overline{\sigma^U} - \sigma^U) \leq \overline{\sigma^U} - \sigma^U \tag{29}$$

$$\lambda * (\overline{\sigma^D} - \sigma^D) \leq \overline{\sigma^D} - \sigma^D \tag{30}$$

$$\lambda * (\overline{\sigma^R} - \sigma^R) \leq \overline{\sigma^R} - \sigma^R \tag{31}$$

$$\lambda * (\overline{\sigma^E} - \sigma^E) \leq \overline{\sigma^E} - \sigma^E \tag{32}$$

where μ_{TP} is the profit satisfaction function. σ^E , σ^D , σ^U , and σ^R are the forecasted energy price (\$/kWh), forecasted price of regulation down, up, and responsive reserve (\$/kWh), respectively. A comparative study on FLP and deterministic approach is also presented, and it is concluded that FLP is more reliable in optimizing the BESS cost and capacity and in identifying the annual profit more perfectly.

The fuzzy satisfying technique is used in [31] and [36] to determine the best outcome from the decision of the bi-objective optimization model. A fuzzy-based EMS is presented in [114] to optimize the power capacity and cost of the BESS. The result shows that an optimized BESS can reduce the cost of the microgrid (MG) by 3.2%, and battery lifetime has a significant impact on the cost of MG.

6.3. Deterministic approaches

Deterministic approaches are based on investigating a series of power system construction with the system components changed being those that should be optimized against predetermined rules. A deter-

ministic approach is a straightforward approach considered by a different researcher to optimize cost [117] and capacity [113]. In [118], a WP-BESS-based framework is designed, where the power and energy capacity are optimized directly from the daily spilled wind power profile. Optimal battery size is conducted from the outcome obtained from a wind farm, as presented in [119]. Both the deterministic and probabilistic methods are used in [120] to determine the simultaneous security-constrained market-clearing procedure and to schedule the reserved service. The deterministic market-clearing formulation is described as follows:

$$\min \{ C_g(u, g) + C_r(r) - B(d) \} \tag{33}$$

where $C_g(u, g)$, $C_r(r)$, and $B(d)$ are described as the total generation cost, cost function for reserve services, and total demand benefit function, respectively. The main disadvantage of the deterministic method is the requirement of a large number of data set, which increases the computational time exponentially while considering a small interval during simulations.

6.4. Mathematical optimization-based approaches

From the perspective of mathematical optimization approaches, BESS sizing optimizations may be stated as linear programming, mixed-integer programming, or even nonlinear programming problems. One of the most common approaches for solving the BESS sizing optimization problem is mathematical modeling. Mathematical optimization-based approaches can be divided into three categories, namely, DP, convex programming, and SOCP. A detailed discussion of these approaches are given below.

6.4.1. DP approach

In the DP model, the entire optimization procedure is divided into several time slots and identifies the solutions in each stage of time, thus being viable and valuable to construct time-varying situations [93]. The main utilization of the DP model in the BESS sizing optimization field is power-split controlling in hybrid EV [121], controlling low-frequency oscillation damping [122], peak shaving operation strategy [123], scheduling of the vanadium redox battery (VRB) energy storage [124], obtaining the optimal allocation of VRB [91], cost analysis and peak load management [78], and minimizing cost in EMS [125]. The primary constraint of DP modeling is that the efficiency is dependent on the degree of state variable discretization, affecting the complexity of calculation. A comparative study of the different applications of DP-based approaches in BESS sizing is given below.

Table 5
Comparative study of different DP-based approaches in the BESS.

Year	Ref.	Method	Objective Function	Key findings
2007	[123]	DP	Cost, capacity	Optimized battery size reduces the electricity bill The investments growth of VRB concerning battery capacity growth is minor than for lead-acid batteries
2012	[121]	DP	Fuel consumption	SoC optimization improve the battery lifetime Under a certain situation, a set of four battery packs, with a total capacity of 1.3 kWh, is the most optimized solution
2014	[122]	Global representation heuristic DP (GrHDP)	Power quality improvement through low-frequency oscillation damping	A comparative study of power oscillation damper (POD), particle swarm optimization (PSO), and GrHDP is presented, and GrHDP proves more efficient An energy-storage damping controller is proposed SoC is considered as a constraint In case of using MG as backup source power, VRB is only a cost-effective serving minimum load in September when the PV power is high
2015	[124]	DP	Cost, VRB scheduling	The cost of abandoned wind and solar power is considered along with the uncertainty of fuel and electricity price to optimize total cost Peat cost, time of use energy utilization cost, and battery degradation cost are considered
2017	[91]	DP	Cost, optimal allocation of VRB	The proposed cost-benefit analysis achieves 77.0% of the optimal offline profit
2018	[125]	DP	Cost	Power balance and SoC are considered as constraints
2019	[78]	DP	Capacity	

6.4.2. Convex programming (CP) approach

One of the most popular mathematical-based approaches is CP. The main advantage of CP is discretization independence. Fig. 7 shows the conventional CP-based optimization stages. The CP-based optimization method is used in [126], where the main objective function is cost along with the MG output stability. A novel home energy management system (HEMS) is introduced along with CP optimization in [34] to reduce household cost and PV consumption.

A CP-based optimization approach is used broadly in the transportation sector, especially in the hybrid bus [127], power train [128],

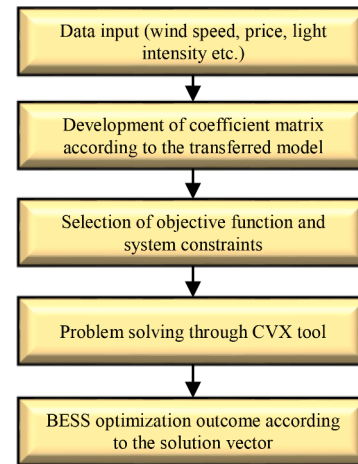


Fig. 7. Flowchart of traditional CP optimization problem-solving stages.

and EV [129], where battery size, vehicular economic operation, and battery dimensioning problem are mostly analyzed and optimized. Table 6 presents a detailed discussion of the CP-based optimization approaches in the existing literature.

6.4.3. SOCP approach

SOCP is another form of CP where a linear objective function is minimized over the intersection of an affine linear manifold and the product of second-order cones [131]. SOCP is another popular approach to optimize BESS size and location [132]. IEEE 34-bus test feeder is considered to optimize cost, deviate voltage, and minimize flow in [131]. The cost function is stated as follows:

$$\begin{aligned}
 Obj_{inv} = & \sum_i ((u_i^{DSS} FC_i) + (S_i^{DSS} InvC_i^p) + (E_i^{DSS} InvC_i^E)) \\
 & + \frac{1}{(1+a)^{(y-1)}} \sum_y \sum_i (MC_i^y)
 \end{aligned}
 \tag{34}$$

where, u_i^{DSS} , S_i^{DSS} and E_i^{DSS} are the energy storage, power rating, and energy reservoir at a given Dispersed storage system (DSS) at bus i . For a given DSS at bus i , the investment cost linked with power rating, reservoir capacity and maintenance cost is denoted as $InvC_i^p$, $InvC_i^E$ and MC_i^y , respectively. A 5-year time span is assumed for the optimal analysis. The maximum number of buses, maximum/minimum capacity, maximum of total DSS power rating, voltage, and power flow are considered as the system constraints. A WP-BESS system is considered, where the key objective is to optimize BESS location and size. The main uncertainty is identified as wind speed variation. To minimize the uncertainty effect, spinning reserve support is provided, which improves the system performance. In [133], 287 node-based networks are considered to verify the SOCP-based optimization method, where cost minimization, network losses, and voltage deviation are considered as the main objective functions. A brief comparative study of SOCP-based approaches is presented below.

6.5. Heuristics approaches

Heuristic strategies permit nonideal arrangements, which are adequate for real-time application. The main advantages of considering the heuristic approach include less computational time, flexibility, high accuracy rate, and comprehensibility. Without mathematically proven basis for obtaining optimal solutions, heuristic approaches such as nature-inspired algorithms like GAs [134], PSO [135,106], tabu searches [136], and bat algorithms [137,138] tend to offer fast convergence, straightforward execution, and solid adaptability [9]. Table 8 presents a brief comparative study of heuristic approaches in

Table 6
Comparative study of different CP-based approaches in the BESS.

Year	Ref.	Method	Objective Function	Key findings
2013	[126]	CP	Cost	Stabilization of the NG output with the consideration of cost is presented Power limit and SoC are considered as the system constraints
2014	[128]	CP	Battery size and fuel consumption	The battery dimensioning problem is optimized through the CP approach SoC, fuel cell capacity, and power loss are considered as the constraints
2015	[127]	CP	Power allocation and battery pack size	The battery size is dependent on the spread of regenerative power request The optimal fuel cell system size is defined as the average and the standard deviation of the propelling power request
2016	[129]	CP	Minimize CO ₂ emission	SoC is considered as the system constraint The proposed method can minimize up to 14% CO ₂ emission
2017	[130]	Convex relaxations based on semidefinite programming	Cost, capacity, and power loss	The main goal of the literature is to prevent the low-voltage network from overvoltage and undervoltage problem A multi-period optimal power flow (OPF) convex relaxation is adopted to determine the size of each storage unit
2019	[34]	CP	Cost	SoC is considered as the system constraint A power converter model is introduced to control the HESS The result shows that up to 32% of household cost reduction can be achieved with the proposed HEMS

optimal BESS sizing. [Table 7](#).

A GA is a method for solving both constrained and unconstrained optimization issues based on a natural selection process that impersonates biological evolution. GA is quite popular among researchers because it is fast and easily adaptable. In [37], GA is performed in DiGSILENT program language (DPL) to minimize system cost, where the reverse power flow and voltage magnitude are considered as the system constraints. GA-PSO-based algorithms, along with a multi-objective PSO (MOPSO), are applied to optimize the maximum system reliability and system cost in [7]. The cost function is derived as follows:

$$CT = CI + CM + CR \quad (35)$$

$$CI = (N_{PV}C_{PV}) + (N_{WT}C_{WT}) + (N_{BAT}C_{BAT}) + (N_{INV}C_{INV}) \quad (36)$$

$$CM = (N_{PV}C_{M,PV} + N_{WT}C_{M,WT} + N_{BAT}C_{M,BAT}) \sum_{i=1}^T \left(\frac{1 + IntR}{1 + IntR} \right)^i \quad (37)$$

Table 7
Comparative study of different SOCP-based approaches in the BESS.

Year	Ref.	Method	Objective Function	Key findings
2014	[131]	SOCP	Voltage deviation minimization, flow minimization	The maximum number of buses, maximum/minimum capacity, maximum of total DSS power rating, voltage, and power flow are considered as the constraints IEEE 34-bus test feeder and 5-year time span have been assumed for the optimal analysis
2015	[133]	SOCP	Voltage deviation, network loss, cost minimization	Capacity, power rating, and power flow are considered the main system constraints 287 node-based networks are considered for the case study
2016	[132]	SOCP	BESS allocation and size	A WP-BESS-based system is constructed where the main considering factor is wind speed The main advantage of the proposed system is the spinning reserve support for WP
2018	[44]	SOCP	Minimalization of loss and minimalization of active power flow	The main drawback of the system is the unspecified power quality issues Power flow, SoC, and voltage limit are considered as system constraints Battery placement and sizing are analyzed A cost-benefit analysis of battery investment in grid-connected mode is presented

where, CT , CI , and CM are the total cost, initial cost, and maintenance cost, respectively. C_{BAT} , and C_{INV} are the per-unit cost of battery and inverter. Number of PV panels, wind turbines, batteries and inverters are denoted as N_{PV} , N_{WT} , N_{BAT} , and N_{INV} , respectively. $C_{M,BAT}$, $C_{M,PV}$ and $C_{M,WT}$ are the maintenance cost of the battery, PV, and WP in (\$/kW) respectively. Three different system architectures, namely, PV-BAT, WT-BAT, PV-WT-BAT system, are presented to verify the optimized result. The result has shown that the PV-WT-BAT has a lesser overall cost than the other two systems. In terms of NPC, PV-WT-BAT provides a 2% maximum probability of loss of power supply (LPSP) which is 42.17% and 29.91% less than the PV-BAT and WT-BAT system, respectively. A modified bat algorithm (MBA) is applied to evaluate generation, storage, and energy management to overcome dynamic optimization problems in [138]. In modeling the PV, four different scenarios are considered, i.e., days with a lot of clouds, days with a lot of sun and cloud, days with a lot of suns, and cold days with a lot of suns. Scenario-based uncertainty is modeled considering the market price, and the result shows promising performance over GA and PSO to minimize the cost of the system.

The main advantages of the PSO algorithm are summarized as a straightforward idea, simple execution, robustness to control strategy, and computational efficiency when compared with the mathematical algorithm and other heuristic optimization techniques. PSO-based cost optimization for a different combination of renewable energy (RE) and ES resources is shown in [106]. Cost of energy (COE) is considered as the key metrics for cost evaluation, whereas SoC and ES rated power are considered as the main constraints. The result shows that PV-WT-PHS-based system has the lowest COE (0.196 \$/kWh) and is considered as the most optimized system for the off-grid system for a

Table 8
Comparative study of different heuristic approaches in the BESS.

Year	Ref.	Method	Objective Function	Key findings
2009	[136]	Tabu search method	Maximize the revenue by determining the optimal size	BESS life cycle, production, emission, and distribution cost are considered while developing the cost function Ramping constraints, the power limit, and SoC are considered system constraints
2011	[147]	Ant colony optimization	Cost, power loss minimization	IEEE 33-bus and 70-bus test distribution systems and 135-bus real distribution systems are used for system verification Adaptive ant colony optimization is used to optimize the loss minimization
2015	[140]	HMPSO + NSGA-II + PLF	Cost, voltage stability	Optimal sizing of BESS along with cost minimization and voltage stability is done in the literature The key advantages are cost minimization and voltage profile improvement System complexity is said as the main drawback
2016	[39]	TS-PSO	Cost	The TS-PSO-based algorithm is used to optimize BESS location, capacity, cost, and power rating in grid-connected mode SoC and power limit are considered as constraints Cost minimization, peak shaving, and reduction of technical violation are the main findings of the paper
2016	[148]	Cuckoo search algorithm	Cost	Cuckoo search algorithm is used to optimize cost while considering the seasonal variations Power flow and SoC are the two constraints considered in the literature Reduce the effect of high wind penetration
2017	[144]	Multi-period AC OPF, MPC, MILP, and CPLEX	Battery lifetime and real-time measurement	Reduced 30% ESS losses and minimized ESS degradation
2018	[139]	HGWO-PSO + MOEM	Cost	Capacity, power flow, SoC, and maximum power limit are considered as constraints Reliability, reduction of operational cost, reasonable, and PQ solution are the key advantages, whereas intermittency of RES is considered as the drawback of the system
2018	[7]	GA-PSO and MOPSO	Maximize system reliability, cost	GA-PSO-based optimization approach is presented A comparative study of GA-PSO and hybrid

Table 8 (continued)

Year	Ref.	Method	Objective Function	Key findings
				optimization model for electric renewables (HOMER) optimization is presented, and it is shown that GA-PSO has a promising outcome over HOMER optimization Three different system combinations are selected to compare the output of GA-PSO. From the output, it is concluded that the PV-WT-BAT system has a lower cost than PV-BAT and WT-BAT systems
2018	[37]	GA	Cost	GA is performed in DPL to optimize the cost The constraints are reverse power flow and voltage magnitude The main advantage of the method is the improvement of the distribution network by minimizing the effect of high photovoltaic penetration
2019	[149]	GA + greedy algorithm	Cost	Planning and scheduling of BESS in the LV grid are presented Capacity, voltage limit, and power flow are considered as constraints MILP-based approach is implemented to measure the potential of hydrogen storage in reducing the CO ₂ emissions
2020	[142]	MILP	Cost, CO ₂ emission	A combination of battery and H ₂ storage is analyzed, and the performance showed that with perfect optimization, the CO ₂ is reduced
2021	[106]	PSO	Cost	Different configurations of RE and ES resources are considered for the off-grid power supply to the remote island PSO is used for system optimization, and the key metric for cost evaluation is COE PV-WT-PHS is considered as the most optimal system with the lowest COE at a different discharge rate
2021	[138]	MBA	Cost	PV system is modeled considering four different scenarios PV, WT, FC, MT, and BESS are considered as energy sources Battery capacity supplied energy and charging–discharging are considered as the system constraints. Scenario-based uncertainty modeling is performed considering the market price and the compared system performance with GA and PSO

remote island. A novel hybrid gray wolf optimizer-particle swarm optimization (HGWO-PSO) along with multi-objective energy management (MOEM) is introduced in [139]. The main advantages of the proposed system are reliability, reduction of operational cost and PQ solution. In [140], hybrid multi-objective particle swarm optimization along with nondominated sorting genetic algorithm (NSGA-II) and probabilistic load flow (PLF) technique is proposed to minimize cost and improve the system stability especially in the case of RE penetration.

MILP is another popular approach for BESS optimization which is used in [30,36,46,81,93], and [141–146]. In [144], multi-period OPF, MILP, and CPLEX-based optimization approaches are presented to assess the battery lifetime. The main goal of the proposed method is to mitigate voltage and line flow violations that are induced by high PV penetrations in low-voltage (LV) grids.

6.6. Other approaches

Other than conventional approaches, some hybrid and unconventional approaches are also introduced by different researchers in the field of BESS sizing and optimization. An extreme learning machine (ELM)-based gravitational search algorithm is introduced in [150] to estimate the SoC of lithium-ion batteries. The main advantage of the model is considered as the independence of internal battery mechanism and mathematical modeling. In contrast, the construction of the model is complicated as it is highly dependent on training accuracy and the number of neurons in a hidden layer. In [151], binary lightning search algorithm (BLSA) is applied to optimize the size and location of the charging station of an EV. A Monte Carlo simulation-based modeling approach is presented in [152] and [153]. In [153], the capacity of the BESS is optimized, and a comparative study between the deterministic method and the Monte Carlo simulation-based method is presented. The result shows that the proposed method has more flexibility to determine the optimum capacity according to the needs of the operation. In [152], the main goal is not only to optimize cost but also to maximize the utilization of wind power distributed generation systems (DGS) with BESS. Different sizing tools, such as HOMER [154] and hybrid power system simulation model (HYBRID2) [155–160], are also widely used by various researchers to optimize the cost and capacity of BESS.

From the above discussion, it can be concluded that various algorithms can be identified from the existing literature in the field of optimal BESS sizing. The most common objective function considered by the researchers is system cost. The consideration of environmental impact is presented in very few articles which can be suggested as future work.

7. BESS applications

Due to the economic and environmental impact, BESS along with RE sources is considered a potential alternative to fossil fuel-based energy sources. Different BESS technology is already applied in different applications, such as the improvement of power system stability by reducing voltage and frequency regulation, microgrid application, hybrid marine power system, wave energy conversion, and EV, ferry, and bus. A detailed discussion on the BESS application is given below.

7.1. Transportation application

Transportation is a sector of BESS in the battery EV critical application. Because of the increasing fuel price, diminution of fuel reserve and to reduce the carbon emission, EV is becoming popular day by day. A fast response time, adaptability, and efficiency are the three main factors that are important while designing an ESS for EV. Lead-acid, Lithium-ion (Li-ion), and Nickel-Metal Hydride (NiMH) are the most popular battery type used for EV [161–164]. Many researchers develop different methods to optimize the ESS SOC, cost, weight, and efficiency such as; Particle Swarm Optimization (PSO) [47,165],

Multilevel converter topology [166], Convex Programming (CP) [129], multi-objective optimization and wavelet-transform-based power management algorithm [167], Dynamic programming (DP) [121], Deep Neural Network (DNN) [168], population-based metaheuristic optimization algorithm named TLBO [169], the binary lightning search algorithm is used for charging station planning and sizing optimization [151] and hybrid Particle Swarm-Nelder-Mead algorithm involving multi-objective optimization for optimizing [52].

With the rapid increase of EV, the increase of EV charging stations have a significant impact on the distribution networks [99,101,170] in loads and voltage flow, power losses, phase imbalance, voltage and frequency regulation, power quality, and reliability [100]. According to [171], charging stations available of fast charging with a rated power of more than 22 kW is considered as a fast-charging station. In [171], a prototype EV charging stations along with energy storage system is presented as shown in Fig. 8.

The combination of RE sources along with storage technologies are used in the fast-charging stations to reduce the demand from the grid explained in [172]. In [172], an optimized EV fast-charging station is presented using GA and PSO. A comparative analysis is presented considering only RE, only grid and grid+RE case and the outcome shows that, using RE with ES can reduce the impact of EV station over grid. a stochastic dynamic simulation modeling framework is presented by Yang et al. in [173], where, dynamic demand-responsive price adjustment (DDRPA) scheme is proposed to decrease the queue length, balance charging and overall increase the revenue of the charging station by 5.8%.

7.2. Microgrid applications

As Microgrid (MG) can operate in both stand-alone and grid-connected mode, so it is becoming an essential part of a Distributed Generation System (DGS). BESS can be integrated with microgrid operation as an external power source or a controller. There are several advantages of MG such as; high efficiency, reduction of grid congestion, stability and reliability of the local electric grid. An optimal BESS can drastically improve the microgrid system frequency [135,174]. In [135], Particle Swarm Optimization (PSO) is used for BESS sizing with load shedding scheme whereas BESS is used as a voltage source inverter in [174] for frequency controlling of microgrid operation. The main contribution of [174] is to implement short-term overloading characteristics of BESS in the initial frequency control of MG operation. Optimal BESS can also reduce the overall microgrid operation cost [36, 114,175–177]. HOMER is also a popular software used by various researchers to model grid-connected or off-grid MG [155,157,159,161, 178]. In [161], a combination of HOMER and PSCAD based hybrid MG is developed by Sarkar et al. where 1 kW/6 kWh VRFB storage is used to fulfill the demand side management. The techno-economic analysis is performed using the HOMER software whereas the peak shaving is simulated using the PSCAD software. The hybrid MG model is shown in Fig. 9.

One of the key components of power system stability is frequency control, and BESS can play a considerably potential role in this sector. BESS can be charging or discharging during the small disturbance period, which is occurred when the frequency is higher or lower than 50 Hz respectively. Significant disturbance can be minimized using BESS through over/under frequency tripping [135]. In [182], it is mentioned that BESS has a high potential to act as a stabilizer in the power system. [182] has identified three aspects where BESS can improve the steady-state stability, transfer capability, small-signal stability, and steady-state stability boundary. The integration of BESS with the power system is shown in Fig. 10.

In [182], a comparative study between STATCOM and BESS is presented. The active power for BESS and STATCOM is expressed as below;

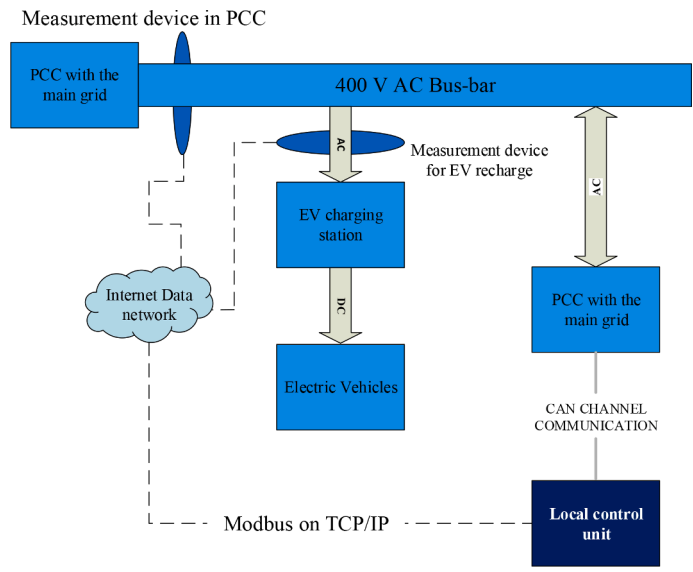


Fig. 8. Prototype of EV charging station along with ESS.

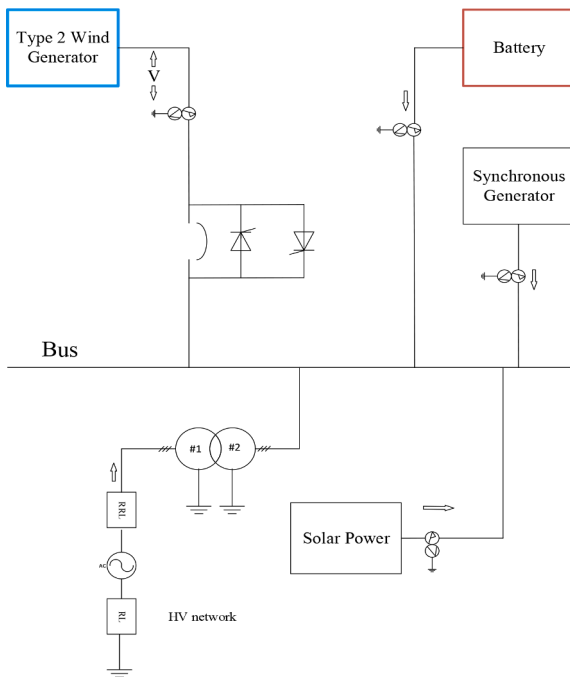


Fig. 9. Hybrid microgrid model [161].

$$P_{BESS} = \frac{V^2}{X} \sin\delta + \frac{V I_c}{2} \cos(\delta - \alpha) \tag{35}$$

$$P_{STATCOM} = \frac{V^2}{X} \sin\delta + \frac{V I_c}{2} \cos\delta \tag{36}$$

where, α is the phase angle between midpoint voltage V_m and V_r whereas, δ is the phase angle between V_s and V_r and X is the series inductance of the line. From the power transfer capacity curve, it is summarized that BESS can release more power than STATCOM while varying the phase angle. It very well may be inferred that BESS is a fast and adaptable component for the power system stability.

7.3. Other applications

Other than EV, MG and power system applications, BESS is also used in the hybrid marine power system [33] and wave energy conversion (WEC) system [186,187]. In [33], the three objective functions that are chosen for optimization such as potential fuel savings, projected lifetime, and cost-benefit analysis. The result illustrated that the Cost-Benefit Index (CBI) decreases with a slope of - 0.225 M€/MWh for nominal energy beyond 1 MWh, and with - 0.15 M€/MW for rated power beyond 2MW. While CBI is proportional to the BESS lifetime; however, not to BESS sizing. Thus, it can be summarized that installing a moderate-sized BESS with proper optimization is more cost-effective than installing an oversized BESS for reducing the cycling stress and increasing fuel saving. According to [187], back to back converter can solve the problem of distorted output power and can maximize the wave

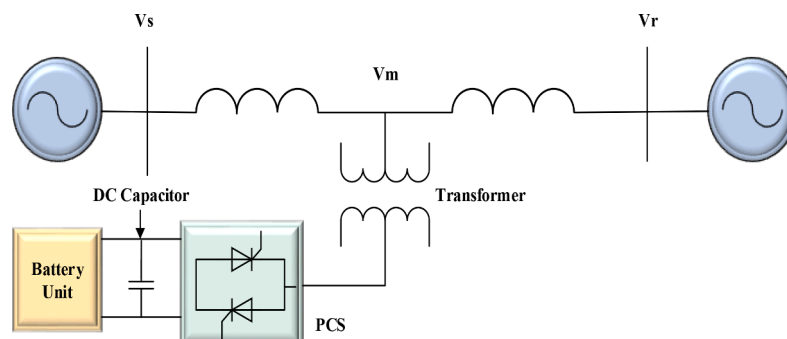


Fig. 10. BESS connected to power system [182].

power. BESS is used as a controller for the grid side converter. The construction of WEC and BES is shown in Fig. 11.

Power resilience is an important factor while achieving the goal of the ultimate reliability of the renewables integrated power system. The resilience of the power system can be defined as the effectiveness of the power system to endure catastrophic events effectively while ensuring the lowest possible disruption in electricity supply, sustaining essential services, and facilitating a swift recovery to the steady-state condition [188]. Following a catastrophic incident, a dynamic microgrid formulation can substantially improve the on-outage area's resilience by providing local load self-sufficiency. A broad review of the role of MG in the power system resilience is described in [189] where the reasons for power outages are mentioned such as; equipment failure (47.86%), natural disaster (30.71%), miscellaneous (10.1%) vandalism (5.71%), supply shortage (4.29%), and cyber-attack (1.43%). In recent times several researchers have focused on developing such an MG model associated with battery to improve the overall grid reliability [188–193]. HOMER is used in [188,190] to find out suitable combination of sources effective in different power outage conditions. A comparative study between traditional backup generator-based systems and HRES systems is presented in [188] and the result shows a similar result for both systems but the economic analysis shows the traditional system as a cost-effective one. In [190], the outcome shows that, for prolonged power outages, the arrangement using the BESS alone as a standby alternative source may not be viable. The proposed grid-connected PV+ BESS system shows promising performance for both enhancing resilience and minimizing the overall cost of the power system.

8. Issues and challenges

Developing an efficient BESS is a tedious job since various factors have to be considered, including cost, reliability, suitable type of storage, power and voltage quality, frequency deviations, and environmental issues. However, researchers are trying to develop newer technologies to consider all the factors and which is feasible to integrate with other ESS technologies as well. A summary of the most common challenges is described below.

8.1. Economic impact

The most common challenge of developing a BESS system is the economic aspects. From the literature, it is a clear indication that for BESS sizing, most of the researchers focused on the cost–benefit analysis. The cost of BESS depends on several factors, including the types of BESS selection, number of energy source integration, geographical condition, installed area feature, installation cost, and maintenance cost. The installation and maintenances costs include the capital power cost of the

converter interface, the capital energy cost of storage capacity, the capital replacement cost, and the annual fixed operation and maintenance cost [85]. The fixed operation cost includes projected annual costs for BESS parts, labor, annual property taxes, and insurance. In contrast, the maintenance cost consists of the operation of the protective devices such as relays and circuit breakers, calibrating sensors, audit operation due to abnormal vibrations or noise, inspecting for abnormal conditions of connecting cables and piping, inspecting insulation resistance, and servicing the battery controller, pumps, fans, and other system components [37]. The factors affecting BESS costs include lifetime, battery capacity, rate of degradation of the battery, power loss, and SoC. The size and capacity of the BESS technology must be determined accordingly to optimize the total cost of the BESS installation. Oversized BESS will increase not only the total cost but also the power loss of the system. On the other hand, undersized BESS will cause a frequency deviation, leading to an imbalance of supply and demand.

Another two key factors that affect cost optimization are peak shaving and load shifting. The most effective way of reducing demand charges is peak shaving, which refers to flattening out the peaks in electricity usage. On the other hand, load shifting is defined as a transient decrease in power utilization followed by a production growth afterward, when the price is low. In [176], complex-valued neural networks and time domain power flow method are used to identify and BESS location and ED model to optimize the capacity of the BESS in the transmission and distribution of power system. In the distribution stage, peak shaving is issued as a quadratic programming method to force BESS to flatten the load curve. In [177], to optimize the peak shaving of Zurich 1 MW BESS, a predictive power dispatch optimization based on an MPC control scheme is proposed to minimize the sudden peak event arising. Therefore, developing an effective BESS considering the economic factors is a challenge, and several aspects need to be considered.

8.2. Power quality impact

The main goal of integrating BESS with the distribution network is to ensure reliability and steadiness of power transmission. The degradation of power quality can affect the overall distribution network performance. Most conventional power quality problems include voltage sag and swell, overvoltage, undervoltage, voltage unbalance, frequency deviation, and harmonics distortion [11]. Various power quality improvement techniques have been developed by many researchers, including power electric transformer with control strategy [178], application of PV capacity firming with BESS to improve voltage unbalance and to smooth power swings [179], and ESS coupled with distribution static synchronous compensator (DSATCOM) for flicker compensation to improve voltage profile through control strategy of receive power [109]. A detailed power quality problem in the distributed and renewable power system from the technical and economic

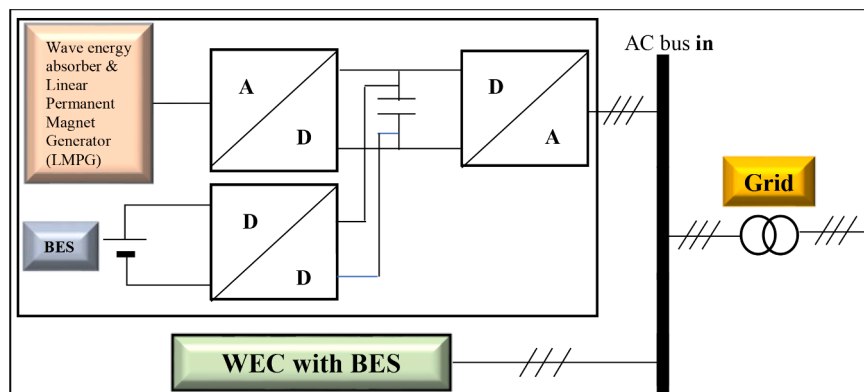


Fig. 11. Formation of WEC and BES with the integration of Grid [187].

perspective is presented in [68] and [69].

8.3. Aging impact

While developing a BES system, the battery aging effect must be considered as it is directly related to the overall cost of the system. The battery consists of various chemical materials, and every battery has a life span. There are two types of aging, i.e., calendric and cyclic aging. Even in idle conditions, the chemical agents of the BES are active due to the temperature and voltage, causing a constant degradation of the battery known as calendric aging. The cyclic aging is dependent on the charging and discharging factor of the battery. The main parameters of an efficient BESS system are fast charging, slow discharging, and long lifetime [180]. To achieve this goal, many researchers proposed different methods for BESS sizing while considering SoC constraint.

8.4. Environmental impact

One of the critical impacts of BESS application is to achieve a sustainable environmental goal through reducing GHG emissions. BESS itself has some environmental impacts on the environment. The cell construction of BESS contains harmful materials/chemicals [181]. After the ending of battery life span, chemical waste can have a significant impact on the environment [182]. The degraded batteries can be recycled and reused. In terms of lead-acid batteries, approximately 95% of the main ingredients can be recycled and reused [183]. The detailed

environmental impact of BESS with the integration of RES is described in [183–185].

8.5. Availability of technologies

With the rapid increase of industrialization, the use of fossil fuel is also increasing, which leads to global warming. To transform the current state-of-the-art fossil fuel-based energy resources, a reliable and clean energy source is needed. BESS has excellent potential to become an alternative to fossil fuel-based energy resources. Nevertheless, a stand-alone BESS installation cannot solve all the problems. BESS should be integrated with other RES or in MG to improve the power quality and reduce the loss. New technological advancement and control strategy are needed to ensure the proper integration of BESS with RES in DG and MG application. Suitable optimization approaches are needed, considering the issues and constraints specially to reduce GHG emissions. Moreover, BESS technology and application are only limited to the high-income country due to the system availability and high installation cost. As a result, the prospect of presenting these technologies in intermedie- and middle-income nations is still to be explored.

9. Conclusions and recommendations

A considerable number of researches have been carried out on BESS optimization and modeling to achieve the objectives, such as cost minimization, capacity estimation, power quality improvement, voltage

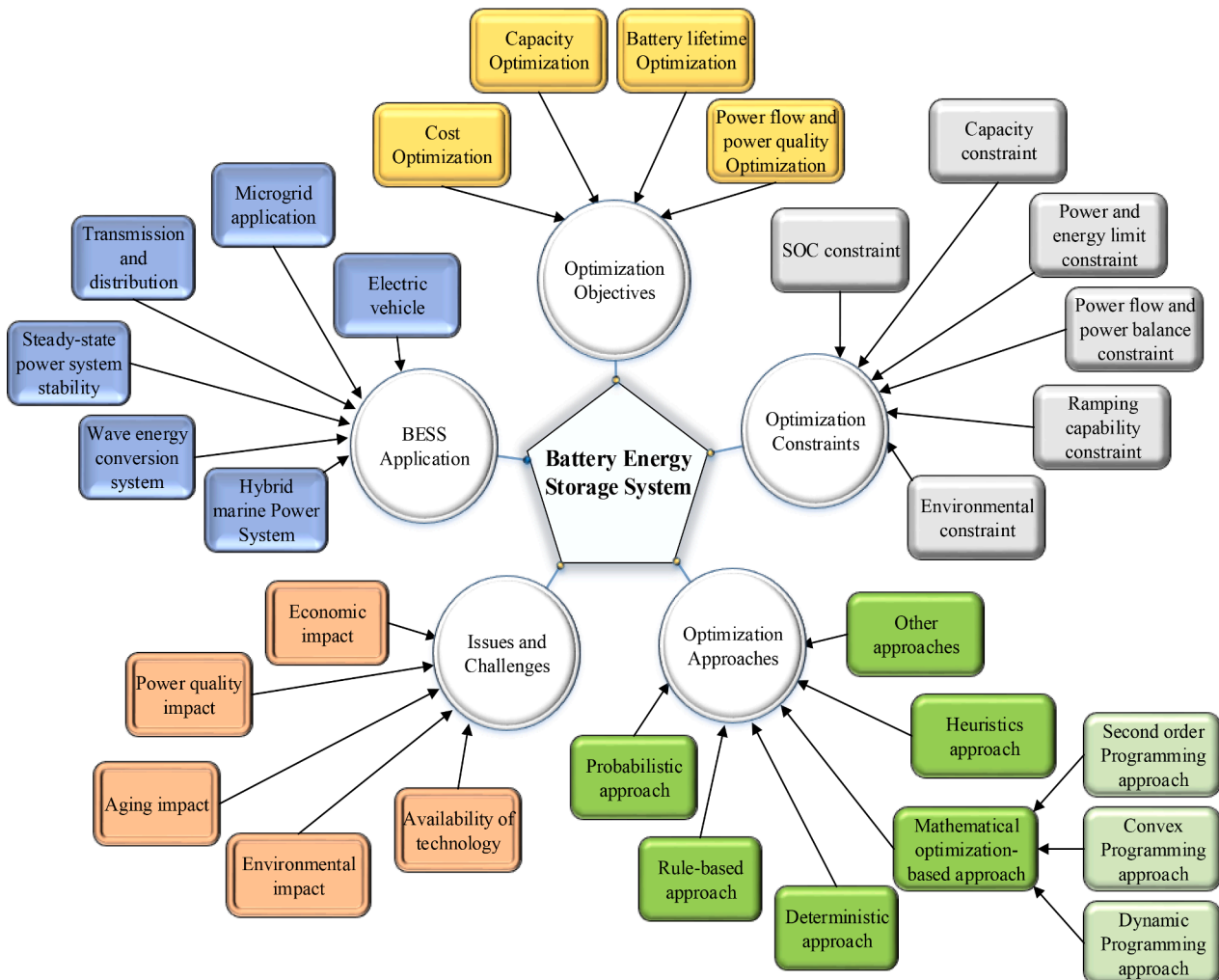


Fig. 12. Summary of the contents of BESS in the manuscript.

stability, frequency deviation reduction, and carbon emission reduction. An improved and efficient optimization strategy is needed to guarantee the robust, reliable, and economic operation of the BES framework. Fig. 12 shows the summary of the whole manuscript. Unlike most of the available review papers, the scope of this paper has been broadened to cover all the possible aspects of BESS sizing, including optimization objectives, constraints, algorithm development, applications and recommendation based on research gaps. Firstly, this survey clarifies the performance of current and noticeable BESS sizing techniques featuring their structure, scientific articulation, and contribution. Additionally, strengths, weaknesses, and the estimation accuracy of each optimization method are provided. Secondly, this survey profoundly researches the constraints affecting the BESS sizing, including the objective functions and optimization algorithms. Thirdly, this survey investigates the key issues and challenges through which new perceptions have been achieved regarding the optimization principles that are proven to be the most vital for the BESS framework development. Fourthly, this survey provides a clear idea about the existing application of BESS along with its advantages and disadvantages. The fifth and final contribution can be stated as the future suggestions. This survey proposes some viable future exploration works for further technological development of BESS sizing methods such as the following:

- Further research into the successful incorporation of BESS with other current sources like PV, wind, hydropower, and concentrated solar energy is required.
- Novel optimization approaches can be applied in BESS sizing to achieve promising outcomes in terms of cost, capacity, power loss, power quality improvement, and carbon emission.
- A careful selection of constraints is needed to obtain a better and more realistic outcome.
- The environmental constraint should be considered more frequently in the future, and the impact of BESS application on the environment should be measured more carefully.
- The introduction of novel battery storage technology can be a great solution to the present limited BESS applications.
- While developing the microgrid model, the decarbonization factor is needed to be considered.
- Microgrid and smart-grid are becoming popular, more research and real-time application of the security technology for smart-grid is suggested.
- The issues and the constraints are needed to be considered during the development of a robust, efficient, and optimized battery ES system.

Declaration of Competing Interest

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

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