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REVIEW ARTICLE

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Energy storage resources management: Planning, operation, and business model

Abstract With the acceleration of supply-side renewable energy penetration rate and the increasingly diversified and complex demand-side loads, how to maintain the stable, reliable, and efficient operation of the power system has become a challenging issue requiring investigation. One of the feasible solutions is deploying the energy storage system (ESS) to integrate with the energy system to stabilize it. However, considering the costs and the input /output characteristics of ESS, both the initial configuration process and the actual operation process require efficient management. This study presents a comprehensive review of managing ESS from the perspectives of planning, operation, and business model. First of all, in terms of planning and configuration, it is investigated from capacity planning, location planning, as well as capacity and location combined planning. This process is generally the first step in deploying ESS. Then, it explores operation management of ESS from the perspectives of state assessment and operation optimization. The so-called state assessment refers to the assessment of three aspects: The state of charge (SOC), the state of health (SOH), and the remaining useful life (RUL). The operation optimization includes ESS operation strategy optimization and joint operation optimization. Finally, it discusses the business models of ESS. Traditional business models involve ancillary services and load transfer, while emerging business models include electric vehicle (EV) as energy storage and shared energy storage.

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1 Introduction

Global warming is a common environmental problem faced by countries worldwide, and greenhouse gases such as carbon dioxide emitted from the burning of fossil fuels have been recognized as an important factor contributing to this problem (Aneke and Wang, 2016). As a major part of energy production and consumption, power generation using fossil fuel-based energy will continue to increase ecological pollution (Zhou et al., 2016; Jiang et al., 2020). The use of various renewable energy sources for power generation has become a necessary path for the transformation of power systems in various countries (Li et al., 2020c; Lu et al., 2020; Zhou et al., 2022). As the installed capacity of renewable energy continues to increase, new issues have emerged. Some inherent shortcomings such as randomness, intermittence, and uncontrollability of renewable energy may impose a negative impact on the stability, safety, and economy of the energy system (Byers and Botterud, 2020; Feng et al., 2021; Zhou et al., 2021b). Energy storage system (ESS) can temporarily store energy and realize bi-directional energy flow, which can support the safe and stable operation of energy systems with large-scale renewable energy access through peak regulation, stabilizing grid fluctuations, improving power quality, delaying grid upgrades, and reserving energy (Suleiman et al., 2019; Lockley and von Hippel, 2021).

Energy storage resources management, including planning, operation management, and business model issues, is an important way to lessen the fluctuation brought by renewable energy, thereby improving the efficiency and economy of energy system operation as well as the performance of ESS itself. ESS planning is the basis for using ESS. Without proper planning, the capacity of ESS may be very large, leading to high cost and waste of resources in the energy system (Hanak and Manovic, 2020; Kiptoo et al., 2020). After determining the ESS configuration, optimizing the operation of the ESS is necessary (Hou et al., 2022). Operation management is an important guarantee for the rational optimization of the ESS, which can maximize the utility of the installed ESS. These studies include two aspects, namely, state assessment and operational optimization. State assessment includes the state of charge (SOC), state of health (SOH), and remaining useful life (RUL) assessments of ESS. Meanwhile, operational optimization involves ESS operation optimization and joint optimization of ESS and other systems. Finally, the business model is selected to explore the application of ESS in real-world settings. The business model is also an important factor that affects the wide deployment and cost-efficient operation of ESS. The summary of business models can support the better understanding of the advantages and disadvantages of existing models and stimulate the business model innovation of ESS. The business models include the traditional business model represented by auxiliary services and load transfer and the emerging business model represented by the electric vehicles (EVs) as energy storage and shared energy storage. The above three aspects have different focuses, involving the whole cycle of ESS from planning to operation and then to application. We hope that summarizing these three aspects can promote the innovation of related theoretical research and the sustainable development of the ESS industry.

This paper is structured as follows. Section 2 investigates the energy storage resource planning from capacity planning, location planning, and capacity and location combined planning. Section 3 focuses on the ESS state assessment, and Section 4 discusses the ESS optimization. Then, Section 5 introduces the energy storage market business models, including conventional and emerging business models. Section 6 provides some discussions, and Section 7 finally draws the conclusions.

2 Energy storage resource planning

According to different ways of storing energy, energy storage technologies can be categorized into mechanical, electrical, chemical, electrochemical, and thermal groups (Luo et al., 2015). Furthermore, each group has many specific energy storage technologies as shown in Fig. 1.

Configuration planning is the first step and the basis of operation optimization when ESS is equipped in an energy system. Capacity planning and location planning are two important contents of ESS planning research. Capacity planning examines appropriate power capacity and energy capacity according to the technical and economic requirements of different application scenarios. Requirements of ESS application, and land, economic, and environmental conditions of different regions are often considered when determining the optimal location for ESS. Capacity and location combined planning that optimizes these two aspects together are more common.

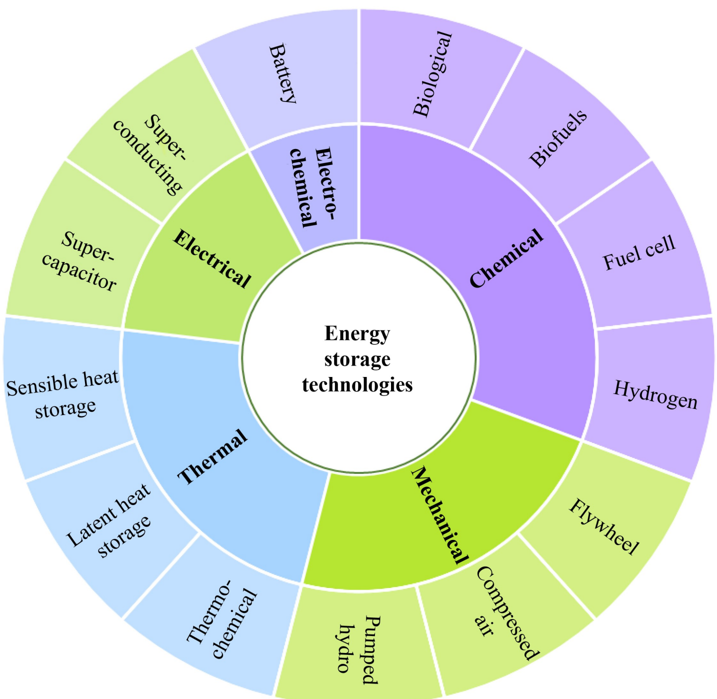

Fig. 1 Types of energy storage technologies.

2.1 Capacity planning

Capacity generally refers to the installed size of the ESS. For cost reasons, larger capacity means higher costs. In addition, wasting resources is possible if the equipped capacity is not fully utilized. However, when the capacity is too small, the ESS will not be able to meet the energy storage needs of users. Therefore, how to reasonably configurate the capacity of ESS is a critical research issue. Capacity planning researchers mostly use multiple methods to analyze and determine the optimal capacity that can balance performance and cost. The generalized capacity planning not only includes determining the installed size of the ESS but also involves the selection of the energy storage type and the setting of the ratio when different energy storage types are mixed. The general research on capacity planning only involves size determination, and the main methods used include statistical probability method, intelligent algorithms, and programming methods.

Different energy storage technologies are suitable for different scenarios and can meet different requirements, and they differ in capacity scale, rapid response ability, and energy conversion efficiency, to name a few. Energy storage technologies with different characteristics can also be combined as a hybrid system called, hybrid ESS (HESS), which could offset each system's shortcomings as well as meet more complex requirements of the energy system (Qi et al., 2021). However, capacity planning of HESS is more complicated than ESS with single energy storage technology. Related studies can be divided into two groups by the number of involved energy storage technologies as introduced in Table 1.

Whether it concerns using energy storage to stabilize the long-term charge and discharge demand of renewable energy fluctuations or the instantaneous power response needs when energy storage is involved in market frequency regulation, these relatively simple application scenarios can meet the demand by choosing the right single energy storage technology. Based on the price of the Polish energy market, Lepszy (2020) uses historical data from the day-ahead market to determine the required storage capacity for a hydrogen storage system constructed from a hydrogen generator. Olaszi and Ladanyi (2017) develop a hidden layer feedforward neural network to analyze the optimal capacity of the battery ESS (BESS) under three different discharge strategies. Zheng et al. (2017) and Dui et al. (2018) examine the optimal configuration of ESS capacity in the power system with power generation equipment. The former study regards each participant as an independent individual and plays a non-cooperative game to determine their own ESS configuration, while the latter study establishes a two-stage optimization model to solve the optimal capacity allocation in the whole system.

As the supply and demand sides of the power system become increasingly diverse, many new types of loads cannot be stored by a single energy storage technology. To illustrate, pulsating load demand is typically characterized by low average power; however, the peak power may be much higher than the average power. HESS can better deal with such loads than ESS with single storage technology. Capacity planning of single technology ESS is relatively simple as it only has to determine the proper

Table 1 Summary of capacity planning related studies categorized by energy storage technologies used

Types	Objectives	Methodology	Uncertainty	Scenarios	References
Single ESS	Electricity cost reducing Arbitrage benefits	Intelligent algorithms	YES	Hydrogen energy storage market	Lepszy (2020)
	Self-consumption-reducing	Intelligent algorithms	NO	Grid connected residential photovoltaic (PV) systems	Olaszi and Ladanyi (2017)
	Reducing operation cost of multiple agents	Game theory Intelligent algorithms	YES	Distribution system	Zheng et al. (2017)
	ESS capacity and operation strategy optimization	Two-stage method Programming method Statistical probability method Intelligent algorithms	YES	Power system with wind farm and thermal plants	Dui et al. (2018)
HESS	Reducing total cost Improving the reliability	Mixed-integer programming	YES	Microgrid Regional integrated energy system	Li et al. (2020b) Wang et al. (2020)
	Reducing cost and environmental impact Improving stability, safety, and reliability	Multi-objective method Statistical probability method	YES	Microgrid	Feng et al. (2018)
	Meeting reliability requirement Reducing life cycle cost	Pinch analysis Design space	YES	PV-based isolated power system	Jacob et al. (2018)
	Increasing smoothing ability Meeting stability requirements	Intelligent algorithms	YES	Standalone hybrid power system	Aravind et al. (2015)
	Improving reliability and optimizing capacity distribution	Intelligent algorithms	YES	Island microgrid	Li et al. (2022)
	Reducing total cost Meeting stability requirements	Two-stage stochastic programming	YES	Distribution system	Baker et al. (2017)
	Reducing total cost	Stochastic programming Statistical probability method	YES	Wind-based isolated power system	Mohamed Abd El Motaleb et al. (2016)
	Improving renewable energy utilization and voltage stability	Intelligent algorithms	YES	Island microgrid	Qiu et al. (2021)

capacity of ESS, while capacity planning of HESS needs to allocate capacity among different technologies.

Economy, stability, and environmental friendliness are goals often considered in studies of capacity configuration. Li et al. (2020b) and Wang et al. (2020) establish mixed-integer programming models. On the basis of the multi-attribute utility method, Feng et al. (2018) optimize the capacity of HESS to reduce cost and environmental impact while increasing the operational performance of microgrids. Jacob et al. (2018) determine the capacity configuration that meets the reliability requirement and reduce life cycle cost with pinch analysis and design space method.

ESS arranged at a renewable energy generation site can even out variation, reduce waste of renewable energy, and thus substantially improve renewable energy utilization. For ESS utilized to offset the shortcomings of renewable energy, considering the variation and randomness of renewable energy is important. Aiming at an independent hybrid power system containing synchronous generators, wind energy, and BESS, Aravind et al. (2015) propose a coherent control strategy to adjust the voltage and frequency of the independent power grid. To improve the ability of island microgrid to deal with uncertainty, Li et al. (2022) propose a flexible island microgrid model on the basis of real-time price demand response, which optimizes the capacity configuration of HESS.

Isolated power system or isolation mode stands for power system operating without interaction with grid and power generation systems, and ESS fully bears the load of the power system. Some studies have been conducted to define proper capacity for the isolated power grid. To reduce the total cost, Cao et al. (2019) use the chance constraint method to optimize ESS and power generation equipment size. Baker et al. (2017) optimize generation outputs and sizes of ESS in different scenarios on the basis of a two-stage stochastic model. Mohamed Abd El Motaleb et al. (2016) perform optimal sizing for a hybrid power system with wind/energy storage sources on the basis of stochastic modeling of historical wind speed and load demand. To provide a reasonable plan for the island microgrid with an electric-hydrogen hybrid ESS, Qiu et al. (2021) establish a planning optimization method that considers unit cost, load loss rate, and excess energy rate.

Capacity planning is conducted to determine the appropriate energy capacity and power capacity of ESS for different purpose in different application scenarios. In summary, optimization objectives are around technology and economy such as improving reliability, increasing smoothing ability, reducing total cost, and reducing investment, among others. Statistical probability method, intelligent algorithms, and programming methods are the three main methods being used. Owing to the influence of the uncertainty of future renewable power generation and loads in the power system on optimization effects, this uncertainty often needs examination in the capacity planning process to ensure the effectiveness and adaptability of the optimization results, and Monte Carlo simulation is the most common method being used.

2.2 Location planning

Apart from capacity, the location of the ESS is also an important factor in its performance. The efficiency of energy transmission in the distribution network and the voltage conditions at each node are influenced by the location of the ESS. Improper location selection can increase the energy loss level, deteriorate the voltage distribution, and negatively affect the safe and stable operation of the whole network. Given that location planning of ESS is inevitably influenced by the storage capacity as well as the operation mode, separate location planning studies are not common. Unlike capacity planning, location planning involves spatial factors, aiming to select a suitable access location for centralized or distributed ESSs and to maximize the reliability of electricity consumption after energy storage access. The main method used in this area of research is the intelligent optimization algorithm.

Related research mostly optimizes the location of ESS to improve the efficiency of renewable energy. Ahmadi et al. (2020) apply a two-steps hierarchical model and multi-criteria decision-making approach, while Satkin et al. (2014) use ArcGIS Boolean logic algorithms to determine optimal sites for wind-compressed air ESS. Das et al. (2018) utilize the artificial bee colony algorithm to optimize ESS in distribution networks with high penetration of renewable energy.

The abovementioned research optimized ESS placement from the aspect of technology and economy, which are to determine the optimal site by investigating its support effect to renewable energy utilization and cost. Intelligent algorithms are often applied to solve optimization problems. ESS allocated in optimized placement can effectively increase the reliability and economy of the energy system, as it can not only offset shortcomings and increase the efficiency of renewable energy but also reduce the investment and operation cost of the power systems.

2.3 Capacity and location combined planning

When planning the configuration of ESS, capacity and location planning are often considered together, especially when designing a new ESS or adding equipment to an old ESS. Compared with separate planning, capacity and location combined planning considers more other factors and thus has additional complexity. Relevant research can be roughly divided into three categories according to optimization goals: Economic, technical, and economic and technical research.

Some studies have optimized the ESS configuration to reduce the economic cost of energy, reduce the investment and operating costs of ESS, and increase the consumption of renewable energy to achieve the goal of improving the economics of power systems. Fernández-Blanco et al. (2017) use the stochastic mixed-integer linear programming. With the optimization goal of maximizing the annual net income of the ESS, Wang et al. (2021) use an improved particle swarm optimization (PSO) algorithm to solve the established ESS optimization configuration model. Nojavan et al. (2017) also consider load loss and establish a bi-objective optimization model to reduce the total cost in optimizing the ESS configuration.

To optimize the ESS configuration with technical optimization goals, many studies focused on intelligent algorithms. You et al. (2014) establish a multi-objective optimization model for the configuration optimization of ESS using the improved PSO algorithm to solve the model. Bridier et al. (2016) propose a heuristic method for the optimal design of ESS for renewable energy. The method is based on adaptive storage operation, which can ensure higher system reliability. Giannitrapani et al. (2017) determine the most suitable configuration of ESS by multi-period optimal power flow framework and economy criterion. Motalleb et al. (2016) combine complex-valued neural networks and time domain power flow to determine a better configuration of ESS, which can support power more effectively. Ramírez et al. (2018) optimize the configuration of ESS with better frequency smoothing ability by the bat optimization algorithm.

Technical and economic objectives are sometimes optimized together in certain research. Zhang et al. (2021b) propose a control strategy for ESS that stabilizes the short-term fluctuations of photovoltaic (PV) power. In line with the proposed control strategy, this study establishes the optimal selection model of ESS to analyze the economy of PV ESS. To improve system economy and renewable energy utilization, Tang and Low (2017) optimize the configuration of ESS on the basis of the continuous tree with the linearized DistFlow model. To improve the regulation capacity of ESS and reduce the total cost, Nick et al. (2018) utilize mixed integer second-order cone programming to determine the optimal configuration of ESS and then apply conditionally the exact convex optimal power flow to optimize ESS configuration. Table 2 classifies the research review related to capacity and location combined planning according to application scenarios.

Considering that the capacity of ESS has a greater impact on its performance than its location, the research on capacity planning is more abundant. By contrast, location planning involves spatial problems, and spatial measures and intelligent optimization algorithms have been the methods to solve them. Intending to increase technology and economy performance of ESS, capacity and location combined planning determines the optimal site and capacity allocated in each site. Different methods such as programming methods, multi-criteria decision-making methods, statistical probability methods, and intelligent algorithms have been applied to model and solve the problem. According to the results of simulations in the literature, capacity and location combined planning can largely increase the support effects of ESS to the energy system. With the popularization of distributed

Table 2 Summary of capacity and location combined planning related studies categorized by application scenarios

Scenarios	Objectives	Methodology	References
Distribution network	Improve utilization of renewable energy Increase economic benefits	Optimal power flow analysis Cost/Benefit analysis Continuous tree with linearized DistFlow model	Atwa and El-Saadany (2010) Tang and Low (2017)
	Reduce the total cost	Two-stage model Genetic algorithm	Awad et al. (2014)
	Avoid over- and under-voltage	Multi-period optimal power flow framework	Giannitrapani et al. (2017)
Active distribution network	Improve the regulation capacity of ESS Reduce the total cost of ESS	Multi-objective optimization model Improved PSO algorithm Mixed integer second-order cone programming Conditionally exact convex optimal power flow	You et al. (2014) Nick et al. (2014) Nick et al. (2018)
An isolated section of the power grid	Improve frequency smoothing	Bat optimization algorithm	Ramírez et al. (2018)
Transmission system	Reduce the economic cost	Stochastic mixed-integer linear programming	Fernández-Blanco et al. (2017)
Power grid	Improve the ability of stabilizing voltage fluctuation of ESS	Genetic algorithm Simulated annealing algorithm	Crossland et al. (2014)
Microgrid	Reduce the total cost	Bi-objective optimization model ε-constraint method Fuzzy satisfying technique	Nojavan et al. (2017)
Transmission system and distribution network	Improve the technical performance of ESS	Complex-valued neural networks and time domain power flow Economic dispatch	Motalleb et al. (2016)
	Reduce the economic cost Improve the system voltage profiles	Hybrid multi-objective PSO	Wen et al. (2015)

renewable energy generation and ESS, many new application scenarios will bring new challenges to the arrangement and operation of ESS. An example is how to install appropriate ESS in sparsely populated areas and extremely cold areas that can not only reduce energy cost but also reduce system cost as much as possible.

3 Energy storage system state assessment

As most related literature is oriented to BESS, this section systematically explores the research of ESS state assessment, including SOC estimation, SOH estimation, and RUL prediction. These three indicators are important to reflect the usability of BESS, and they have a guiding role in the practical application of BESS (Waag et al., 2014). Figure 2 illustrates the relationship among the three indicators.

SOC refers to the ratio of the amount of electricity stored in the battery to its capacity, and it is an important indicator for the safe and effective application of the battery. Certain research has been devoted to predicting SOC more accurately. In most cases, the adopted method is based on an empirical analysis model, and the parameter values are derived from experimental data using an empirical model. Additionally, with the continuous development of information technology, many studies have started using machine learning methods to build data-driven SOC evaluation models. Two forecasting models, namely, energy reservoir model and the charge reservoir model, are modified and applied to forecast SOC by Rosewater et al. (2019), and the two models have been proven effective and suitable for different types of batteries. Chen et al. (2019) believe that polarization of battery will lower the accuracy of SOC estimation on the basis of electric charge and thus define SOC on the basis of voltage. Research proposed a new estimation method on the basis of particle filter to estimate the SOC. Dineva et al. (2021) use a machine learning model combined with a direct multi-step prediction strategy to predict the SOC of lithium-ion batteries. The simulation results prove the effectiveness of its prediction performance. Tang et al. (2017) analyze SOC estimation error caused by sensor drift and modeling mismatch and improve the accuracy by rectifying the interference of different influence factors.

Future usability assessment is the other important aspect of ESS state assessment and is often represented by life assessment. Battery life has two definitions: Nominal life and actual life. Nominal life is the lifetime marked by the manufacturer, which is the longest range of battery life. Owing to the influence of current, voltage fluctuation, and frequent charging and discharging, the actual useful life of the battery will be shorter than the nominal life. Most of the research on battery life is focused on prediction based on the actual application scenario, charge–discharge behavior, and relevant historical data. SOH and RUL are two key indicators of battery life that cannot be obtained directly. These two indexes must be estimated by capacity, resistance, and other parameters. Abundant literature related to SOH and RUL forecasting exists, and a variety of measurement technologies are proposed.

Research about SOH assessment can be roughly divided into two categories: Model assessment method and experiment-based assessment method.

Model assessment method focuses on various methods for SOH assessment, compares and summarizes different methods, or proposes a new assessment model by analyzing previous studies. Berecibar et al. (2016) summarize SOH forecasting methods as experimental techniques, including a comparison of adaptive models, advantages and disadvantages, and estimation quality. Li

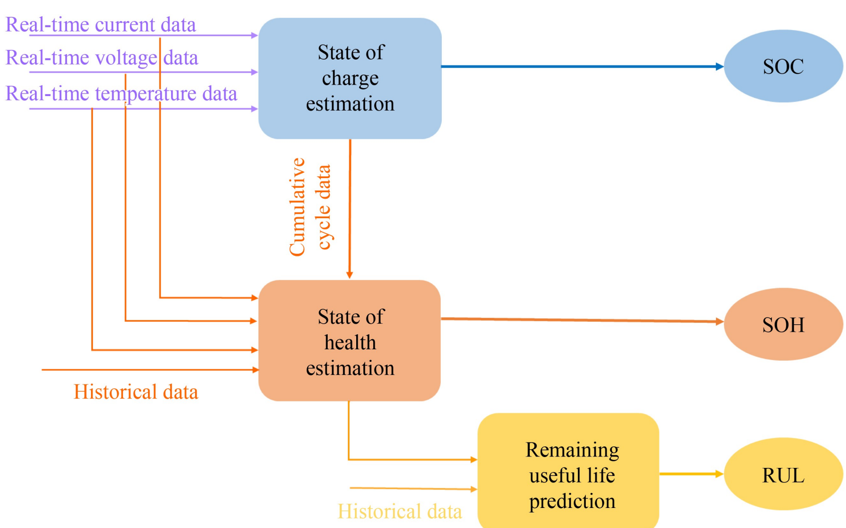

Fig. 2 Relationship among SOC, SOH, and RUL.

et al. (2018) believe that estimation method based on incremental capacity (IC) and/or differential voltage (DV) analysis is the third type. The IC analysis method based on the charge voltage capacity curve was established, and the characteristics of the IC curve obtained by Gaussian filter smoothing were used to extract the relationship between the battery capacity evolution and the characteristic index, which was used to identify SOH online. Roman et al. (2021) design and evaluate a machine learning pipeline to estimate battery SOH on 179 cells cycled under various conditions. The proposed model can be used for real-time estimation of SOH.

Most of the experiment-based assessment methods estimate the battery SOH through the actual operation data of BESS. This method does not depend on a specific model. Mao et al. (2021) propose an online SOH monitoring method for lithium-ion batteries based on the real-time charging and discharging characteristics of the battery. The proposed method has good robustness. Bian et al. (2021) combine the open circuit voltage model and incremental capacity analysis to propose a new fusion-based SOH estimator. The proposed method uses the terminal voltage curve measured during constant current charging to extract charging characteristics. Wang et al. (2016) develop a center least squares method based DV curve generation method; a function of capacity loss and DV curves has been obtained through offline experiments, and a new online SOH estimation method is proposed on the basis of the DV curve generation method and the function. Weng et al. (2013) use several algorithms in analyzing IC to identify aging law, and support vector regression shows the best output.

In many studies, SOC and SOH are estimated by one model, but the variabilities along their time scales are quite different. Estimating the two indexes at one time will cause extra calculation complexity. To solve this problem, Zou et al. (2015) employ two different extended Kalman filters to estimate SOC and SOH in different time scales, respectively.

Some research combines the above experimental based method and adaptive model method when estimating SOH. Hu et al. (2012) estimate SOC and capacity of the battery using a multi-scale method, which is based on coulomb counting and adaptive filtering. Dubarry et al. (2017) adapt the two kinds of methods, forming an aging look-up table on the basis of the evolution law of different characteristics of the chemical cell through simulation experiments; the proposed method can remove the dependence of simulation experiments on historical cyclic data while decreasing the calculation complexity of the adaptive model method.

The assessment of RUL of battery is another important content of battery management and an important index of battery aging identification. Existing RUL assessment methods can be divided into the model-based method and data-driven method. The model-based method usually establishes a mathematical model to describe the relationship between battery aging index (e.g., capacity, resistance, etc.) and lifetime (commonly represented by cycle times). Then, the model is optimized and adjusted with other methods. The data-driven method does not need to establish a mathematical model but must learn the historical data to determine the evolution law related to battery aging. Zhang et al. (2018) utilize long short-term memory-recurrent neural network algorithm to predict RUL online, with the process optimized by using a resilient mean square backpropagation method and a dropout technique. They also propose another online RUL prediction method based on Box–Cox transformation in follow-up work (Zhang et al., 2019). Severson et al. (2019) propose a battery cycle life prediction method which only needs data indicators of the first 100 cycles. The method is based on the study output of a large number of battery characteristic data under different quick charging modes. Liu et al. (2019) use the genetic algorithm and particle filter to predict SOH and RUL.

Assessment of SOC, SOH, and RUL are the three important items of BESS utilization and management. As these indexes cannot be measured directly, they must be estimated with the help of current, voltage, temperature, cycle times, and other real-time and historical data. When estimating SOH and RUL, IC/DV curve is a common tool in both methodological and adaptive methods. At present, the forecasting and assessment method systems are relatively perfect, but these indicators cannot be measured directly and are affected by many factors. How to further improve the accuracy of the results has puzzled the researchers.

4 Energy storage system optimization

Operational optimization achieves an overall improvement of the power system by formulating better operating strategies for ESS. ESS is utilized to support energy system in ways such as improving power quality, reserving energy, and improving renewable energy utilization, among others. The timing of the ESS equipment's storage and release of energy, the amount of energy required for storage and release, and the proper transmission power are all problems that should be determined in combination with actual situations. According to the optimization object, it can be divided into ESS operation strategy optimization and joint operation optimization. The former only optimizes the control of ESS, while the latter optimizes the combination of ESS and other subsystems in the smart energy system.

4.1 Operation strategy optimization

ESS operation strategy optimization is the basis for optimizing the operation of the power system and improving the operation efficiency of ESS by regulating the charging and discharging power and depth, coordination between different equipment, and other behaviors of ESS. Application scenarios, technologies, and optimization objectives will all impose considerable influence on ESS operation strategy optimization. Relevant research can be divided into three categories according to the optimization goals, which are to improve economy and efficiency, optimize the support role of ESS on the energy system, and extend the life of ESS.

Optimizing the operation strategy of ESS can improve the consumption of renewable energy, reduce load loss, and minimize damage to ESS equipment. van de Ven et al. (2013) reduce average electricity cost by using ESS reserve energy when the price is low, and operation optimization based on periodic-review and single-item inventory models is applied to determine the behavior of ESS. To improve penetration and efficiency of wind power in the power system, Lou et al. (2016) determine operation strategy for HESS by grouping wind power output with discrete Fourier transform.

Operation strategy optimization can improve the support of ESS to energy system, such as improving power quality, reserving energy, and reducing energy loss. To improve the support of ESS to the energy system, the research can be divided into static operation optimization based on historical data and model solving and dynamic operation optimization based on real-time data according to the optimized time dimension.

Static operation optimization analysis of historical data is carried out to obtain operation law of power system and then develop an operation strategy for ESS. For the electric-heat-gas multi-energy hybrid energy center with ESS, Dini et al. (2022) propose a new optimization model to ensure its flexible and reliable operation. Zhang et al. (2021a) propose a feasibility pump-based column and constraint generation solution algorithm for solving two-stage robust optimization problems in ESS, and the simulation results prove the robustness and high efficiency of the algorithm. Kazhamiaka et al. (2016) develop an operation strategy for ESS based on integer linear program without prediction data under differential pricing and peak-demand pricing law, respectively. To increase penetration of wind power in power system, Li et al. (2017) establish an evaluation system for wind power prediction based on wind power control error, and the prediction error is absorbed on the basis of ESS. Teo et al. (2021) propose a fuzzy logic-based energy management system for grid-connected microgrids containing ESSs to reduce the average peak load and operating costs through ESS arbitrage operation.

As static operation optimization is heavily dependent on historical data, responding to emergencies or exceptional cases could be difficult for ESS. Some studies determined real-time operation strategies for ESS with real-time data of the power system and ESS itself. Lyu et al. (2020) propose a segmental degradation cost model for the real-time management of lithium-ion batteries. A tube-based model predictive control approach is newly proposed in accommodating the real-time operation of ESS. Levron et al. (2013) allocate energy in network domain and time domain based on power flow solver and dynamic programming recursive search with real-time factors of BESS and power system, thus possibly obtaining a global optimal solution. Malysz et al. (2014) optimize management of BESS with mixed-integer-linear-program optimization based on variable time scale prediction data of the power system; particularly, this model can formulate the operation strategy of ESS according to the optimization goals proposed by users. To increase the revenue of wind ESS in the real-time energy and regulation markets, Xie et al. (2021) propose a bidding strategy optimization model based on robust predictive control. Mueller et al. (2019) regard the operation of BESS as a stochastic decision problem, subsequently employing the Markov decision method to optimize the management of BESS.

Improper operation of ESS could cause equipment damage. Accordingly, some researchers develop optimal operation strategies for ESS to minimize damage to equipment and thus extend equipment life and cut cost. Most of the research is focused on BESS. Zhao et al. (2013) optimize the management of BESS in standalone microgrid based on nondominated sorting genetic algorithm; the proposed strategy can significantly reduce energy cost and prolong battery life. Maia et al. (2019) optimize the traditional constant current and constant voltage (CC–CV) charging protocol commonly used in lithium-ion batteries, develop an optimization algorithm to couple it into the dynamic model, and consequently obtain a charge–discharge curve that maximizes battery life. Wei et al. (2017) develop a self-learning algorithm to determine better management rules for BESS based on real-time indicators, which could allow the smart grid to realize lower power cost and extend the lifetime of BESS.

Operation optimization develops an appropriate operation strategy for ESS to increase the economics and reliability of energy system and prolong the lifespan of ESS equipment. The above analysis suggests that researchers have developed different system models and applied different optimization methods to solve problems according to the characteristics of the envisioned energy systems. Three common optimization methods include mixed integer linear programming, mixed integer nonlinear programming, and metaheuristic algorithms. As the operation is a dynamic process, the operation strategy developed for ESS should be equipped with strong adaptability to future changes, thus necessitating the prediction data or dynamic optimization methods. Especially, prediction error requires consideration when the optimization process relies on prediction data. Given that errors are inevitable, how to obtain a more precious prediction of the power system and how to mitigate the influence of the prediction error are persisting problems worth studying.

4.2 Joint optimization

Merely optimizing the ESS may sometimes be insufficient to achieve the optimization goals of the whole energy system. Joint operation optimization refers to taking ESS and other subsystems or individuals in the power system as a whole, optimizing and regulating the overall operation behavior to achieve economic and technological optimization.

To improve the economy, safety, and wind power penetration of the power system, some articles optimize wind farms and ESS as a whole. Taking the operation cost and the capacity degradation of the ESS as the optimization objectives, Liu et al. (2020) use a dynamic programming global optimization method to determine the best capacity of the wind-ESS. Han et al. (2017) establish a cooperative game model aiming at maximizing the overall economic benefits of wind power generation and storage system, and they realize the joint optimal control by combining the filter.

Some studies optimize the operating economy of ESS and flexible load regulation systems. Sha et al. (2016) establish a multi-objective optimization model optimizing operation of ESS and flexible load, subsequently applying an adaptive particle swarm algorithm to solve the model. To optimize the flexible power supply, Yan and Li (2020) propose a multi-time-scale flexible dynamic optimization model for the active distribution network based on the participation of smart loads. The designed model can dynamically adjust the output sequence of the ESS.

Combined with probability methods, intelligent algorithms, and other solutions, joint optimization could substantially improve the economics, efficiency, and reliability of ESS in specific scenarios. As renewable energy is increasingly applied in other scenarios, extra attention should be paid to the cooperation between ESS and renewable energy power generation equipment. With the rapidly developing intelligent technologies, ESS will further improve the performance of the smart energy system in coordination with intelligent commodities.

5 Energy storage market business models

The business model in the energy system is often service-oriented, including energy supply, energy management, and energy efficiency services, among others (Bryant et al., 2018; Reis et al., 2021). In the context of supply-demand interaction, ESS has different business models (van der Linden, 2006; Hamelink and Opdenakker, 2019). In chronological order, we divide the business model of ESS into the conventional business model and the emerging business model.

5.1 Conventional business models

The business models of ESS in power system involve power generation, transmission, and distribution (Loisel and Simon, 2021) and have many applications (Ramos et al., 2021). Conventional business models include ESS as ancillary services and load transfer.

5.1.1 Ancillary services

Ancillary services play a crucial role in the electricity market (Aghaei et al., 2009; Kargarian et al., 2011). They are defined as all auxiliary measures required to deliver electrical energy from power plants to users while ensuring safety and quality, including power generation and transmission and distribution emergencies. The auxiliary services that ESS participates in include frequency regulation, voltage control, backup power, and black start (Zhang et al., 2021d).

Frequency is one of the basic indicators to measure power quality, and it is a symbol to reflect the balance of power supply and demand in power system (Nguyen and Mitra, 2016). Frequency regulation refers to adjusting the frequency of power system so that its change does not exceed the specified allowable range to ensure power quality (Zhang et al., 2017). The large-scale use of renewable energy makes the power system susceptible to large frequency offsets (Akram et al., 2020). In this context, the use of ESS for frequency adjustment has attracted widespread attention in the academic community (Shim et al., 2018). ESS provides frequency regulation by dynamically injecting/absorbing power to/from the grid in response to the decrease/increase in frequency (Akram et al., 2020). Different types of ESS are suitable for frequency regulation in different scenarios and can provide frequency regulation from the second level to hour level (Zakeri and Syri, 2015). Dhundhara and Verma (2018) explore the impact of the ESS device and optimization techniques to enhance the frequency regulations during sudden load change in a multi-source, multi-area power system in a complex deregulated framework.

Voltage is one of the most important parameters to maintain the stability of the power grid (Zhang et al., 2021d). Similar to frequency regulation, the main purpose of voltage control is to maintain the voltage profile within an acceptable range (Zhang et al., 2021c).

The large-scale integration of variable loads and distributed energy sources will cause power fluctuations and voltage instability in the distribution system (Murray et al., 2021). This scenario adds challenge to the voltage control work (Vandoorn et al., 2011). Taking the voltage rise process as an example, reducing the active power injected into the grid can reduce the voltage rise; adding the ESS can also store this part of the reduced energy, thus somewhat avoiding loss and waste (Tant et al., 2013). Ariyaratna et al. (2019) study the control of the charging and discharging of the integrated BESS to alleviate the slow and fast voltage fluctuations caused by rooftop PVs.

The ESS as a backup power supply includes two forms: Emergency power supply and uninterruptible power supply. The emergency power supply is an independent power supply device that provides power supply for critical loads in the event of a power outage, enhances the flexibility of the grid, and protects lives and properties against losses from power outages (Zhou et al., 2018). The uninterruptible power supply is a power supply system that guarantees an uninterrupted power supply, providing clean, adjustable, and uninterrupted power for sensitive loads such as data centers, communication systems, and medical support systems (Aamir et al., 2016). Emergency power supply emphasizes the function of continuous power supply. The uninterruptible power supply is generally used for precision instrument load, which requires high power supply quality, provides near-instantaneous protection, and prevents input power interruption. It emphasizes inverter switching time, output voltage, frequency stability, and purity of output waveforms. Both emergency and uninterruptible power supplies are inseparable from the participation of ESS. Mitra (2010) studies the determination of the power and energy capacity of the ESS as backup power to meet specific reliability goals.

Black start refers to the self-recovery process of the system after a large-scale power failure (Qiu et al., 2016). This process does not rely on the help of other networks. The generator units with self-start ability drive the generator units without self-start ability and gradually expand the recovery scope to the whole system. When the power grid fails as “all black”, the ESS enters an island operation state, which completely relies on the stored electric energy to maintain its operation and can supply power to important loads in the area. The independent control system of the ESS can adjust the voltage frequency and phase during island operation and participate in the black start of the power grid as the black start power supply at any time (Liu and Liu, 2020). As a black start power supply, ESS has the advantages of simple start-up scheme, short start-up time, and low cost. Li et al. (2020a) propose a multi-energy storage coordinated control strategy to solve the unstable black start. The article also establishes the black start model of the multi-wind power storage system.

Apart from the above functions, the participation of ESS in auxiliary services also has functions such as delaying transmission and distribution investment, and improving power quality and stability. As a mature model, ESS as auxiliary service has been applied in many fields. Relevant research should pay extra attention to starting from reality and combine with application to carry out new research.

5.1.2 Load transfer

Load transfer is another relatively important business model of ESS. This model adjusts the charge and discharge time of ESS according to the load change on the supply side or demand side to achieve different purposes. Accordingly, we divide the load transfer into four modes: Renewable energy integration, peak shifting and valley filling, price arbitrage, and seasonal energy storage.

Renewable energy integration is a mode of dispatching power from the perspective of the power grid or renewable energy investment operators to use ESS when consuming additional renewable energy. Owing to the strong intermittence and uncertainty of renewable energy, renewable power generation will have difficulty in directly meeting the power demand (Tan et al., 2021). A large amount of renewable energy incorporated into the power grid will also cause load fluctuation of the power grid, thereby requiring the regulation of renewable energy power generation. The ESS eliminates its intermittency by smoothing the power generated by renewable energy. During the peak period of renewable energy output, when the power supply is far greater than the power demand, excess power will be used to charge the ESS. Correspondingly, during the low period of renewable energy output, the insufficient power supply will be supplemented by the ESS to realize the transfer of power. To effectively integrate renewable energy, Harsha and Dahleh (2015) carry out the optimization management and scale planning of ESS under dynamic pricing law.

From the standpoint of the power grid, peak shifting and valley filling are aimed at alleviating the imbalance of load at different times and dispatching the power delivered to the demand side through the ESS. The load demand frequently encounters substantial variations at different times. The complete distribution of power according to the load demand will cause power imbalance in the power grid, which is not conducive to the safe operation of the power grid. Shifting peak and filling valley aim to provide part of power through ESS during power peak hours to reduce power grid pressure. However, in the period of power trough, the power grid distributes more power than the load demand, and the excess power will be used to supplement the energy of the ESS. Accordingly, the effect of “transferring” the power in the peak period to the low period can be achieved, and the stability and security of the power grid can be ensured. Chen et al. (2022) analyze the economic feasibility of the joint operation of nuclear power and BESS for peak shaving, which provides an effective solution for determining the construction scale and battery type.

The main body of price arbitrage is demand-side users, which can be household users, industrial parks, commercial buildings, or aggregators. Owing to the quarterly mismatch between supply and demand of power system, many places have adopted time-of-use price or even real-time price policy, resulting in marked differences in power costs at different times. Price arbitrage means that the ESS stores energy when the electricity price is low and then uses or sells the stored energy when the electricity price is high to reduce electricity costs or gain revenue. Research in pursuit of cost minimization often adopts this model. Krishnamurthy et al. (2018) propose a stochastic formula for maximizing the arbitrage profit of storage owners under the uncertainty of day ahead and real-time market price. The proposed model can help ESS owners conduct market bidding, engage in operational decision-making and evaluate the economic feasibility of ESS.

Distinct from other load transfer modes, seasonal energy storage achieves load transfer on a longer time scale. Owing to the limited time and storage efficiency, its scale is generally large and it is often invested by power grid or power operators. Seasonal energy storage refers to the long-time and large-capacity energy storage technology that needs to be used to realize the energy translation of long-time scale, stabilize the power fluctuation of days, weeks, and even seasons, and participate in the regulation process of months, seasons, years, and even cross years (Converse, 2012). Seasonal energy storage involves two energy storage modes. One mode is to convert electrical energy into other forms of energy for long-term storage, then converting them back into electrical energy when used. The other mode converts electrical energy into other forms of energy for storage, and subsequently directly uses the forms of stored energy without converting them back into electrical energy. The forms commonly used for seasonal energy storage include the power to gas, pumped energy storage, and compressed air, heat, and cold storage, among others. The emergence of the seasonal energy storage mode allows stabilizing the seasonal fluctuation of renewable energy. It can also be used to smooth the load fluctuation on a long-time scale and even realize spatiotemporal multi-scale transfer through other forms of energy storage. Taie et al. (2021) investigate feasibility of using underground hydrogen storage devices for seasonal energy transfer in northern climates and evaluate the technical, economic, environmental, and policy aspects of seasonal energy storage in the studied area.

Load transfer is another relatively mature business model of ESS, which is reflected in the scheduling model of ESS. ESS scheduling models, including day ahead scheduling, day scheduling, and other short- and medium-term scheduling, have been widely applied in real life. Future research should focus more on the real-time scheduling of ESS in the complex supply and demand environment after renewable energy access or how ESS can better participate in the long-term scheduling of energy to help implement seasonal energy storage and even longer-term load transfer projects.

5.2 Emerging business models

Apart from traditional business models, many new business models are emerging in the current ESS. Here, we introduce two emerging business models: EV as energy storage and shared energy storage.

5.2.1 EV as energy storage

As a representative of clean transportation, EVs have constantly received widespread attention (Wu et al., 2021; Ling et al., 2022). Especially in recent years, the number of EVs has been rising. EVs can be used as mobile energy storage devices to provide effective support for the safe operation of the power grid. Using EVs as energy storage is an emerging business model for ESS. Here, we introduce three modes: Orderly charging, vehicle to grid (V2G), and EVs as auxiliary services.

Large-scale random charging of EVs will increase the instability of the grid load (Kennedy and Philbin, 2019) and may increase the peak-to-valley load difference of the grid. The orderly charging strategy can potentially alleviate this problem. The orderly charging strategy refers to the use of economic or technical measures to guide and control the charging time of EVs on the premise of meeting their charging demand, to avoid the peak power consumption caused by a large number of EVs charging simultaneously (Zhou et al., 2021a). Figure 3 illustrates the target effect of orderly charging. On the one hand, this strategy can reduce the negative impact of large-scale EV access on the power grid. On the other hand, it can enable users to further reduce their costs while meeting their charging needs. The main research problem of orderly charging is how to coordinate the charging time of all EVs while meeting the needs of all users under the established goal, that is, the minimum cost of users, the maximum income of charging stations, or the minimum impact on the power grid. Zhou et al. (2020) propose a coordinated charging scheduling method for micro-grid EVs to shift the load demand from the peak period to the trough period. The proposed

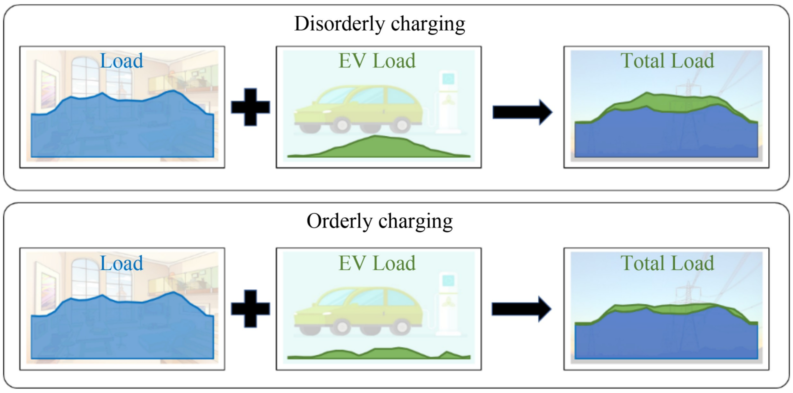

Fig. 3 Target effect of orderly charging.

method can support more friendly power supply–demand interaction to accommodate the increasing penetration of EVs and the rapid development of flexible microgrid. In the scenario of orderly charging, the EV does not act as an energy storage unit but an energy consuming unit to interact with the grid. In this process, the charging load of the EV is regarded as a “transferable load”. However, the capacity of load transfer is constantly limited. Thus, this model does not give full play to the peak shaving potential of EVs.

Owing to the energy storage characteristics of EVs, they can theoretically be used as energy storage devices to realize the two-way flow of energy, and this function is realized by V2G. V2G refers to the reverse transmission of the stored electric energy to the grid when the EV is not in use, which can alleviate the pressure of the grid or users to obtain benefits. Figure 4 shows the basic architecture of the V2G mode. The movable nature of EVs makes their theoretical peak shaving ability better than ordinary energy storage equipment. Uddin et al. (2018) consider the feasibility of V2G operation from the perspective of battery technology and policy. In the scenario of V2G, the EV interacts with the power grid as a “movable energy storage unit”, giving full play to the peak shaving potential of the EV. However, implementing this model is difficult and requires both EVs and EV access equipment. Therefore, this model is not widely used in real life. Subsequent research should focus on evaluating its actual operation and designing the implementation scheme.

The use of EVs as auxiliary services is another application mode of EVs as energy storage. The types of EVs participating in auxiliary services generally include frequency regulation and spinning reserve. EVs are connected to the power grid through power electronic equipment. They have the ability to make rapid power adjustment and have substantial load regulation potential in large-scale scenarios. They are expected to become important auxiliary service resources in the future. Yang et al. (2021) propose a two-layer optimization model for the charging and discharging of a power exchange bus, which considers carbon emission allowances and the market for peaking auxiliary services. Recognizing that EVs are used as auxiliary services with high requirements for required software, hardware, and communication conditions and participating in auxiliary services will accelerate battery aging and capacity attenuation, many obstacles persist in promoting this mode. The design of dispatching plans and compensation mechanisms for EVs involved in auxiliary services as well as the feasibility and economic evaluation after large-scale implementation can be used as follow-up research directions.

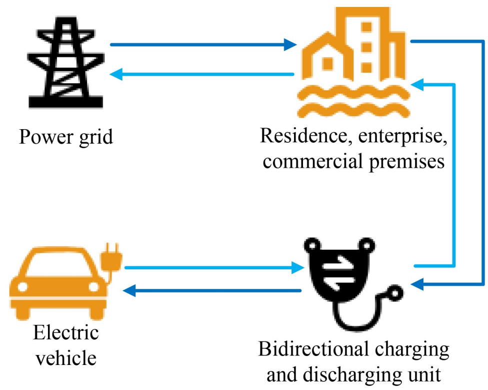

Fig. 4 Basic architecture of V2G mode.

Although the use of EVs as energy storage has always been a relatively popular research direction, the application of this business model in real life is not extensive. Although the research has been quite mature, the orderly charging technology has not been applied in real life on a large scale. Following the successful attainment of the technical level of hardware equipment, studying the design of the top-level solution and how to further reduce the cost of each link to promote its application is necessary.

5.2.2 Shared energy storage

With a large number of distributed energy sources connected to the grid, installing an independent ESS for each user requires high investment costs. Conversely, not fully utilizing the ESS equipment installed by users is also a waste of investment. Installing large-scale ESS, reducing the fixed cost of ESS, and reducing the workload of ESS maintenance led to the emerging business model for shared energy storage. Shared energy storage has many different application scenarios and modes. Here, we introduce four modes: Peer-to-peer (P2P) power trading, community shared energy storage, cloud energy storage, and virtual energy storage. Figure 5 shows a simple architecture of four modes of shared energy storage.

P2P power trading mode was born with the continuous deployment of distributed energy. In this mode, different power prosumers do not need middlemen to trade power directly, and the traders determine the transaction price. Compared with the direct transaction with the power grid, this transaction mode enables the seller to obtain additional benefits and the buyer to issue lower costs. When all prosumers involved in power trading are equipped with ESS, this mode realizes the connection of ESS between different users and the real-time cross-user flow of energy. Therefore, we classify this mode as shared energy storage. Nguyen et al. (2018) propose an optimization model for rooftop PV distributed power generation with BESS in a P2P power trading environment.

Community shared energy storage refers to the installation of the same ESS for multiple users in the community, and the installed ESS provides energy storage services for multiple families or buildings in the area. Benefiting from economies of scale, community shared energy storage has a lower cost than users installing ESS alone. In this scenario, users can share the stored capacity. Apart from realizing the real-time balance of energy supply and demand, it can also realize the cross-time and cross-user flow of energy. He and Zhang (2021) propose a double auction mechanism to realize the interaction in the community energy sharing market composed of distributed solar energy producers and consumers.

Starting from the concept of cloud service and sharing economy, some scholars put forward the concept of cloud energy storage. Cloud energy storage uses centralized energy storage equipment to provide users with distributed energy storage services. Users can choose the rental capacity and duration according to the price of cloud energy storage and cannot continue to use it after the lease expires. Compared with shared energy storage in the community, cloud energy storage has a larger scale, which not only further reduces the cost but also enriches the user groups. With the transmission advantages of the power grid, the users of cloud energy storage can cover a large number of different types such as

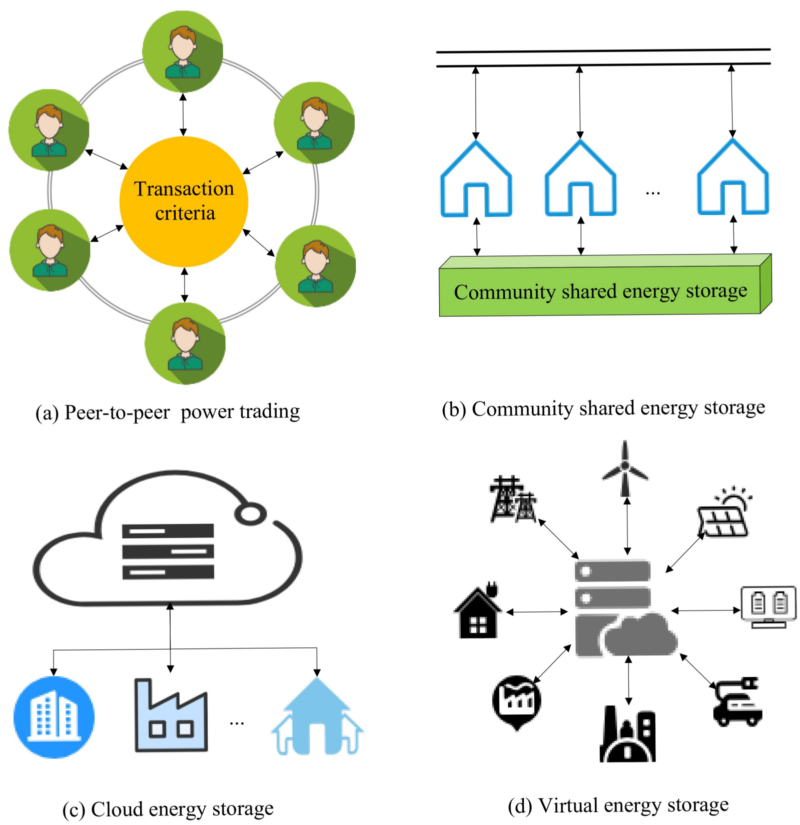

Fig. 5 Four modes of shared energy storage.

families, industrial and commercial buildings, and utilities within a certain range. Liu et al. (2017) put forward the concept of cloud energy storage, analyzes the architecture and business model of cloud energy storage, and analyzes the profitability of cloud energy storage on the basis of the actual power system data.

Virtual energy storage is another application mode of shared energy storage. Unlike cloud energy storage, virtual energy storage is not limited to using a centralized energy storage device. Virtual energy storage uses aggregators to integrate centralized and distributed energy storage units distributed in the power grid and then virtualize them into separable virtual energy storage capacity, which can be sold to end users at an appropriate price. Zhao et al. (2020) express the interaction between the virtual energy storage aggregator and the user as a two-stage problem. The first stage determines the virtual energy storage investment and pricing, and the second stage determines the user's purchase capacity and storage operation.

As one of the business models that have emerged in recent years, shared energy storage has been constantly emerging with different application models. Follow-up studies can design corresponding application models for different scenarios and explore the economics and feasibility. In addition, the pricing and capacity allocation of different application modes are worthy of in-depth study.

6 Discussion

In this section, we will discuss some challenges faced by energy storage resource management, future research directions, and some policy implications.

(1) Energy storage resource management considering safety and risks. ESS is widely used in high-capacity applications and plays an important role in voltage regulation and frequency regulation of power systems. Additionally, ESS safety accidents occur frequently. Energy storage safety has become a key issue restricting the healthy development of energy storage industry. For example, after large amount and varied ESS scales are connected to the distribution network as distributed energy sources, the topology of the distribution network will inevitably change and become increasingly complex. In addition, protecting some branches may affect the normal operation of relay protection devices in a distribution network. In the research framework of energy storage resource management, considering how to measure and reflect the safety factors of the ESS in the established model is important to ensure more robust operation and risk minimization.

(2) Energy storage resource management considering more factors under various application scenarios. With the increasing maturity of related technologies and the decreasing cost of ESS, the application scenarios of ESS are becoming more diverse. In this situation, how to combine own characteristics of each type of energy storage device and analyze the economic benefits of different types of energy storage technologies are highly valuable when selecting the type and allocating capacity of energy storage. Energy storage is highly sensitive to its price and market compensation price, and the whole life cycle cost of ESS should be fully considered in the process of operation optimization. Most of the current studies have taken the operating cost as the objective function. However, how to make the model fully consider various costs and better fit the actual operation of the ESS is a problem that requires further investigation.

(3) Energy storage resource management under Energy Internet environment. ESS is an indispensable part of Energy Internet. In the Energy Internet environment, a comprehensive policy system is the foundation for the sustainable development of ESS. Industry development and market system are the drivers of new ESS business models. With the rapid development of Energy Internet, the efficient operation of wind-PV-storage microgrid system in grid-connected mode can improve the utilization rate of new energy. Stable operation in islanding mode also provides solution for power shortages in areas not covered by the main power grid. In the future, with the improvement of technology and policy system, wind-PV-storage integration and multi-energy complementarity have an excellent development potential. Therefore, exploring the emerging energy storage resource management issues is vital under the complex microgrid, energy hub, and integrated energy service environment.

7 Conclusions

ESS is an important part of an energy system and can compensate for the randomness, intermittence, and uncontrollability of distributed energy resources and improve the interaction between producers and consumers. Apart from the electrical engineering and chemical materials related issues, the energy storage resources management is also a critical research concern for the investment, deployment, operation of ESS, as well as coordination with other distributed renewable energy resources and the whole power system. From the engineering management perspective, we present a systematic review of the ESS planning, ESS operational management, and ESS business model.

ESS has been widely used in real life. Energy storage resource management is an essential part of the continuous development of ESS. The continuous innovation of energy system operation mode and information technology has provided new background and technology for energy storage resource management, which continues to give rise to new research. Representative directions include but are not limited to the following.

(1) Synergistic optimization of multiple loads in the context of integrated energy services with ESS. With the increasing synergy of different energy resources, integrated energy services have become an important model for energy systems. Simple power storage is no longer sufficient for the multi-energy interaction process. In terms of energy storage, the organic combination of various forms of energy storage such as electricity, heat, and cold storage is a new research point. Whether for planning, operation management, or business model, huge changes brought by the demand for diversified energy storage are anticipated.

(2) Integration of big data and artificial intelligence with energy storage resource management. The operation process of energy system generates a huge amount of data, and various machine learning algorithms can help organize and analyze big energy data, which in turn can provide extra reliable support for the planning and operation of ESS.

(3) Blockchain models and methods supporting the emerging business model of ESS. In view of the transparency, privacy protection, tamper-evident, and smart contract features of blockchain, the blockchain platform can provide a unique management model for the market mechanism and scheduling of EVs and the interaction between users of shared energy storage.

In the future, with the transformation of energy systems in various countries, managing energy storage resources will gain increasing attention. Effective and efficient management of ESS resources can provide a strong support for building cleaner, low-carbon, flexible, and secure energy systems.

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