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A review of battery energy storage peak-shaving dispatch strategies: operational performance and battery degradation

Zihan Zhou

College of Mechanical Engineering, Yancheng Institute of Technology, Yancheng, China

3356421371@qq.com

Abstract. The substantial proportion of renewables connected to the grid and the continuously widening peak-to-valley load difference is the reason for placing significant pressure on peak-shaving in power systems. Battery energy storage systems have become a key enabling technology for peak shaving and valley filling because of their fast response times and flexible deployment. Existing study has concentrated mainly on short-term peak-shaving performance and operational economics. Nevertheless, the interaction among cycle aging, calendar aging, dynamic changes in State of Health (SOH), and dispatch strategies has received insufficient attention. Furthermore, research on degradation models, evaluation metrics and parameter settings lacks consistency. This paper summarizes four mainstream control strategies for peak-shaving dispatch of battery energy storage systems—ranging from threshold control and time-of-use pricing to predictive optimization and intelligent dispatch—and summarizes the evolutionary logic and operational characteristics of each technology. Based on representative studies, this paper carries out a comparative analysis in terms of operational performance and battery degradation. The results show that existing methods have not yet established a consistent evaluation and optimization framework that balances peak-shaving performance, battery lifespan, and full-life-cycle economics. Finally, the paper summarizes current technical challenges and outlines future research directions, including multi-objective coordinated dispatch, the incorporation of aging models, and engineering validation. This paper serves as a reference for the selection and evaluation of different peak-shaving dispatch strategies and provides a theoretical basis for developing energy storage dispatch methods that balance operational benefits, battery lifespan, and economic efficiency.

Keywords: battery energy storage, peak shaving and valley filling, energy storage dispatch strategies, battery degradation

1. Introduction

As the fluctuations of renewable energy output and the peak-to-off-peak load difference keep widening, the demand for flexible peak-shaving resources in the power system has continued to rise. Because of fast response time and flexible regulation, battery energy storage systems have become a key technological means for peak shaving and valley filling. According to different control objectives, existing research has developed

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diverse dispatch schemes, some studies focus on threshold setting and real-time response, emphasizing control simplicity and peak-shaving reliability, other investigations aim at higher operational efficiency and centre around time-of-use pricing and peak-to-off-peak arbitrage, load forecasting, State of Charge (SOC) and rolling adjustments stand as major research directions for predictive optimization and model predictive control, Data-driven routines reach beyond this, pursuing adaptive choices when load conditions turn intricate [1, 2]. However, evaluation metrics of the load curves, energy storage capacity, electricity pricing conditions exhibit notable discrepancies across various investigations, and their research emphases diverge. For this reason, it is difficult to direct comparison of results about peak shaving rates, economic benefits, and battery degradation. In the meantime, most prior investigation indirectly restrict battery degradation through operational constraints such as SOC and Depth of Discharge (DoD).However, the available literatures fail to sufficiently account for the synergistic effects of cycle aging, calendar aging, and dynamic changes in SOH [3].

On the basis of the above analysis,, the methods of literature synthesis and comparative analysis are adopted in this paper. From the two perspectives of operational performance and battery degradation, this paper conducts a comparison of threshold control, time-of-use pricing control, predictive optimization, and intelligent dispatch, with emphasis on analyzing their decision-making criteria and approaches to managing battery degradation. The aim is to clarify the applicability boundaries and identify research gaps for different technical pathways, thereby providing a reference for the design and engineering application of energy storage dispatch systems that balance peak-shaving capacity, battery lifespan, and full-lifecycle economics [4].

2. Battery Energy Storage Systems and their operational characteristics

2.1. Structure and composition of Battery Energy Storage Systems

The main components of Battery Energy Storage Systems (BESS) are battery cells/modules, a Battery Management System (BMS), a Power Conversion System (PCS), and an Energy Management System (EMS). Battery cells are connected in series and parallel to form battery packs, which provide energy storage capacity, their rate performance and aging characteristics affect peak shaving capability and long-term economic efficiency [5]. The BMS has three primary functions.Its functions are specified as follows: measuring voltage, current, and temperature, estimating SOC and SOH, implementing protection functions. Deviations in SOC estimates may lead to inaccurate assessments of available charge. It can affect sustained discharge during peak periods [6]. The PCS undertakes bidirectional AC/DC conversion. Another function of PCS is to execute charging and discharging power commands [7]. EMS develops dispatch plans based on load, electricity prices, and battery status to coordinate system operation [8].

2.2. Key parameters affecting peak-shaving performance

Operational status parameters and equipment specification parameters together define the feasible scope for peak-shaving operations. Both of them serve as critical parts of the key parameters of a BESS. Among the operational status parameters, SOC represents the proportion of remaining charge and is used to schedule charging and discharging. SOC is also used to build up a reserve of charge prior to the arrival of peak electricity demand. SOH reflects the health of the battery and can be measured by capacity retention, DoD indicates the proportion of capacity consumed during a single discharge cycle, and its relationship with cycle life influences the trade-off between energy utilisation and life loss. Among the equipment parameters, the rated power limits the instantaneous peak-shaving magnitude, whilst the rated capacity affects the duration of sustained discharge. Round-trip efficiency reflects energy losses during charging and discharging and affects

operational returns. The charge–discharge rate influences power output and battery degradation. Calculating life-cycle costs relies primarily on cycle life [9].

2.3. Comparison of battery technologies for peak-shaving applications

Table 1 compares mainstream battery technologies in terms of energy density, round-trip efficiency, cycle life, response time, safety, cost and suitability for peak-shaving applications.

Table 1. Comparison of battery technologies for peak shaving

Battery type	Energy density (unit: Wh/kg)	Round-trip efficiency	Cycle life (in cycles)	Response time	Safety features	Cost Characteristics	Adaptability of peak shaving scenarios
Lithium-ion Batteries	130–300	85.0%–95.0%	6,000–15,000	Milliseconds to seconds	Moderate risk, potential for thermal runaway	The cost per unit of capacity is relatively high, but the levelized cost of electricity over the full life cycle is the lowest among the four categories.	Suitable for medium-duration peak shaving (1–6 hours) on the grid side, in the commercial and industrial sectors, and on the consumer side, the most widely used in engineering applications
Lead-acid Batteries	30–50	75.0%–90.0%	500–2,500	Millisecond-level	Moderate safety, lead contamination must be controlled	The initial investment is low, but the cycle life is short, and the cost per kilowatt-hour over the full life cycle is relatively high.	Suitable only for small-scale, short-term load leveling, not suitable for high-frequency, deep charge-discharge cycles.
Sodium-sulfur Batteries	220–240	80.0%–90.0%	4,500	Milliseconds to seconds	Requires operation at high temperatures, seal failure poses a safety risk.	Power costs are moderate, but capacity costs are high, resulting in the highest levelized cost of electricity over the entire lifecycle.	Suitable for grid-side peak shaving lasting 1–8 hours, less commonly used on the consumer side, primarily in demonstration projects
Vanadium Redox Flow Batteries	50–140	75.0%–85.0%	15,000	Milliseconds to seconds	Low risk of thermal runaway and excellent safety performance	High initial investment, the electrolyte drives up the cost per unit capacity, long cycle life	Suitable for grid-side peak shaving lasting 4–10 hours, not suitable for residential, commercial, or industrial distributed generation applications.

In terms of current engineering applications, lithium-ion batteries, owing to their high energy efficiency, rapid response times and a relatively mature supply chain, are widely used in peak-shaving scenarios on the

grid side, in the industrial and commercial sectors, and at the consumer level. Lead-acid batteries, constrained by their cycle life and energy density, are primarily suited to small-scale applications where cost is a key consideration and charging and discharging frequencies are low. Sodium-sulfur batteries offer good energy density and sustained discharge capability, however, due to the requirements for high-temperature operation and safety management, their actual scale of application remains relatively limited. Vanadium redox flow batteries are characterised by a long cycle life and high safety, and hold good potential for application in long-duration energy storage and continuous peak-shaving scenarios. Different battery technologies each have their own characteristics in terms of efficiency, lifespan, safety and cost, these hardware performance characteristics and parameter constraints form an important basis for the design of peak-shaving dispatch strategies and engineering selection.

3. Peak-shaving battery energy storage strategy

3.1. Basic principles of peak shaving and valley filling and rule-based strategies

BESS reduces peak demand at the point of interconnection by charging when load demand drops and discharging during periods of high load [8]. Rated power constrains the magnitude of instantaneous peak shaving, while available energy governs the duration of discharge, dispatch must reasonably allocate energy to avoid premature depletion.

When the load exceeds the upper limit, the BESS discharges to compensate for the excess. With the load below its lower limit and the SOC permits, it charges, within this range, it typically remains in standby mode. Threshold control adopts two main models to trigger charging and discharging. One is the real-time load, the other is SOC, it possesses two major merits, no requiring load forecasting and involving minimal computational effort. Even so, it struggles to proactively address subsequent peaks. Kaiser et al. [9] studied threshold tuning under different scenarios, highlighting the trade-off between peak shaving reliability and capacity utilization.

Charging at off-peak periods and peak discharging constitutes the main approach for Time-of-Use (TOU) pricing control, its effectiveness depends on the degree of alignment between pricing periods and load peaks [10, 11]. Chaudhari et al. [10] investigated the joint optimization of peak shaving and arbitrage. Electricity costs and the peak-shaving rate should be calculated individually in the case of evaluating performance. And the peak-shaving rate is defined as the relative reduction in maximum load between the pre-dispatch and post-dispatch peak loads within the same period. The results of the case studies are subject to energy storage configuration, time-of-use pricing periods, and objective weights.Therefore, the case studies do not represent the general performance of TOU-based control. Adding a maximum demand may reduce arbitrage profits, although it contributes to ensuring peak shaving.

3.2. Predictive optimization and data-driven dispatch

Forecasts provide information on future load. Optimization algorithms determine charging and discharging schedules. Peak periods are predicted through the controller by virtue of historical load data, weather conditions, and renewable energy output. Then, the controller arranges charging and discharging within SOC, power, and energy constraints. At the same time, it updates these schedules according to actual measurement data [12-14]. Accounting for the range of load variations is the dominant way that Robust optimization addresses forecast errors.Stochastic optimization balances benefits and risks by considering scenarios and their probabilities. Bao et al. [12] studied real-time energy storage control under forecast uncertainty. Reserving energy can reduce the risk of insufficient power supply through peak periods. It will reduce capacity utilization

under normal operating conditions if conservative settings have been adopted. Model Predictive Control (MPC) employs a rolling update mechanism [13]. For instance,The controller forecasts the next 4 hours and solves for an optimal schedule, nevertheless, of the schedule, only the first 15 minutes are ever carried out.. According to the latest load and SOC data, the system generates a new forecast and performs optimization subsequently. For reserving the SOC required to address peak periods reliable forecasting helps schedule charging and discharging beforehand. It is helpful to improve the stability of peak-shaving operations. Nevertheless, forecast errors skew the energy allocation, so shaving misses its target [15]. Each optimization objective and constraint added to the model pushes up the complexity of model solving, dragging the computational load of real-time calculations along with it. Hence, not only computational power, but also engineering deployment capabilities of energy storage controllers need to be strengthened [16].

Machine learning adjusts control parameters. Reinforcement learning taps data and interacts with environmental. Deep reinforcement learning goes one step further. It reads load, SOC and the price signal together, and settles on a charge and discharge strategy of its own [17]. Compared to methods that rely on models and optimizers, these approaches focus on learning the relationship between states and actions.

4. Comparative evaluation of peak-shaving strategies and battery degradation

This chapter selects representative literature to compare the decision-making approaches, constraints, and limitations of different peak-shaving strategies in terms of operational performance and battery degradation management. Given variations in load, energy storage configuration, and electricity pricing conditions, this chapter does not directly compare numerical results from case studies, instead, it focuses on analyzing how strategy structures affect peak-shaving performance, energy allocation, and lifespan degradation.

4.1. Comparative analysis of representative peak-shaving strategies

Five representative studies were selected and compared in terms of decision-making approaches, operational advantages, and limitations.

Table 2. A qualitative comparison of representative peak-cutting control strategies

References	Control Strategy	Decision-Making Processes	Key Advantages	Major Limitations
Shang Ying et al. [18]	Interval Threshold Control	Trigger charging and discharging based on real-time load and threshold values	No forecasting required, the calculation is simple.	A threshold that is too high results in under utilization, while one that is too low may cause the battery to run out prematurely.
Chaudhari et al. [10]	Multi-Objective Optimization of Time-of-Use Electricity Pricing	Schedule operations based on electricity rate periods and target weights	Coordinated Arbitrage and Peak Shaving	When electricity prices and peak demand do not align, there is a conflict between these two objectives.
Bao Yan et al. [12]	Robust Real-Time Control	To account for forecasting errors, set aside a reserve of electricity	Handling load variations within a specified range	Conservative settings reduce capacity utilization, and disturbances outside the specified range still affect performance

Table 2. Continued

Sun Zhou et al. [13]	Model Predictive Control	Based on the NewMeasurement Rolling Adjustment Plan	Correct the power distribution promptly	Depending on the prediction quality, the solution must meet the controlcycle requirement.
Yang Ruifeng et al. [15]	Reinforcement Learning Control	Learning Charging and Discharging Actions Based on State and Rewards	Can handle complex relationships and coordinate multiple objectives	-

As shown in Table 2, the differences among the various strategies are primarily reflected in how battery charge is managed: threshold control provides immediate response, price-based control operates according to time periods, predictive control reserves charge in advance and adjusts the plan, and learning control makes decisions based on training strategies. Their applicability depends on load characteristics and operating conditions. SOC and DoD constraints do not equate to calculations of aging costs, and improvements in peak shaving performance do not directly prove superior battery life or long-term economic efficiency.

4.2. Performance differences and application constraints of peak-shaving strategies

Threshold control is simple to calculate, but its peak-shaving effectiveness is sensitive to the threshold setting and available capacity [19]. Too high a threshold and the storage goes unused. Too low, and it burns through its reserve before the next peak even starts. SOC limits are only part of it. Depth of discharge matters. So does cycling frequency, and a fixed window tracks neither.

Time-of-use pricing, robust real-time control, and model predictive control all share certain characteristics of planning and scheduling. Time-of-use pricing control primarily schedules charging and discharging according to electricity price periods. Attaining peak shaving and economic benefits concurrently may occur conflict, unless high-price periods coincide with peak load. Chaudhari et al. [10] obtained a peak shaving rate below 20% in a specific case study. The pricing structure moves this number, and the load curve pushes it again, whatever storage configuration sits behind the two decides where it finally lands. That is one study's figure, not a yardstick for the whole class of strategies.

Robust real-time control holds peak shaving steady when the load swings: it leaves room for prediction errors, then parks a slice of storage capacity where the schedule cannot touch it. This reliability is obtained by reserving spare capacity rather than by improving forecast accuracy. Bao et al. [12] achieved a peak shaving rate of approximately 40%–50% in a specific fast-charging station scenario. Nonetheless, this outcome is associated with not only load characteristics, but also energy storage configuration and the range of uncertainty . So this result should not be directly generalized. Through rolling the charging and discharging schedules forward, model predictive control mitigates the cumulative impact of prediction errors [13], but three things cap what it can do: forecast quality, the control step size and the hardware. Although the aforementioned strategies employ constraints such as SOC and DoD, their quantification of cycle aging and life-cycle costs remains limited.

Deep reinforcement learning learns scheduling strategies through state and reward functions, even under complex conditions. Yang et al. [15] validated its peak-shaving effectiveness in specific simulation scenarios, that said, change the training data, retune the energy storage parameters, or reset the reward function, and these results move. Better than traditional methods here, but not everyone. On the whole,peak-shaving rates and peak-to-valley differences gaps shift from one scenario to the next, and how much capacity a strategy puts

to work follows the same pattern. Specific percentages should be tied to the example conditions reported in the original literature. This prevents the results of a single study from being treated as a general rule.

4.3. Limitations of the current study

The primary challenge in current aging analysis lies in the differences in model specifications. Cycle aging and calendar do not run the same course. Nor do SOC, DoD, temperature and charge/discharge rates pull the battery in one direction. Lean on a single cycle count, or on one fixed degradation coefficient, and the model stops matching how the battery actually ages. Each cell ages on its own terms. Parameters fitted to one do not survive the move to the next [20]. Second, It is unavoidable to remain a trade-off between model accuracy and real-time computation. Model accuracy and real-time computation cannot both be raised freely. A high-fidelity model needs more parameter identification and optimization. A simplified model is easier to deploy, but it may miss how changing operating conditions affect the battery. Therefore, the selection of an aging model must comprehensively consider the control cycle, computational capacity, and actual application scenarios [21]. Furthermore, long-term operational validation is essential. Take a laboratory or simulation model off the bench and put it on a real system: the parameters still need calibrating, and the model has to adjust as operating conditions shift.

5. Conclusion

This paper compares battery energy storage peak-shaving strategies—including threshold control, time-of-use pricing control, predictive optimization, and intelligent scheduling—from the perspectives of operational performance and battery degradation. The core differences among these strategies lie in the basis for charging and discharging decisions, the method of energy allocation, and the extent to which future load information is utilized. Their peak-shaving effectiveness is influenced by factors such as load curves, energy storage configuration, electricity pricing structures, and control parameters, therefore, the relative merits of these strategies cannot be directly judged based on peak-shaving rates in different case studies. Threshold control is structurally simple and responds in real time, but it cannot reserve energy in advance for upcoming peaks. Time-of-use pricing control reduces operating costs, but only when electricity prices and load peaks coincide. Predictive optimization and model predictive control schedule SOC in advance and adjust dispatch dynamically, but they depend on forecast accuracy and consume considerable computational power. Data-driven methods can handle complex load profiles and multi-objective problems, but the generalizability and interpretability of such methods remain uncertain, and their long-term operational reliability in engineering applications has not yet been verified.

A major shortcoming of existing research is the lack of a fully coordinated mechanism between battery degradation and peak shaving scheduling. SOC and DoD bound the operating range, and that is all. How fast the pack ages, and what that costs across its life, they do not say. A tidier curve does not prove the economics either. Future research should focus on two main directions: One direction starts from SOH. Let it set the available capacity and the power limits, a simplified aging model, once fitted to operational data, belongs inside the rolling dispatch. What comes out of that is a number: peak shaving gains weighed against lifespan loss. The other direction is a framework for the field—load forecasting, rolling optimization, aging constraints, all in one loop. It has to run on edge hardware inside a fixed control cycle, hold the three together—peak shaving, arbitrage, demand response—and still answer in time. For intelligent methods such as deep reinforcement learning and digital twins, field data validation and testing under abnormal operating conditions

must be strengthened to address issues related to model interpretability, generalization capabilities, and deployment complexity.

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