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A Review of Optimal Energy Storage Allocation in New Power Systems

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Abstract. With the rapid development of renewable energy, large-scale grid integration of renewable sources such as wind and solar power has become prevalent. However, their intermittent and volatile nature poses significant challenges to the stability and reliability of power systems. As a key technology for peak shaving, valley filling, and smoothing fluctuations, energy storage technology has attracted considerable attention. Consequently, the optimal allocation of energy storage has become a hot research topic. This paper provides a systematic review of energy storage optimal allocation in new power systems from three perspectives. First, energy storage technologies are categorized based on energy types, and their respective characteristics and applicable scenarios are compared. Second, four major solution algorithms for energy storage optimization are summarized, including traditional optimization algorithms, swarm intelligence algorithms, hybrid optimization algorithms and machine learning approaches, with a discussion on their advantages and disadvantages. The paper also highlights that multi-objective optimization will become mainstream. Finally, based on the characteristics of new power systems, the paper discusses specific energy storage optimal allocation strategies from the perspectives of changes in energy structure and grid topology. This review offers theoretical support and technical references for constructing reliable, economical, and intelligent energy storage systems in new power systems.

Keywords: new power systems, optimal energy storage allocation, renewable energy integration

1. Introduction

With the advancement of the "dual carbon goals", the adoption of wind and solar energy has increased significantly, driving the transformation of traditional power systems into new power systems. This shift brings multiple challenges, primarily due to the integration of intermittent and volatile renewable energy sources. These challenges include intensified output fluctuations and insufficient frequency regulation capability. Energy storage technology plays a critical role in addressing these challenges. It aids in peak shaving, smoothing fluctuations, and enhancing system flexibility, making it a key solution to issues arising from high renewable energy penetration.

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In recent years, notable progress has been made in the optimal allocation of energy storage. References [1-2] discuss the iterative advancements in optimization algorithms used for energy storage allocation in power systems. Reference [3] focuses on energy storage optimization strategies tailored to specific operational scenarios.

This paper aims to systematically summarize and categorize the research on optimal energy storage allocation. It also analyzes future development trends from three perspectives. First, it compares the characteristics and applicable scenarios of various energy storage technologies. Second, it reviews the advantages and disadvantages of common algorithms used for energy storage allocation. Finally, it discusses energy storage optimization strategies in the context of changes in energy structure and grid topology within new power systems.

2. Classification of energy storage technologies

Energy storage systems offer a range of advantageous characteristics, such as peak shaving, valley filling, smoothing fluctuations, and supporting the integration of renewable energy. These capabilities help mitigate the negative impacts of renewable energy integration and provide timely technical support. Energy storage can be categorized based on its charging and discharging response characteristics into two main types: energy-oriented storage and power-oriented storage. Energy-oriented storage is distinguished by its large capacity, long lifetime, and high energy density, making it suitable for handling low-frequency components in frequency regulation. This type of storage is ideal for large-scale, long-duration energy storage applications. Conversely, power-oriented storage features smaller capacity, fast response times, high cycle life, and high power density, primarily addressing high-frequency components of frequency regulation. It is best suited for applications requiring rapid response times [4].

Energy storage systems can also be classified according to their combination mode, geographical distribution, and form of stored energy. Based on the combination mode, energy storage systems are divided into single-type and hybrid storage. Geographically, they are classified as centralized or distributed storage. Regarding the form of stored energy, energy storage technologies are categorized into electrochemical storage, mechanical storage, electromagnetic storage, and thermal storage. Figure 1 illustrates these energy storage technologies categorized by their energy form.

Electrochemical energy storage is currently the most widely used form of energy storage due to its flexibility in configuration based on actual grid conditions. However, its lifetime is relatively shorter compared to other energy storage technologies. Mechanical energy storage, in contrast, offers higher efficiency and the longest lifetime among the various storage types. Specifically, flywheel energy storage, pumped hydro storage, and compressed air energy storage are suitable for large-scale storage, rapid response, and peak shaving applications, respectively.

Electromagnetic energy storage exhibits the highest efficiency among the storage technologies. Due to its rapid response characteristics, it is suitable for emergency fault scenarios. Superconducting energy storage, however, is rarely applied in practice due to its high cost and maintenance requirements. Thermal energy storage is known for its environmental friendliness and is commonly used in clean heating and power peak shaving applications.

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Characteristics	Electrochemical Energy Storage			
	Lithium-ion Battery	Vanadium Redox Flow Battery	Sodium–Sulfur Battery	Lead-acid Battery
Cycle Life (Cycles)	1000~20000	12000+	2500~4500	2000
Lifetime (Years)	5~20	5~10	10~15	5~15
Efficiency (%)	85~97	75~90	85~90	80~90
Environmental Sensitivity	Medium	Medium	Medium	Medium
Applicable Scenarios	1.Renewable Energy Generation 2.Peak Shaving and Valley Filling 3.Mitigating Power Fluctuations 4.Improving Power Quality			

Characteristics	Mechanical Energy Storage		
	Flywheel Energy Storage	Pumped Hydro Energy Storage	Compressed Air Energy
Cycle Life (Cycles)	>100000	>15000	>13000
Lifetime (Years)	>15	30~60	20~60
Efficiency (%)	90~95	70~85	50~89
Environmental Sensitivity	None	High	High
Applicable Scenarios	Large-Scale Energy Storage	Rapid Response	Peak Shaving and Valley Filling

Characteristics	Electromagnetic Energy Storage	
	Compressed Air Energy	Superconducting Magnetic Energy Storage
Cycle Life (Cycles)	>100000	>100000
Lifetime (Years)	15~20	15~20
Efficiency (%)	95~98	95~98
Environmental Sensitivity	Medium	None
Applicable Scenarios	High Power Output and Rapid Response	

Characteristics	Thermal Energy Storage	
	Low-temperature Thermal Energy Storage	High-temperature Thermal Energy Storage
Cycle Life (Cycles)	—	>13000
Lifetime (Years)	20~40	5~15
Efficiency (%)	30~60	30~60
Environmental Sensitivity	Low	Low
Applicable Scenarios	Clean Heating and Electricity Peak Regulation	

Figure 1: Classification of Energy Storage Technologies by Energy Form [4-6]

Renewable energy projects are commonly situated in desert, Gobi, and barren regions due to the abundance of solar and wind resources in these areas. These regions also offer vast open spaces and relatively low construction costs, making them ideal for large-scale wind and solar base development. Reference [7] introduced a sand-based energy storage system that combines gravitational energy storage with thermal energy storage. This innovative system utilizes fast-moving sand in deserts as the energy storage medium. The system takes advantage of the sand's fluidity, thermal stability, and low cost.

The energy storage process in this system is divided into two parts: gravitational storage and thermal storage. Compared to traditional electrochemical energy storage systems, the sand-based storage system offers significant advantages. These include lower generation costs and enhanced utilization of wind and solar power.

As power systems continue to evolve, energy storage will play an increasingly important role. Beyond traditional storage technologies, there is a need to explore new types of energy storage that are suitable for different specific scenarios. This exploration will enable the full utilization of environmental resources in various contexts. Such advancements will contribute to the continuous enhancement of the safety and stability of new power systems.

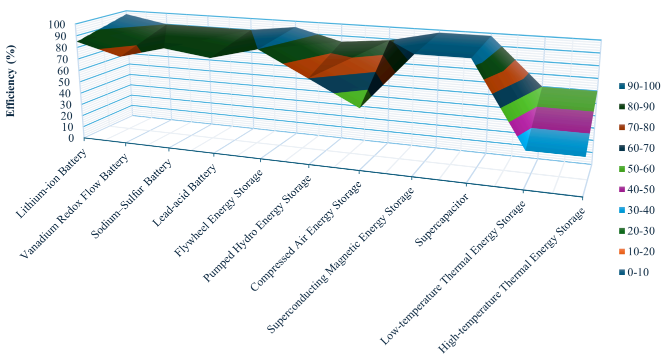

Figure 2: Comparison of Efficiency Ranges for Different Energy Storage Technologies

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3. Solution algorithms for optimal energy storage allocation

In optimal energy storage allocation, the objective function and its constraints must be defined based on the specific application scenarios. In practical engineering, objective functions often involve complex decision variables. Therefore, selecting appropriate algorithms to balance computational accuracy and efficiency is essential. Optimization algorithms used in energy storage allocation can be broadly classified into four categories: traditional optimization algorithms, swarm intelligence algorithms, hybrid optimization algorithms, and machine learning methods. Traditional algorithms include linear programming and dynamic programming. The following sections primarily introduce the latter three algorithm types and provide a comparative analysis of the advantages and disadvantages across all four categories.

3.1. Swarm intelligence algorithms

Particle Swarm Optimization (PSO) is characterized by a simple structure, strong implementability, and rapid convergence to the global optimum. It is particularly suitable for solving high-dimensional and multi-objective optimization problems and is widely applied in the optimal allocation of energy storage systems. Reference [1] employed a Multi-objective Particle Swarm Optimization (MOPSO) algorithm to address the energy scheduling problem in a wind-solar coordinated storage system. The study considered operational costs, penalty costs, and renewable energy penetration. Optimization through MOPSO effectively enhanced the utilization of wind and solar energy while significantly reducing system operating costs.

Reference [2] utilized an Improved Particle Swarm Optimization (IPSO) algorithm to optimize the capacity ratio between battery packs and supercapacitors, aiming to minimize the Life Cycle Cost (LCC) of the energy storage system. The improved algorithm achieved a better balance between computational speed and accuracy. As a result, IPSO reduced operating costs and improved system stability and power supply reliability.

However, PSO is sensitive to parameters such as acceleration coefficients, often requiring extensive tuning through experiments. As the number of iterations increases, particle diversity may decrease, leading to a reduction in the search capability. In problems with multiple local optima, PSO is prone to premature convergence to suboptimal solutions.

3.2. Hybrid optimization algorithms

Hybrid optimization algorithms outperform traditional optimization methods when applied to large-scale energy systems. In addressing challenges related to improving system scheduling efficiency and resource allocation, bi-level hybrid optimization algorithms have become a crucial tool. Reference [3] applied a bi-level optimization framework using the Line Search - Global Levenberg-Marquardt (LSGLM) method to solve the energy storage resource scheduling problem in multi-region energy systems. The upper-level model optimized the dispatch strategy of generation units to maximize profits, while the lower-level model optimized power market clearing to maximize social welfare. The improved LSGLM algorithm enhanced both the economic and stability performance of the system.

Reference [8] proposed a bi-level optimization framework based on the Newton-Raphson Backtracking Optimization (NRBO) method to address the re-utilization of retired batteries in energy storage systems. The upper-level model estimated the remaining useful life of retired batteries to maximize their economic value, while the lower-level model optimized battery

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configuration to maximize usage benefits across various scenarios. The NRBO algorithm successfully optimized the capacity configuration of retired batteries.

However, hybrid optimization algorithms are often tailored for specific scenarios, limiting their generalizability. Due to their multi-layered structure and complex optimization strategies, these algorithms tend to exhibit higher computational complexity. Additionally, their interpretability is often reduced. As a result, hybrid optimization algorithms may not be as adaptable to diverse applications as other optimization methods.

3.3. Machine learning

In the optimal energy storage configuration of new power systems, machine learning has shown significant advantages in data modeling and managing uncertainty. Current research primarily applies machine learning to the predictive modeling of renewable energy generation and load forecasting. These applications enhance both the foresight and adaptability of storage configuration strategies. Reference [9] introduced deep neural networks into the Robust Model Predictive Control (RMPC) framework, incorporating technologies such as combined heat and power, power-to-hydrogen, and power-to-gas methane to simulate the dynamic behavior of complex energy systems. The neural network was trained for state and output prediction, and the forecasted results were integrated with the RMPC objective function. This approach improved system robustness and control accuracy in dynamic operational environments.

Reference [10] proposed a hybrid microgrid optimization model utilizing Multilayer Perceptron Artificial Neural Networks (MLP-ANN) to predict solar radiation, wind speed, temperature, and load. These predictions were then fed into a fuzzy Multi-Objective Improved Kepler Optimization Algorithm (MOIKOA) to achieve optimal site selection and capacity configuration for the microgrid.

However, deep learning techniques require substantial amounts of training data, which limits their applicability in data-scarce environments. These methods are often unsuitable for scenarios where data acquisition is constrained. In addition, deep learning models exhibit high computational complexity and limited interpretability.

As the complexity of new power systems increases, the requirements for optimal energy storage configuration become more stringent. Ensuring system safety, operational stability, and power quality necessitates more advanced approaches. In this context, and multi-objective optimization are expected to become mainstream methods. With the rapid advancement of machine learning, its predictive accuracy can be effectively utilized. By integrating machine learning with optimization algorithms, the overall computational efficiency and precision of energy storage configuration can be significantly improved.

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Table 1: Comparison of Advantages and Disadvantages of Energy Storage Optimization Algorithms

Algorithm	Advantages	Disadvantages
Linear Programming	Simple and intuitive with high computational efficiency.	Only applicable to linear problems and often requires integer or mixed-integer programming to handle discrete variables.
Dynamic Programming	Suitable for discrete and nonlinear scenarios, with guaranteed global optimality.	High implementation complexity and sensitive to initialization and boundary conditions.
Particle Swarm Optimization	Straightforward and easy to implement.	Sensitive to parameter settings, requiring extensive experimentation for tuning.
Hybrid Optimization Algorithm	Robust and adaptive, with capability for multi-objective collaborative optimization.	High computational complexity, low interpretability, and poor generalizability.
Deep Learning	Capable of efficiently handling large-scale data with high prediction accuracy.	Requires high-quality sample data, high computational complexity, and low interpretability.

4. Optimal energy storage configuration based on the characteristics of new power systems

With the continuous development of renewable energy, the increasing integration of wind and solar power into the grid has led to significant changes in both the energy structure and the grid topology of power systems. As a result, the characteristics of modern power systems have diverged notably from those of traditional systems. These changes present both challenges and opportunities in terms of system stability, efficiency, and integration of renewable energy. The following section analyzes the impacts of these changes and discusses strategies for optimizing energy storage configuration to ensure the reliable operation of new power systems.

4.1. Energy storage optimization configuration in response to changes in the energy structure

The transformation of the energy structure is primarily characterized by the increasing penetration of renewable energy sources, such as wind and solar power. However, the intermittent and volatile nature of these sources presents significant challenges to the stability of power grids. These challenges particularly affect the reliability, frequency stability, and voltage stability of the grid. As renewable energy integration continues to grow, ensuring the stable operation of new power systems through optimized energy storage configuration has become an urgent issue that requires attention.

To address the challenges of frequency and voltage instability, as well as reduced reliability in weak grids with high renewable energy integration, reference [11] proposed a joint optimization model. This model considers energy storage siting, sizing, and control parameter tuning under extreme conditions. A Multi-Objective Particle Swarm Optimization (MOPSO) algorithm was employed, incorporating objective functions such as the Root Mean Square (RMS) of system frequency deviation, grid vulnerability index, and net cost of energy storage. This approach significantly improved the frequency regulation, security, and reliability of high-renewable power systems.

Reference [12] introduced the Short-Circuit Ratio (SCR) into the preliminary selection process for Battery Energy Storage Systems (BESS). This method was combined with an Adaptive Grey Wolf Optimization (AGWO) algorithm for joint siting and sizing of energy storage systems. The proposed approach aimed to enhance three critical performance metrics in weak grid systems: reliability, transient voltage stability, and frequency stability. By optimizing the configuration of

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energy storage systems, the solution provided significant improvements in the stability and reliability of the grid.

4.2. Energy storage optimization configuration in response to changes in grid topology

The change in grid topology is primarily reflected in the increasing proportion of distributed generation and microgrids. These systems are categorized into off-grid and grid-connected scenarios, which present distinct operational challenges and optimization strategies. The integration of distributed generation and microgrids significantly alters the dynamics of power systems, requiring novel approaches for energy storage optimization to ensure stability and reliability.

In off-grid scenarios, distributed generation and microgrids are predominantly applied in remote islands and nature reserves, where traditional power generation methods fail to meet the demand for a stable power supply. Distributed renewable energy generation has emerged as a practical solution in such areas. To address issues like instability, energy waste, and poor economic performance in wind-solar microgrid systems, reference [13] proposed an enhanced Zebra optimization algorithm. This algorithm optimizes the component configuration of hybrid energy storage systems, focusing on balancing the capacity of batteries and supercapacitors. The approach improves operational stability, reduces the probability of load shedding, and significantly lowers the total cost of the energy storage system. Furthermore, reference [14] introduced a hybrid energy management strategy for multi-stack integrated hydrogen energy storage systems in nature reserves. The strategy aims to reduce equipment degradation rates, enhance system efficiency, and optimize the annualized costs, thereby extending system life and lowering both hydrogen consumption and operational costs.

In grid-connected scenarios, the integration of distributed generation into the distribution grid introduces the challenge of managing the uncertainty associated with wind and solar power output. Energy storage capacity optimization becomes crucial to maintaining power quality and ensuring the economic feasibility of the system. This process addresses issues such as voltage fluctuations, reduced power quality, and enhances the grid’s ability to absorb renewable energy. Reference [15] proposed a bi-level optimization model for the joint optimization of distributed photovoltaic (PV) and hybrid energy storage systems. The model balances multiple objectives, including investment costs, system operating costs, renewable energy consumption, and the enhancement of grid flexibility and stability. In addition, reference [16] introduced a Genetic Algorithm-based Chaotic Particle Swarm Optimization (GA-CPSO) method for optimizing PV and storage capacity configurations. This method uses a multi-objective optimization model to simultaneously improve power quality and economic performance. The GA-CPSO algorithm enhances computational efficiency and optimization accuracy in solving the model.

Current research primarily focuses on optimizing energy storage capacity configurations, whether addressing issues such as declining grid reliability, frequency, and voltage stability in new power systems, or solving problems related to energy waste and degraded power quality in off-grid and grid-connected scenarios. In grid-connected systems, the siting and sizing of energy storage systems require careful coordination. Multi-objective optimization techniques must be employed, constructing multi-dimensional objective functions tailored to the specific energy storage needs. By integrating various energy storage optimization algorithms, multiple performance metrics can be enhanced simultaneously, ensuring the safe and stable operation of new power systems.

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5. Conclusion and future outlook

This study provides a systematic review of the current research on energy storage optimization configurations in new power systems. It examines the topic from three perspectives: the classification of energy storage technologies, optimization algorithms for energy storage, and the impact of new power system characteristics on energy storage configurations. The section on energy storage technologies compares and contrasts the features and application scenarios of various storage types, categorized by energy form. The discussion on optimization algorithms summarizes and evaluates the strengths and limitations of four major types of algorithms used in energy storage optimization. Finally, the paper addresses the impact of changes in energy structure and grid topology in new power systems, presenting strategies for optimal energy storage configuration.

In addition to enhancing traditional energy storage technologies, leveraging environmental resources in real-world applications is crucial. For example, energy storage projects in desert regions could integrate innovative sand-based systems that capitalize on sand's flowability, thermal stability, and low cost. Furthermore, hybrid energy storage systems, which combine the benefits of different technologies, are increasingly seen as a promising solution for peak shaving and fluctuation smoothing.

As the complexity of new power systems grows, demands for their multidimensional performance—encompassing safety, reliability, stability, and economic efficiency—have also increased. Multi-objective optimization is expected to be the central approach for addressing multiple performance metrics simultaneously. The application of machine learning techniques strengthens the accuracy of energy storage optimization configurations, further enhancing their adaptability. Additionally, integrating various algorithms helps to balance computational efficiency with solution accuracy, ensuring the sustainable and stable operation of new power systems.

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