Core Function and Synergistic Optimization of Energy Storage Systems in Community Microgrids

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Abstract. To address the volatility issues that the introduction of wind, photovoltaic power and other renewable energy sources, community microgrids have emerged as a promising platform to support the absorption of clean energy as well as augment the grid resilience. Energy Storage Systems (ESS) is a significant provider of their operation. This paper innovatively proposes a hierarchical technical architecture based on "Physical-Interface-Control-System". Specifically, it entails turning the equipment selection of the physical layer relating to energy storage, AC/DC conversion and mode switching at the power conversion layer, droop control and model predictive control algorithms at the control layer and optimization of multi-timescale scheduling at the system layer. The paper also cohesively expounds on the twofold applications of ESS in dynamic peak shaving and valley filling in addition to enhancing the grid resilience. By analyzing a commercial microgrid case study in South Carolina, USA, this paper proves the usefulness of intelligent optimization strategies at the system layer. In a strong compliance with equipment constraints, the collaborative optimization of ESS configuration and dynamic scheduling with a 23% decrease in the annual demand charges, a 90.5% rate of renewable energy penetration and 48 minutes of full-load backup (scalable to 8 hours on the critical loads). Nevertheless, large capital requirements, sensitivity to forecasting and battery life are still some of the issues that restrain the widespread application of ESS. To optimize the economic viability, future research should focus on improving the intelligent algorithms and developing some supportive business and policy mechanisms.

Keywords: Community microgrid, energy storage system, peak shaving, synergistic optimization.

1. Introduction

The massive introduction of renewable energy is an unavoidable trend of the development of power systems in the background of the global energy transformation and sustainable development. However, renewable sources such as wind and solar power are intermittent and volatile, making it difficult to keep the grid stable when they are linked in bulk [1]. The development of smart microgrid systems has become a potential solution to these problems, making it possible for the localization and intelligent electricity control of traditional energy sources. As localized energy networks which can integrate and coordinate distributed energy resources, loads, and energy storage systems, microgrids are generally recognized as a promising method of reinforcing grid resilience, accelerating the clean energy utilization, and enhancing the self-sufficiency energy [2, 3]. It is noteworthy that community microgrid have attracted significant interest over the recent years as they are very close to the end-user thereby allowing the efficient utilization of energy and complex demand-side management. Figure 1 shows the energy flow dynamics within the integrated energy system of the smart community, including the microgrid configuration.

The ESS is an important infrastructure in the community microgrids. Not only does it mitigate fluctuations in output caused by renewable sources and enhance the power quality, but also serves as a backup power source to enable critical loads during emergencies, which significantly reinforce the stability and reliability of microgrid [4]. Additionally, through energy arbitrage and provision of ancillary services, the ESS generates high economic gains into the operation of the microgrid. This capability also promotes the synergistic optimization and efficient integration of different energy systems, such as integrating electricity and heat networks.

The potential of ESS in application has been promising as shown by theoretical and practical researches. However, there are still a number of challenges that face its widespread use in community microgrids, such as level of technological maturity and compatibility with the policy [5]. Thus, the comprehensive analysis of the core functions, the techniques of collaborative optimization, and real-world performance of ESS in this context have considerable theoretical and practical weight.

This research based on the technical framework of the "Physical-Interface-Control-System" makes an analysis of the core functions, technical contributions, and optimization pathways of ESS use in the microgrids of communities. South Carolina case analysis demonstrates how intelligent dispatch of ESS can maximize economic and environmental benefits to foster synergistic conversion and integration of various energy forms. The last two sections of this paper distinguish the major challenges that the ESS is presently facing in technological, economic, social, and policy levels, and subsequently pinpoint some major research directions in the future. The general objective is to establish the theoretical framework and practical recommendations towards the ongoing development and utilization of energy storage technologies in community microgrids.

2. The Technical Foundation of ESS in Microgrids

2.1. Hierarchical Technical Architecture and Functional Presets

The integration of the property of physical equipment, power control logic, and system-level dispatch strategies forms the functional accomplishment of ESS in the microgrid. Based on this, a hierarchical architecture of "Physical-Interface-Control-System" is built (as shown in table 1). This framework gradually decouples technical components from the physical hardware to the system-level management, thus precisely addresses the multifaceted needs of the microgrid in terms of reliable power supply, power quality, and economic performance. Therefore, the architecture establishes a fundamental structure for the analysis of future energy storage technologies.

Table 1. Hierarchical Technical Architecture and Functional Mapping of ESS

Layer	Technological Factors	Function	Point of Common Coupling
Physical	Battery/Supercapacitor/ Flywheel Selection	Energy Storage, Rapid Response	Matching energy density, power density with load requirements
Interface	Bidirectional Power Converter (PCS), DC/AC Conversion	Bidirectional Power Control	Seamless grid-connected/islanding transition
Control	Droop Control, Model Predictive Control (MPC)	Real-Time Power Allocation, Voltage/Frequency Support	Coordination with PV inverters and load controllers
System	Energy Management System (EMS), VPP Communication Protocol	Multi-Timescale Optimal Dispatch	Dispatch cycles from second-level frequency regulation to day-ahead economic scheduling

The Physical Layer constitutes the foundational energy carrier. High energy density batteries are used here to support long-duration storage and the high-power density provided by supercapacitors and flywheels are used to support the second-level power demands. And the components selection at this layer directly determines the overall load-matching capability of the system. The Interface Layer, orchestrated by PCS, manages core functions including power conversion and bidirectional energy flow. This layer provides seamless interoperability between distributed energy resources and AC loads and also has continuous supply through smooth transitions between the grid connected and islanded operational modes. To achieve real-time stability, the Control Layer combines the quick frequency and voltage response of droop control with the predictive and multi-objective power allocation strategies introduced in the MPC. At the uppermost level, there is the System Layer which executes global optimization via the EMS. It collects data on every asset and leverages Virtual Power Plant (VPP) protocols to facilitate coordinated dispatch across multiple timescales, ranging from second-level frequency regulation to day-ahead economic scheduling.

2.2. The Technical Implementation of Core Functions

The interaction between the aforementioned hierarchical technologies is the keystone of the functions of ESS in a microgrid. Its role is primarily manifested through the managed intervention of internal load via advanced control strategies, such as peak shaving and valley filling. This section will clarify the operational logic of these functions in two aspects: one is dynamic optimization of load shifting, and the other is grid resilience improvement.

2.2.1. The technical principle and dynamic optimization of peak shaving and valley filling

Peak shaving and valley filling are primary applications of ESS to mitigate load fluctuations and minimize the difference between the peak and valley of the grid. Existing technical approaches to achieve this can broadly be classified into three categories as shown in figure 1: economic incentive-based strategies, technology supporting and management controlling strategies.

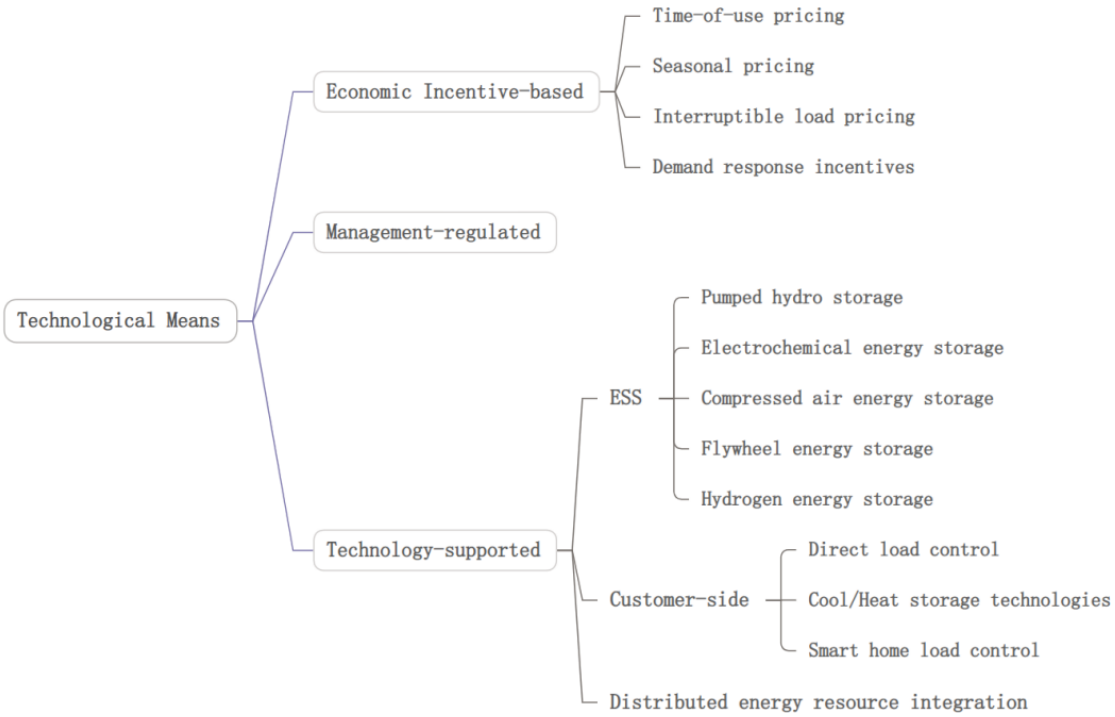


Figure 1. Current primary methods for peak shaving and valley filling

The essence of these technologies involves modifying the load profile through temporal energy transfer. Specifically, Particularly, the ESS is charged at off-peak periods on the grid characterized by low cost of electricity or excess supply of renewable energy thus absorbing unnecessary power. Conversely, it discharges during peak demand periods to offset the deficits in power supply. Besides alleviating stress on the main grid supplied side, this mechanism also lowers the frequent cycling of conventional peak-shaving units, which can improve overall energy utilization efficiency. Technically, implementation is mainly concerned with it establishing an optimization model and formulating proper control strategies. A typical ESS optimization model targeting peak shaving and valley filling includes the following components [6]:

Objective Function: This generally aims to minimize the load variance, where a lower variance corresponds to a flatter load profile as well as better peak shaving and valley filling capabilities:

$$\min f = \frac{1}{N}\sum_{i=1}^{N}[L'(i) - \bar{L}]^2 \tag{1}$$

Where $L'(i)$ represents the net load after ESS adjustment during time interval i, $\bar{L}$ denotes the average daily load, and N is the total number of time intervals.

To guarantee system security and equipment longevity during actual operation, the optimization model must incorporate the following constraints:

a) Power Constraint: The ESS charging/discharging power P_{ess} must remain within its rated limits. The minimum and maximum charging/discharging powers are respectively denoted as P_{min} and P_{max}:

$$P_{min} < P_{ess} < P_{max} \tag{2}$$

b) Capacity Constraint: Similarly, the state of charge of the ESS must always remain within a safe operating range to prevent over-charging or over-discharging:

$$SOC_{min} < SOC(t) < SOC_{max} \tag{3}$$

c) Energy Balance Constraint: Over a complete dispatch cycle (e.g., 24 hours), the total charging energy $\sum E_{ch}$ should approximately equal the total discharging energy $\sum E_{disch}$ to maintain periodic SOC balance:

$$\sum E_{ch} \approx \sum E_{disch} \tag{4}$$

With such strict constraints, the hierarchical technologies mentioned above may achieve temporal coordination. At the physical layer, battery and supercapacitor complements are used to meet various power regulation requirements across different periods with combination of their respective charge discharge characteristics. The control layer employs MPC algorithm based on current load predictions and forecasts of the distributed generation output, which carries out rolling optimization of the charging and discharging power of the ESS in each time period. Simultaneously, to implement these diverse power regulation demands, the bidirectional power converter of the interface layer must be able to monitor the real-time power commands of the control layer. Ultimately, the EMS of the system layer is to coordinate the SOC balance with multiple storage units and manage the global power distribution, preventing localized overcharging or over-discharging. With this "prediction-decision-execution" closed-loop control, the system can effectively peak and valley the load curve while ensuring the SOC remains within its safe operating range.

2.2.2. Multi-Time-Scale support for grid resilience

Microgrid resilience refers to its capability to sustain continuous power supply under faults and swiftly recover from disturbances. Traditional grid resilience assessment methods mostly rely on deterministic physical models and static infrastructure analysis, which cannot suitably account for the high-dimensional uncertainties introduced by the high penetration of renewable energy. Therefore, the dynamic response characteristics of the system under complex operating conditions are challenging to precisely identify [7]. To resolve this, a hierarchical control strategy based on multi-timescale coordination is proposed. This strategy decouples the tasks of enhancing resilience in the temporal dimension and establishes a comprehensive resilience framework that covers the entire process of pre-fault prevention, fault-time resistance, and post-fault recovery.

a) Second-Level Response

This layer mainly suppresses the drop or surge of key parameters (like frequency and voltage) at the initial moment, so that it can realize instant power balance during transients. In terms of hardware, flywheel energy storage and supercapacitors can rapidly compensate for power deficits caused by distributed photovoltaic disconnection or sudden load changes due to their high-power density (up to 10 kW/kg) and millisecond-level response characteristics. At the control level, droop control is implemented by using local measurements to regulate the primary frequency. Its active power-frequency droop characteristic can be expressed as:

$$P = P_0 - k_p(f - f_{nom}) \tag{5}$$

Where P represents the actual output power, P_0 denotes the set power, k_p is the droop coefficient, f is the measured system frequency, and f_{nom} is the rated frequency. When a frequency dip happens, the energy storage unit automatically increases its power injection according

to the droop characteristic, thereby effectively limiting frequency deviation and securing a critical time window for subsequent control actions.

b) Minute-Level Regulation

After the second-level response, the PCS at the interface layer needs to possess seamless grid-connected and islanding transition capability to promptly shift to islanded operation during grid faults. For low-inertia islanded systems, Virtual Synchronous Generator (VSG) technology is used to provide virtual inertia support by emulating the rotor motion equation of a synchronous generator:

$$J\frac{d\Delta\omega}{dt} = T_m - T_e - D\Delta\omega \tag{6}$$

Where J is the virtual inertia coefficient, $\Delta\omega$ is the frequency deviation, T_m and T_e are the mechanical torque and electromagnetic torque respectively, and D is the damping coefficient. This mechanism effectively suppresses the rate of change of frequency and enhances the system damping properties, which ensures a stable power supply for critical loads during minute-level transitions.

c) Hour-Level Reserve

At the system layer, EMS uses high-accuracy meteorological and load forecast to achieve two operational objectives namely minimizing operational costs and maximizing resilience margin. Subject to power balance constraints and energy storage SOC limits, it proactively dispatches energy reserves to offset power gaps in case of long grid outages or insufficient renewable output. This strategy can ensure the continuous power supply at hourly timescales.

The resilience metrics, as determined by reference are computed by integrating the system performance curve over time, where a larger integral value indicating higher resilience [8]. In microgrid faults, second-level suppression will decelerate the rates of performance degradation, minute-level stabilization will minimize the magnitude of functional loss, and hour-level reserve will accelerate recovery to the initial performance levels. This integrated "second–level suppression–minute-level stabilization–hour-level reserve," framework, achieved with deep coordination of various energy storage methods combined with hierarchical control strategies, demonstrates an immense potential in improving the disturbance resistance and self-healing capabilities of the microgrids with a high degree of renewable energy infiltration.

3. Review on Control and Optimization Strategies for ESS

Due to the rapid development of intelligent technologies, the robustness and distributed coordination of ESS control strategies are gradually improving. MPC overcomes uncertainties by dynamic optimization, and Multi-Agent System (MAS) uses distributed decision-making to achieve global optimization. This section systematically reviews the MPC, MAS control, and hierarchical coordinated control architectures. Besides, this section also introduces a detailed study of a commercial facility microgrid in South Carolina, USA conducted by Anzalchi et al. as representative case analysis, exploring the application scenarios and feasibility of above strategies in practice. This analysis reveals how to combine intelligent optimization algorithms and multiple real constraints to systematically solve the classic "energy trilemma" of economy, sustainability, and reliability.

3.1. Centralized Optimization Control (Exemplified by MPC)

Dynamic uncertainty modeling increases robustness in MPC. The stochastic optimization methods translate the variations in renewable generation (like wind or PV intermittency) and the stochasticity of load into probabilistic constraints. It is a hierarchical time-varying rolling optimization design that the distribution network layer aims to adapt the control layer in real-time based on local measurement data. Planning tools like HOMER software used by professionals in microgrid, have the multivariate sensitivity analysis capabilities, which can quantify the fluctuation boundaries of hybrid wind-PV-storage configurations. Then they can provide fundamental data for generating robust constraints in MPC [9].

As a major centralized optimization control tool, MPC is effective in managing the uncertainties in the system through its rolling optimization and feedback correction mechanisms. Its primary strength is forecasting future system states by operating on present conditions and solving optimal control sequence within reach of power and capacity constraints (like $P_{min} < P_{ess} < P_{max}$, $SOC_{min} < SOC(t) < SOC_{max}$).

Most of the early studies mainly used relatively simple control strategies (such as constant power control) and neglected some realistic constraints in simulations, which might potentially limit the applicability of their findings in actual engineering scenarios. Comparatively, the main innovation and methodological improvement of the mentioned South Carolina case lie in the adoption of the optimal dispatch algorithm namely "perfect foresight" incorporated into the HOMER Grid software. This case study demonstrates the notable effectiveness of centralized optimization in practical applications through rigorous modeling of multiple real-world constraints. The comprehensive benefit analysis indicates that following optimization, the facility realized the reduction of the annual demand rates by 23 percent, the annual energy expenditures by 17 percent, and the utilization rate of the renewable energy is 90.5 percent [10]. The case demonstrates the possibility of centralized optimization of the pursuit of economic and environmental objectives under complex electricity price conditions, and it confirms its inherent reliance on the accuracy of prediction. In addition, it verifies the significant potential of the advanced intelligent optimization algorithms in reality. Although computational complexity prevents their routine application in practical scenarios, they are completely accessible to engineering practitioners thanks to their implementation in easy-to-use software, which effectively reduces concerns about the actual application of complex algorithms.

3.2. MAS Collaborative Optimization

MAS collaborative optimization adopts the hierarchical decision-making architecture. The physical layer agents are the terminal devices and make decisions at the millisecond level, whereas the coordination layer uses the VPP agents to aggregate distributed resources. All these agents collaborate to achieve the global system level goals through communication and negotiation, such as operational cost reduction, enhanced energy efficiency, or voltage stabilization [11, 12]. In the application of community microgrid, MAS will facilitate decentralized energy dispatch and market transactions. It enables energy storage, distributed PV, as well as flexible loads to build energy coalitions and negotiate to achieve local energy balance and optimal energy scheduling without central controller intervention.

Furthermore, different types of agents can also represent users or devices involved in demand response programs. For instance, for an electric vehicle, it can autonomously decide its optimal charging or discharging strategy based on grid status, electricity price signals, and user travel needs. It can negotiate with the central management system of the microgrid or aggregator, providing ancillary services to the grid and meeting users' requirements.

In comparison with traditional centralized control methods, MAS architecture is more flexible and scalable. It provides a technical basis for the later optimization of intelligent control strategies for community microgrids with large number of distributed resources and dispersed ownership.

3.3. Hierarchical Coordinated Control Architecture

The coordinated implementation of the hierarchical technical architecture mentioned in Section 2.1 demonstrates strong practical applicability, as the case study of South Carolina demonstrates. Tesla Powerwall 2.0 batteries are used at the Physical Layer. VSG technology is employed at the Control Layer to make available the virtual inertia support, and the System Layer adopts lifecycle optimal dispatch through the EMS. This combination of coordination enables the system to provide a full-load reserve time of 48 minutes (which can be expanded to 8 hours for critical loads) and satisfy rigorous equipment constraints, thus confirming the effectiveness of the hierarchical architecture in solving the "economy-sustainability-reliability" trilemma [10].

Meanwhile, it also highlights the new trend of value diversification in community microgrids. ESS is no longer merely a tool for "peak shaving and valley filling", but has become a fundamental resource that can be used to undertake the following major missions: cost reduction and revenue increase, green transition, and business continuity assurance. This development provides new and broader perspectives in future investment decisions and policy formulation.

4. Analysis of Systemic Challenges of ESS

4.1. Techno-Economic Challenges: High-Performance Dependence and Cost Barriers

The aforementioned advantages that the case study shown are highly dependent on the "perfect foresight" optimization algorithm of HOMER Grid software, making them extremely sensitive to uncertainties in load and renewable energy output. This sensitivity directly results in the failure of dispatch strategies. Furthermore, the 132kWh energy storage configuration is fundamental to achieving these comprehensive benefits, but its high initial investment cost remains a major barrier for most potential users. Additionally, the operational condition of maintaining the plateau between battery SOC (12%~88) as a condition of simulation validity indicates that there is a close interrelationship between battery degradation and operational strategy. In order to be economically viable in the long term, it is important to balance between performance and lifespan in actual management.

4.2. Policy and Market Challenges: Fragile Economy and Institutional Gaps

The 23% reduction in demand charges is largely dependent on the local specific time-of-use structure in demand charges. Such high dependence on existing policies leads to the vulnerability in economic case of the project. Since any modification of the policies on electrovalence would also nullify its viability. Regrettably, there is a general absence of long-term, stable incentive policies and market mechanisms to ensure investment returns. In addition, the case study, which is founded on an "owner-invested" model, faces challenges in reproducing its business viability on community scenarios involving multiple investors. This reflects the absence of mature business models and fair benefit distribution mechanisms.

5. Conclusion

This study thoroughly proves the important position of ESS as the core of community microgrids. Faced with the technical difficulties posed by high-penetration renewable integration, this paper proposes hierarchical technical architecture of "Physical-Interface-Control-System" for the first time and provides a clear theoretical framework for the functional realization and coordinated optimization of ESS. The technical division of labor of layers is defined as follows: Physical Layer sets the hardware foundation by selecting appropriate components; Interface Layer realizes bidirectional power flow and seamless mode transition; Control Layer adopts advanced algorithms (improved Model Predictive Control algorithm, droop control) to achieve precise real-time regulation; System Layer adopts EMS to comprehensively optimize economy and reliability of the global situation on multiple time scales.

Furthermore, this study reviews implementable ESS intelligent control and optimization strategies through three main ways: centralized optimization control, multi-agent collaborative optimization, and hierarchical coordinated control architecture. Taking the commercial microgrid in South Carolina, USA as the case, this study verifies the practical significance of intelligent optimization algorithms at system-layer. The results demonstrate that, under strict constraints of equipment, the co-design of energy storage configuration and operational strategies can effectively resolve the "energy trilemma". Additionally, this solution also brings certain economic benefits (reduce demand charges), environmental benefits (increase renewable energy penetration), and enhanced resilience (extend backup power duration).

In the future, energy storage technology for community microgrids should be broken through in both technology and policy. In terms of technology, future research should focus on these following specific areas: Firstly, to mitigate the dependence on forecast accuracy as shown in centralized control like MPC, distributed optimal control strategies based on cloud-edge coordination and multi-agent reinforcement learning should be adopted to improve system robustness and scalability. Secondly, after changing the theoretical concept of the proposed multi-timescale resilience framework, it is necessary to further realize the real-time resilience assessment and decision-making, which is an important method to ensure the security of grid against extreme events in the future. At the policy and business level, Future study should design long-term, adaptive incentive mechanism and market rules which are resilient to policy fluctuations. Meanwhile, it is also necessary to further develop innovative business model and quantitative benefit distribution mechanism for multi-stakeholder community scenarios to reduce investment risks and attract private capital. These measures will ensure the economic sustainability of projects, enabling the transition of ESS from demonstration project to widespread commercial application.

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