Optimization of Battery Energy Storage System Capacity for Peak Load Shaving in Distribution Networks Based on Real Data

Olesya O. Oleynikova
Russian State Agrarian University - Moscow Timiryazev Agricultural Academy
Moscow, Russian Federation
lesiaoleynikova@gmail.com

Natalya V. Sergeyeva
Russian State Agrarian University - Moscow Timiryazev Agricultural Academy
Moscow, Russian Federation
sergeewanv78@mail.ru

Ilya A. Panfilov
Bauman Moscow State Technical University
Moscow, Russian Federation
crook_80@mail.ru

Ekaterina Fedorovna Malykha
Russian State Agrarian University - Moscow Timiryazev Agricultural Academy
Moscow, Russian Federation
Ekaterina Fedorovna Malykha

Abstract* — In the context of global energy transformation and massive deployment of distributed generation and electric vehicle charging infrastructure, intelligent distribution networks face a critical problem of sharp peak loads. This phenomenon leads to overload of transformer equipment, degradation of power quality, and the need for expensive, often economically inefficient modernization of grid infrastructure. This paper proposes a deterministic method for determining the optimal power and capacity of battery energy storage systems for peak shaving tasks in local networks. Unlike approaches based on synthetic or averaged data, this work is based on in-depth analysis of a real smart meter dataset, including high-frequency consumption profiles of thousands of households. A control algorithm has been developed and verified that minimizes the maximum load on the substation while strictly observing physicochemical constraints on the storage device's state of charge. Simulation results on real historical data demonstrate a reduction in peak loads by more than twenty percent when using an optimally sized storage device. The obtained results convincingly substantiate the technical and economic feasibility of integrating energy storage systems as a reliable alternative to traditional grid reinforcement.

Keywords—smart grids, hybrid energy systems, battery energy storage systems, peak load shaving, time series analysis, capacity optimization, real data.

I. INTRODUCTION

Traditional distribution electrical networks were historically designed considering a relatively uniform, predictable, and slowly growing consumption profile. Engineering calculations were based on averaged load indicators and simultaneity coefficients, which ensured stable and failure-free operation of equipment for decades [1]. However, the modern paradigm of energy development is radically changing the nature of loads at all levels. Decarbonization, massive deployment of electric vehicles, proliferation of heat pumps and rooftop solar power plants lead to the formation of sharp, short-term, and often unpredictable consumption peaks [2]. A typical example is the evening peak that occurs when consumers return home simultaneously, turn on powerful household appliances, and begin charging electric vehicles.

These short-term peaks create serious challenges for distribution network operators. They cause overheating of power transformers, which accelerates insulation aging, lead to voltage drops at the ends of distribution lines, and significantly reduce the overall service life of grid equipment. The classical engineering solution to this problem is extensive infrastructure modernization: replacing transformers with more powerful ones, reconstructing cable lines with increased cross-sections, and installing new transformer substations. However, this approach requires colossal capital expenditures, long coordination periods, and excavation work. Moreover, new equipment will be used at full capacity for only a few dozen hours per year, making such investments extremely inefficient from an economic perspective [3].

An alternative and more flexible solution is the use of battery energy storage systems for peak load shaving. This concept, known as an alternative to building new networks, allows accumulating electricity during low demand hours and delivering it to the grid during peak hours, effectively cutting off the top of the load curve. Classical methodologies for determining storage size exclusively for peak shaving purposes have laid the foundation for such research [4]. Nevertheless, many existing approaches rely on synthetic or theoretical load profiles, which reduces the practical value and reliability of results for real grid companies [5]. The main contribution of this work is the development and verification of a battery energy storage system capacity optimization algorithm exclusively based on real high-frequency smart meter data..

II. LITERATURE REVIEWS

The problem of optimal placement and sizing of battery energy storage systems is widely covered in modern scientific literature. Comprehensive reviews of storage planning methods in distribution networks highlight three main approaches: heuristic methods, mathematical programming methods, and machine learning methods [6]. The accuracy of results directly depends on the quality and detail of input load data, and optimal placement requires consideration of multiple grid constraints [7].

Modern research demonstrates the application of stochastic optimization for sizing battery energy storage systems considering the uncertainty of renewable generation and spatial-temporal flexibility of networks [8]. Nevertheless, many models ignore real demographic consumption patterns, using idealized load curves, which leads to overestimated assessments of required storage capacity [9]. Recent works are beginning to actively use real

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smart meter data for model calibration and optimal equipment placement in distribution networks [10].

Particular attention is paid to the physicochemical aspects of battery operation. It has been shown that ignoring depth of discharge during optimization can lead to a thirty percent or more reduction in the service life of lithium-ion batteries [11]. The choice of specific energy storage technology for microgrids and distribution networks requires careful analysis of their characteristics [12], and comprehensive assessment of the role of storage systems in smart grids confirms their multifunctionality [13]. Economic evaluation of battery energy storage systems for peak shaving demonstrates high commercial viability of such projects with proper power sizing [14]. This paper fills an existing gap by combining a real high-resolution dataset with a deterministic control model that explicitly considers system efficiency and depth of discharge limits.

III. SYSTEM DESCRIPTION AND DATA USED

The considered hybrid system consists of three main components: the external distribution network, local aggregated load, and battery energy storage system. To ensure high reliability and practical applicability of results, this study uses an open smart meter dataset collected as part of a large-scale pilot project in London [15]. This dataset contains electricity consumption measurements at thirty-minute intervals for more than five thousand households from late 2012 to early 2014. Each meter is assigned an anonymized identifier and demographic profile, which allows forming representative groups of consumers with similar behavior and avoiding distortions inherent in averaged model data [16].

For the purposes of this modeling, a group of one hundred random households was selected. A typical winter week was chosen as the test period. The winter period was chosen deliberately, as it is characterized by maximum demand due to active use of electric heating and lighting, as well as the most pronounced evening peaks, creating the greatest load on transformer substations and presenting the greatest risk to network stability. [17]

The fundamental principle of operation of the considered hybrid system is the continuous balance of active power. At any given moment, the power consumed from the external distribution network equals the difference between the aggregated power of the local load and the power delivered or consumed by the battery energy storage system.[18] When household consumption exceeds the permissible limit, the battery switches to discharge mode, compensating for the power shortage and preventing grid equipment overload. Conversely, during low demand periods, the battery charges, drawing excess power from the grid, which also contributes to load curve leveling.[19]

The key parameter characterizing the state of the battery energy storage system is the state of charge. The change in state of charge at each time step, constituting thirty minutes, directly depends on the charging or discharging power, as well as the full nominal battery capacity. When modeling, the overall system efficiency coefficient must be considered, which includes power conversion losses in the inverter and thermal losses in battery cells [20]. This work adopts an efficiency coefficient value of 0.92, which corresponds to modern commercial lithium-ion technologies. To ensure safe operation and prevent premature degradation of battery chemical elements, the algorithm strictly limits the minimum charge level at ten percent and the maximum at ninety percent. This prevents deep discharges and overcharges that critically reduce battery service life [21].

IV. PROPOSED METHODOLOGY

To solve the peak shaving problem, a deterministic threshold-based control algorithm is proposed. This algorithm simulates the operation of a real energy management system controller that can be deployed on physical equipment. The algorithm performs the following sequential steps:

A. Data Aggregation and Analysis: Consumption profiles of selected households are summed to obtain the feeder's overall load profile. The historical profile for the selected period is analyzed to identify the baseline maximum load value, which poses a threat to grid equipment.

B. Target Peak Setting: A target limit on grid power is established, which is lower than the baseline peak. In this study, the target reduction is set at twenty percent of the historical maximum. This threshold is a typical requirement for grid operators to prevent transformer overload without excessively increasing storage system cost.

C. Simulation Modeling: For a given battery capacity, its operation is modeled according to strict logical rules. If the current load exceeds the target threshold, the battery discharges with the power necessary to maintain grid consumption at the target level. This process continues until the minimum permissible charge level is reached. If the current load is below the target threshold and the charge level has not reached the maximum, the battery charges with available power not exceeding the difference between the target threshold and current load, with mandatory consideration of the system efficiency coefficient.

D. Iterative Capacity Selection: The algorithm iterates through battery capacity values with a specified step of ten kilowatt-hours. The process continues until the minimum capacity is found at which the grid power limit condition is met throughout the entire modeling period without violating physicochemical state of charge constraints. This approach guarantees finding an economically optimal solution.

V. SIMULATION RESULTS

To verify the proposed methodology, a series of simulation experiments were conducted based on the described real dataset.

- Load Profile Analysis

Figure 1 presents a comparative analysis of the power profile for a typical winter day. The original aggregated load has a pronounced evening peak around eighteen to twenty-one hours, reaching 145.2 kilowatts. The power profile drawn from the grid after implementing the optimized battery energy storage system demonstrates that the peak load is successfully and stably limited at 115.5 kilowatts. Smoothing occurs smoothly, without interrupting consumer power

supply and without creating new, artificial peaks at other times of the day.

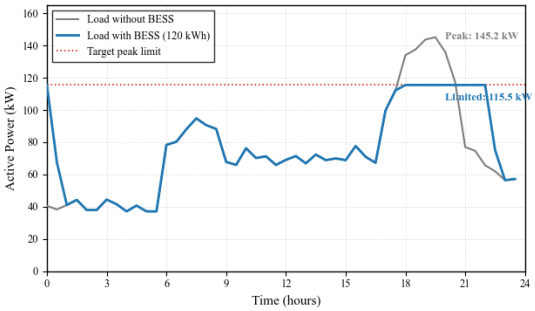

Fig. 1. Load profile comparison before and after BESS application

- State of Charge Dynamics

Figure 2 shows the dynamics of the battery charge level at optimal capacity. The battery actively charges during night hours when the load is minimal and electricity is most available and, as a rule, cheaper. In the evening, controlled discharge occurs to cover the peak. It is critically important to note that the charge level never drops below the established minimum of ten percent, which guarantees the absence of deep discharges that destroy battery chemistry and reduce its service life. Similarly, the battery does not overcharge above ninety percent, which also favorably affects its durability.

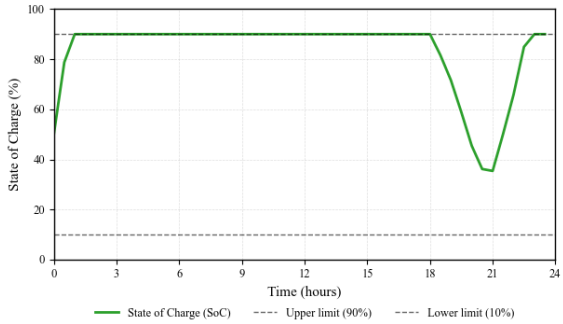

Fig. 2. State of charge dynamics of the battery energy storage system over 24 hours.

- Efficiency and Sensitivity Assessment

Table 1 presents modeling results for various battery energy storage system capacity values, which allows conducting a sensitivity analysis and substantiating the choice of optimal size.

TABLE I. Influence of Battery Energy Storage System Capacity on Distribution Network Parameters

Capacity (kWh)	Max. Grid Load (kW)	Peak Reduction (%)	Average Depth of Discharge (cycles/day)
Without storage (Baseline scenario)	145.2	0.0	0.0
60	131	9.8	0.8
120	115.5	20.4	0.9
180	112.1	22.8	0.95

As the data shows, increasing capacity from sixty to one hundred twenty kilowatt-hours provides a significant gain in peak reduction, exceeding twenty percent. This confirms the high efficiency of deploying medium-sized storage systems. Further increasing capacity to one hundred eighty kilowatt-hours provides only a marginal improvement of two and a half percent, but at the same time leads to unjustified growth in capital costs. Moreover, larger capacity leads to increased time the battery spends in a fully charged state, which also negatively affects its durability due to calendar aging. Thus, for this group of one hundred households, the optimal capacity is 120 kilowatt-hours, providing the best balance between technical effect and economic costs.

VI. CONCLUSION

This paper presents a practical, data-driven approach to determining the optimal capacity of battery energy storage systems for peak load shaving in distribution networks. Using a real smart meter dataset made it possible to prove that deploying a 120 kilowatt-hour battery energy storage system for a group of one hundred households allows reducing peak load on the substation by more than twenty percent.

The results confirm the hypothesis that intelligent storage management is an economically and technically more effective alternative to traditional grid equipment modernization. The proposed algorithm is easily scalable and can be integrated into modern distribution network management systems to postpone expensive infrastructure projects, ensuring reliable power supply to consumers.

As directions for future research, it is planned to expand the model by integrating distributed solar power plant generation forecasts, considering the stochastic nature of electric vehicle charging, and applying dynamic tariff formation in the wholesale electricity market to maximize economic returns from battery energy storage system operation.

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