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(Review Article)

Optimal sizing of battery energy storage system for mitigation of RES fluctuation

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Abstract

The integration of renewable energy sources (RES), such as wind and solar, into the electricity grid is crucial in the pursuit of sustainable energy. However, their inherent intermittency poses challenges to grid stability and reliability. Battery Energy Storage Systems (BESS) offer promising solutions to buffer these fluctuations, providing flexibility and scalability. The study examines optimal sizing methods for BESS to mitigate the unpredictability of RES output. It identifies strategies such as forecasting models, stochastic optimization, and hybrid systems that enhance predictability. Additionally, it addresses challenges like battery degradation, safety concerns, and grid integration hurdles. Innovations in Battery Management Systems (BMS) are highlighted for their potential to extend battery life and improve cost-effectiveness. Ultimately, optimizing BESS integration is critical to maximize renewable energy utilization, reduce fossil fuel dependence, and support a sustainable energy future.

Keywords: Renewable Energy Sources; Battery Energy Storage; Battery Management System; Optimal Sizing; Microgrid.

1. Introduction

The integration of renewable energy sources (RES) such as wind and solar into the electricity grid is increasingly vital in the context of climate change and sustainable energy goals. However, the inherent intermittent of these sources poses significant challenges for maintaining grid stability and reliability [1-2]. This variability leads to fluctuations in power output, impacting the quality of the electricity supply. Energy Storage Systems (ESS), particularly Battery Energy Storage Systems (BESS), are explored as solutions to buffer these fluctuations and enhance grid reliability. BESS are favored for their flexibility, scalability, and rapid response capabilities, but their optimal sizing is crucial for effective integration and maximizing the benefits of RES [3-4].

The importance of accurately sizing these batteries to fully leverage their benefits while addressing the associated challenges involve a detailed analysis and comparison of methods for optimizing BESS size to effectively manage the unpredictability of RES output, highlighting significant contributions from existing studies and identifying gaps for future research.

Several inherent challenges complicate the optimization of battery storage for RES integration. These include the unpredictability of RES outputs due to environmental factors, which makes it hard to forecast the required energy storage capacity, leading to potential over- or under-sizing of battery systems [5]. Additionally, battery degradation over time affects performance and increases costs, while the high initial costs of battery systems pose a significant barrier to widespread adoption. Safety concerns and technical hurdles related to grid integration further complicate the effective use of BESS in managing RES integration.

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Addressing the unpredictability of RES, various strategies like forecasting models, stochastic optimization, and hybrid systems combining multiple types of RES are proposed to mitigate the impacts of output variability. Demand response programs are also suggested to adjust consumption based on energy availability [6]. These approaches are evaluated through various studies, highlighting their potential to enhance the predictiveness and reliability of battery storage systems in grid integration.

Battery degradation is another critical issue, with factors such as high operational temperatures and depth of discharge contributing significantly to reduced battery life and performance [7]. Innovations in thermal management and battery management systems (BMS) are discussed as solutions to mitigate these effects. Studies suggest that advanced BMS can optimize battery use and extend their operational life by managing charge and discharge cycles more effectively, demonstrating significant potential to improve the overall efficiency and cost-effectiveness of battery storage in renewable energy systems.

The integration of BESS into the electric grid is critical for optimizing renewable energy use and reducing dependence on fossil fuels. It involves various complex scenarios such as peak shaving, load shifting, and frequency regulation [8]. Each scenario presents unique challenges and requires tailored solutions, including advanced algorithms, predictive models, and robust control systems, to effectively manage the dynamics of energy storage and grid interaction. This paper reviews sizing optimization methods for BESS with RES penetration, namely: Cost-Benefit Analysis-Based Sizing Strategy for Distributed BSS [9], Predictive Controller-Based Optimal Sizing of BESS [10], Optimal Sizing and Selection of Energy Storage System Considering Load Uncertainty [11].

2. Sizing optimization methods for BESS with RES penetration

This section explores the topic of battery optimization sizing for grid-connected systems, analyzing five research methods. It focuses on the critical role of battery energy storage systems (BESS) in enhancing electric grid functionality through various optimization strategies for frequency regulation, voltage control, and peak shaving. A comparative analysis of these methods will discuss the advantages and disadvantages of each, aiming to provide a comprehensive understanding of BESS integration challenges and opportunities. The study seeks to advance knowledge in battery sizing optimization, offering valuable insights for policymakers, energy stakeholders, and researchers working towards a sustainable and reliable energy future.

2.1. Sizing Strategy of Distributed Battery Storage System with High Penetration of Photovoltaic for Voltage Regulation and Peak Load Shaving

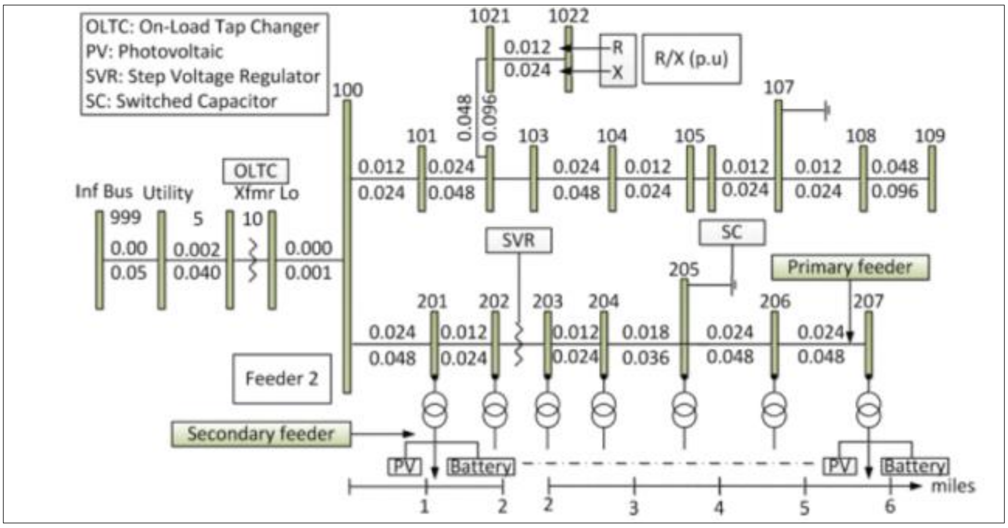

Figure 1 The modified GE distribution power system model

A method to optimize battery energy storage systems (BESS) sizing is presented in distribution systems with high grid-tied photovoltaic (PV) penetration [12]. Traditional voltage regulation using on-load tap changer (OLTC) transformers and step voltage regulators (SVR) struggles with voltage rise issues under high PV outputs [13]. The proposed approach integrates a BESS at each PV bus of a General Electric (GE) distribution model, utilizing a physical model of a lithium-ion phosphate (LiFPO4) battery that includes aging effects. This model helps evaluate BESS performance, usage, and lifespan across different operational conditions. It performs a cost-benefit analysis to identify economically efficient BESS sizes for voltage regulation and peak load shaving [14]. The study aims to enhance distribution system stability and efficiency in environments with significant PV integration [15]. A modified GE distribution power system model is selected as case study which has been presented in Figure 1.

2.1.1. Distribution System Description

The research presents a modified GE distribution power system model to analyze the impact of integrating Battery Energy Storage Systems (BESS) on system performance [16]. The system encompasses distributed photovoltaic (PV) units, BESS, various loads, and fundamental components such as On-Load Tap Changers (OLTC), Step Voltage Regulators (SVR), and switched capacitors, primarily focusing on Feeder 2 [17]. This feeder, spanning approximately 6 miles with a peak load of 11 MVA, incorporates seven varied loads that blend residential and commercial uses, indicating the capacity to handle significant fluctuations in power demand. The detailed setup, including technical specifications and feeder configurations provided in the model, facilitates an in-depth exploration of BESS's utility and efficiency in modern power distribution networks. Figure 2 shows the specification of feeder 2.

Feeder 2 Line Impedance

From	To	Length (mile)	Conductor	X/R
100	201	1.3	Z1	2
201	202	0.65	Z1	2
203	204	0.65	Z1	2
204	205	0.97	Z1	2
205	206	1.1	Z2	2
206	207	1.1	Z2	2

Feeder Conductor Selection

Z1	0.648 Ohm/mile	ACSR 556.6 18/1
Z2	0.768 Ohm/mile	ACSR 266.8 18/2

Feeder Voltage Equipment

Type	From	To	Rating	
Transformer	5	100	20MVA	
SVR	202	203	10MVA	
Switched capacitor	205		2.5MVar	

Figure 2 Feeder Information in the Distributed Power System

2.1.2. The Energy Management System (EMS)

The EMS plays a crucial role in regulating power distribution among the battery, PV installations, load, and grid, ensuring effective voltage control and peak load management. By employing a sophisticated control strategy depicted through a detailed flowchart, the EMS reacts dynamically to voltage fluctuations by either charging or discharging the battery, thereby stabilizing the system [18]. The strategy includes mechanisms for both overvoltage and undervoltage conditions, ensuring that the system operates within a predefined voltage range. This proactive approach not only optimizes power flow but also enhances the overall reliability and performance of the distribution system.

2.1.3. Physical Battery Model with Aging Effect Estimation

An intricate battery model, focusing on a commercial LiFePO4 battery, estimates aging effects based on cyclation and calendrical factors to predict battery life accurately. By integrating this model within the system, it calculates the State of Charge (SOC) and State of Health (SOH), critical indicators of battery performance and lifespan. The model considers environmental temperature and operational history to evaluate the battery's aging process, which aids in understanding its degradation over time [19]. This methodical estimation of battery health is vital for maintaining efficiency and prolonging the operational capacity of batteries in power systems, ensuring sustainability and cost-effectiveness. The state of health of the battery can be expressed as:

$$\begin{Bmatrix} \Delta SOH = SOH_C + SOH_t \\ SOH_C = \frac{Coulomb_{used}}{Coulomb_{total}} \\ SOH_t = t \times \frac{Capacity\ loss}{days} \end{Bmatrix} \quad (1)$$

SOH_c, which is calculated by counting the transferred coulombs and reflects changes in battery capacity due to cycling up to a limit of 2,000 cycles, influenced by environmental temperature (T); and SOH_t, which represents capacity loss in a non-operating state, affected by temperature (T), current state of charge (SOC), and non-operating time. SOH_c is estimated by dividing used coulombs by total available coulombs, while SOH_t is calculated as the product of daily capacity loss and non-operating time (1-c). Both factors are crucial for understanding battery degradation.

2.1.4. Cost-Benefit Analysis and BESS Sizing

The cost-benefit analysis and sizing of the Battery Energy Storage System (BESS) for voltage regulation and peak load shaving includes various factors like annual costs, benefits from reduced OLTC/SVR work stress, benefits from shaving peaking power generation, and load shifting benefits. This method adopts the levelized cost over the lifetime (CL) method to evaluate BESS costs, incorporating a levelized factor over n years (LFn), calculated using a discount rate (d) and the battery's lifetime (n). The annual cost of BESS on bus i is given by LC_{BESSi}, which factors in costs from the power conversion system (PCS), the unit cost of the battery, and system efficiency [20].

The methods also elaborate on calculating the annual benefits of using BESS for peak load shaving and voltage regulation. These benefits are derived from the unit levelized annual cost of gas combustion turbines for peaking power generation from $BESSi$ and the cost differential between peak and off-peak electricity rates during load shifting. Additionally, the saved operational and maintenance (O&M) costs from BESS usage are quantified by the reduction in annual operation times. The annual net cost of installing BESS for voltage regulation and peak load shaving is calculated by subtracting these benefits from the total annual cost, thereby defining the optimal BESS size that minimizes annual costs using Equation 2, which is applied across the distribution network.

$$AC_{BESSi} = LC_{BESSi} - B_{PPGi} - B_{PLSi} - B_{OLTC\&SVRi} \rightarrow (i = 201, \ldots 207) \quad (2)$$

Where LC_{BESSi} is the annual cost of installing $BESSi$ to regulate voltage and shave peak load, B_{PPG} is the annual benefit depending on the peaking power generation from $BESSi$. B_{PLSi} is the annual benefit for bus i from load shifting. $B_{OLTC\&SVRi}$ is the annual benefit as of the annual saved OLTC&SVR operation.

2.2. Predictive Operation and Optimal Sizing of Battery Energy Storage

The "predictive controller" method leverages Battery Energy Storage Systems (BESS) to tackle energy imbalances caused by wind energy, as sample, in the power grid. By using updated forecasts, it improves storage performance and reduces the required size. Simulated with a NaS battery, it outperforms other methods while a new battery lifetime estimation approach evaluates its impact on battery depreciation [21-22].

2.2.1. Problem Statement

This section discusses the primary purpose of integrating Battery Energy Storage Systems (BESS) with a large wind farm, which is to reduce wind power fluctuations. The use of BESS is assumed to be limited by the error between the wind farm's actual output and the day-ahead forecasted power. It further explores the modeling of a wind farm combined with BESS.

System Modeling:

where the power balance of a wind farm without BESS is expressed as:

$$P_{error}^{Sch}(k) = P^{Sch}(k) - P^{W}(k) \quad (3)$$

By adding a BESS, it can be improved as:

$$P_{error}(k) = P^{Sch}(k) - P^{W}(k) - P^{B}(k) \quad (4)$$

Grid-scale energy storage aims to reduce the error between predicted and actual wind farm output by compensating for shortages or storing excess wind energy. $PB(k)PB(k)$ is negative during charging and positive during discharging.

BESS Modelling

This section discusses BESS modeling, highlighting that SOC is calculated using prior values and the energy exchanged. SOC is constrained within specific limits, and charging/discharging efficiencies vary with several factors. Per-unit values aid scaling, and charging/discharging constraints prevent overloading, ensuring the BESS operates within capacity.

$$\mathrm{SOC}(k) = \mathrm{SOC}(k-1) - \frac{\eta(k-1)\cdot K \cdot P^B(k-1)}{12E^B_{\mathrm{rated}}}$$
$$\eta(k) = \begin{cases} \eta_c, & P^B(k) \le 0 \\ \eta'_d = 1/\eta_d, & P^B(k) > 0 \end{cases}$$
$$\mathrm{SOC}^{\min} \le \mathrm{SOC}(k) \le \mathrm{SOC}^{\max}. \tag{5}$$

Battery Lifetime Estimation

This paper proposes a method for estimating battery lifetime based on the number of cycles and the depth of discharge (DoD) of each cycle. It calculates the battery's lifetime by counting the DoD and total number of charging/discharging cycles within a given timeframe. Environmental factors like temperature and humidity, as well as the charging or discharging current rate, significantly affect battery longevity and performance [23]. The equation for this estimation is provided by:

$$L_{BESS} = \frac{T}{\sum_{i=1}^{m} \frac{N_i}{CF_i}} \tag{6}$$

The variables are defined as follows: T represents the simulation duration in years; CF_i indicates the number of cycles to failure for a particular depth of discharge (DoD); N_i specifies the count of cycles at each DoD; and m is the total number of DoD ranges considered.

2.2.2. Control Algorithm

The control algorithm for frequency regulation as detailed in the paper encompasses primary, secondary, and tertiary control steps, primarily engaging generators, frequency-responsive loads, and fast-acting energy storage devices. The primary focus is to compensate for imbalance errors within a minute-to-hour timeframe, aiming to enhance battery availability and diminish power mismatches. A strict simulation criterion is set with an error range of ±5% being acceptable 90% of the time. In the discussed section, a simple controller and a novel predictive control strategy are introduced. The minute-by-minute control, a standard in current Battery Energy Storage Systems (BESS), operates based solely on the discrepancy between forecasted power a day ahead and actual wind generation. The system reacts only if the error exceeds or drops below 0.05 per unit by either sinking power to the grid or charging the BESS, respectively, with no penalty applied to minor mismatches within this range [24-25].

The paper also introduces a predictive control strategy to regulate the BESS's charge/discharge rate, ensuring the bus voltage remains between 0.95 and 1.05 per unit. This strategy adapts to the network's characteristics and specifies a 5% error margin for simulations. Predictive control utilizes a receding horizon approach, continuously solving and updating the control problem based on forecasted future states of variables, constraints, and disturbances. This method involves solving the control problem at each time step over a fixed horizon, applying the immediate control input, and then shifting the prediction horizon for the next step. This ongoing adjustment process is vital for maintaining network stability and reliability, especially as renewable energy penetration increases and potentially necessitates new market standards and policies. The basic concept of this predictive control is shown in Figure 3.

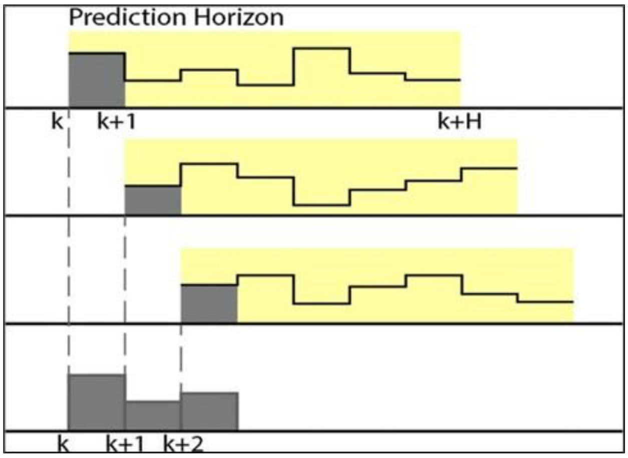

Figure 3 Model predictive scheme using receding horizon

To conserve energy for upcoming time intervals, the controller reduces the Battery Energy Storage System's (BESS) output if the anticipated energy demand exceeds its capacity. A control coefficient (K), determined by the latest forecast data, helps regulate the BESS output. Energy surplus or deficit predictions for the next 2-3 hours are calculated using updated data at intervals of 5, 10, or 20 minutes. More frequent updates provide a clearer forecast of wind generation. K is set at each time step to maximize energy conservation based on upcoming energy requirements. When the battery charge is adequate, the controller employs a minute-by-minute strategy. The proposed method is illustrated in a block diagram in Figure 4. While the "payoff and penalty" block does not directly provide feedback to the controller, it can be used to economically assess the Battery Energy Storage System (BESS).

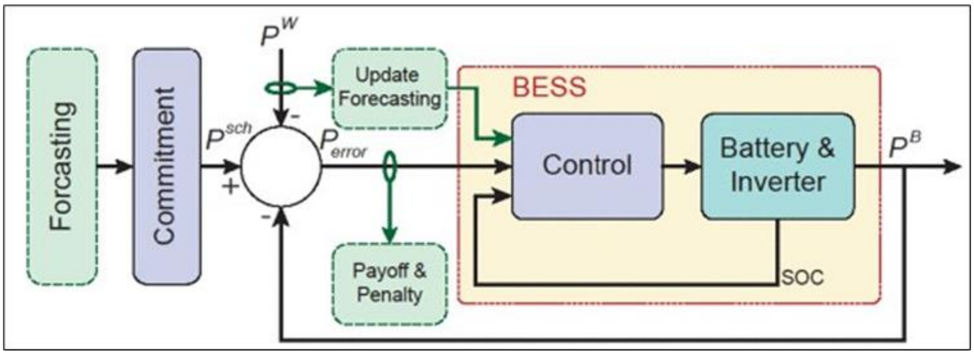

Figure 4 Block diagram of using predictive control in wind production commitment. The controller uses SOC, updated wind data, and $P_{error}(k)$.

2.3. Optimal Sizing and Selection of Energy Storage System Considering Load Uncertainty

An optimization model is introduced to employ nonlinear programming to determine the ideal size of an energy storage system while considering operational constraints and costs. It uses hourly generation data from a solar farm and load demand to compare results between normal and probabilistic load conditions. The probabilistic data is generated through Monte Carlo Simulation. The study underscores the influence of load uncertainty on energy storage system sizing and advocates for the use of probabilistic load data for more accurate analysis [26-27].

To determine the optimal size of an energy storage system, the operation is framed as an optimization problem focused on minimizing system costs. The model uses nonlinear programming within a 24-hour period and considers a renewable energy farm linked to the grid through a transmission line with assumed unlimited capacity. The energy storage system is modeled to activate instantaneously upon starting. The optimization aims to minimize the total cost by factoring in 24-hour energy generation, load demand, efficiency constraints, and other limitations applicable to both deterministic and probabilistic load demands. Developed in the General Algebraic Modeling Software (GAMS) and solved using the CONOPT solver, the model calculates the objective function by minimizing costs based on the energy and power capacity limits and per-unit energy and power costs. The model balances the energy generated by the solar farm and the energy demanded, guided by specific equality and inequality constraints. Equations (7) and (8) enforce energy balance in the system, while Equation (9) ensures that the stored energy level remains positive and exceeds the energy delivered. Equation (10) determines whether generated energy is stored or sent directly to the grid. Equation (11) prevents simultaneous charging and discharging of the storage system. Equations (12) and (13) limit the energy delivered and stored to stay below the power-related capacity of the system and maintain positive energy storage. Lastly, Equation (14) ensures that the stored energy at any time doesn't exceed the energy storage system's depth of discharge (DOD).

$$En_{de}(\mathrm{t}) = En_{gen}(\mathrm{t}) + En_{del}(\mathrm{t}) - En_{str}(\mathrm{t}) \quad (7)$$

$$En_{dem}(\mathrm{t}) = En_{del}(\mathrm{t}) + En_{grd}(\mathrm{t}) \quad (8)$$

$$En_{sl}(\mathrm{t}) = En_{slv}(\mathrm{t}-1) + (En_{str}(\mathrm{t}) \times Ef) - En_{del}(\mathrm{t}) \quad (9)$$

$$En_{gen}(\mathrm{t}) = En_{grd}(\mathrm{t}) + En_{str}(\mathrm{t}) \quad (10)$$

$$En_{str}(\mathrm{t}) \times En_{del}(\mathrm{t}) = 0 \quad (11)$$

$$En_{del}(\mathrm{t}) \leq En_{cap} \quad (12)$$

$$0 \leq En_{slv}(\mathrm{t}) \leq P_{cap} \quad (13)$$

$$En_{sl}(\mathrm{t}) \leq En_{cap}|DOD \quad (14)$$

The model uses specific variables to describe the energy flows: $Endem$(t) denotes the energy demand at time t, $Engen$(t) represents the energy generated by the solar farm, $Endel$(t) refers to the energy delivered by the storage system, $Enstr$(t) is the energy stored in the storage system, $Engrd$(t) indicates the energy sent to the grid by the storage system, $Enslv$(t) measures the energy level of the storage system in megawatt-hours (MWh), and Ef defines the round-trip efficiency of the storage system.

Load demand uncertainty is a significant challenge in power systems, stemming from factors like fluctuating consumer energy use patterns, unscheduled outages, and measurement errors. To evaluate and predict this uncertainty, probabilistic load modeling utilizes a normal probability density function (PDF). The load probability at each hour is treated as a random variable with a normal distribution, characterized by a specified mean and variance derived from historical or statistical data. Monte Carlo Simulation (MCS) generates deterministic outputs, with the most probable load value identified by mapping sample frequencies to likely load levels. This method captures the probabilistic nature of load demand, aiding in effectively planning the operation and management of the power system.

3. Comparison of different methods

Renewable energy sources like wind and solar have seen a significant uptick in power systems. However, their intermittent nature necessitates energy storage systems (ESS) to ensure a stable and reliable power supply. Battery energy storage systems (BESS) are a popular solution because of their high efficiency, rapid response time, and relatively low cost. In this section, we'll analyze and compare the methods and results of three methods focused on optimizing the size of BESS across different scenarios.

3.1. Sizing Strategy of Distributed Battery Storage System with High Penetration of Photovoltaic for Voltage Regulation and Peak Load Shaving

3.1.1. Methods and Criteria

This study introduces a sizing strategy for distributed battery storage systems aimed at regulating voltage and reducing peak loads in systems heavily reliant on photovoltaic (PV) power. The strategy employs a two-stage optimization method to determine the optimal battery storage size by minimizing the system's total annualized cost. The criteria for sizing are based on the system's requirements for voltage regulation and peak load shaving. The authors propose a method for calculating the optimal battery size by evaluating the net present value (NPV) over the system's lifetime. The simulation of the battery and PV generation system is conducted using MATLAB/Simulink, modeling the battery storage system, PV power generation, load, and distribution network. However, the specific energy storage system (ESS) used remains unspecified, and photovoltaic power is the primary energy source.

3.1.2. Storage Type and Findings

The study demonstrates that the proposed sizing strategy effectively manages voltage regulation and peak load shaving in systems with significant photovoltaic penetration. It also reveals that the optimal battery storage size is influenced by the load profile and the level of photovoltaic penetration. A notable advantage of this strategy is its focus on the cost of maintaining system reliability, resulting in more precise sizing of the storage system. However, the study's limitation is its omission of the impact of battery degradation on the optimal size calculation.

3.2. Predictive Operation and Optimal Sizing of Battery Energy Storage with High Wind Energy Penetration

3.2.1. Methods and Sizing Criteria

The proposed method employs a predictive control approach to optimize the operation of battery energy storage systems (BESS) and determine the optimal BESS size for a specific level of wind energy penetration. This method uses a model predictive control (MPC) algorithm that formulates the optimization problem as a quadratic programming (QP) issue. The solution is then obtained using the interior-point method. The sizing criteria focus on minimizing the levelized cost of energy (LCOE), which accounts for capital and operating costs, as well as revenue from energy sales. The objective is to minimize LCOE while ensuring the BESS can deliver the required power and energy capacity at the specified wind energy penetration level.

3.2.2. Storage Type and Findings

The study employs Sodium-Sulfur (NaS) batteries, with wind power as the energy source. Results indicate that the proposed method optimizes BESS operation and identifies the optimal size for a given level of wind energy penetration. The optimized BESS size reduces LCOE by up to 27% compared to a baseline case without energy storage. Additionally, the MPC algorithm accurately predicts wind power output, facilitating effective BESS operation. The predictive control approach provides an advantage by dynamically adjusting BESS operations based on fluctuating wind power output, offering a framework to determine the optimal BESS size for different wind energy penetration levels. However, the MPC algorithm's relatively high computational cost may hinder its application in real-time control scenarios.

3.3. Optimal Sizing and Selection of Energy Storage System Considering Load Uncertainty

3.3.1. Methods and Sizing Criteria

The article presents a mathematical model to optimize the sizing and selection of an energy storage system (ESS), accounting for load uncertainty in a microgrid. This two-stage approach starts by analyzing load uncertainty to determine the appropriate ESS type and capacity. In the second stage, a Monte Carlo simulation identifies the optimal location for the ESS and estimates its capacity. The primary objective is to minimize the total cost of the ESS while ensuring reliable and sustainable microgrid operation. The sizing criteria focus on energy demand, load duration, round-trip efficiency, and battery cycle life. The model also incorporates Monte Carlo simulations to analyze load uncertainty and evaluates the reliability requirements of the microgrid.

3.3.2. Storage Type and Findings

The study concentrates on Lithium-ion (Li-ion) batteries as the ESS due to their high energy density, long cycle life, and minimal maintenance needs. Various energy sources—solar PV, wind turbines, and diesel generators—are modeled based on availability and output power to supply the microgrid. The results reveal that the optimal sizing and selection of the ESS depends on load uncertainty, available energy sources, and the reliability requirements of the microgrid. Li-ion batteries are found to be the most cost-effective ESS for the considered microgrid. The model effectively factors in load uncertainty, available energy sources, and the reliability demands of the microgrid, providing a comprehensive strategy for optimal ESS selection. Li-ion batteries offer significant benefits, including high energy density, long cycle life, and low maintenance. However, the model assumes continuous energy source availability, which isn't always realistic. Additionally, it doesn't consider the effects of ESS sizing and selection on microgrid power quality.

4. Conclusion

Based on the comparison of these three methods, it is evident that battery sizing optimization for renewable energy systems is a complex and multifaceted issue that requires consideration of a range of factors such as energy sources, storage types, simulation platforms, and sizing criteria. The studies demonstrate that accurate and efficient optimization algorithms are necessary to ensure the optimal sizing of energy storage systems that can effectively manage power fluctuations and improve the reliability of the power grid. Furthermore, the findings of these studies suggest that there is no one-size-fits-all approach to battery sizing optimization, as each method has its strengths and weaknesses. However, a common trend among all studies is the need to incorporate uncertainties and dynamic conditions into the optimization process to ensure the resilience of the power grid. Looking forward, battery optimization solutions will continue to evolve with the development of new technologies and algorithms. For instance, there is a growing trend towards incorporating machine learning and artificial intelligence techniques to improve the accuracy of predictions and enhance the optimization process. Additionally, advancements in battery technology and data analytics will likely lead to the development of more efficient and cost-effective battery sizing optimization solutions. In summary, the studies reviewed demonstrate the importance of accurate and efficient battery sizing optimization for renewable energy systems. The use of a range of methods, including heuristic and mathematical optimization, highlights the complexity of the problem and the need for further research in this area. As new technologies and algorithms emerge, it is likely that the accuracy and efficiency of battery optimization solutions will continue to improve, leading to a more resilient and reliable power grid.

Compliance with ethical standards

Disclosure of conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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