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# Modeling and Optimization Methods for Controlling and Sizing Grid-Connected Energy Storage: A Review

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## Abstract

**Purpose of Review** Energy storage is capable of providing a variety of services and solving a multitude of issues in today's rapidly evolving electric power grid. This paper reviews recent research on modeling and optimization for optimally controlling and sizing grid-connected battery energy storage systems (BESSs). Open issues and promising research directions are discussed.

**Recent Findings** Recent studies on BESS dispatch, evaluation, and sizing focus on advanced modeling and optimization methods to maximize stacked value streams from multiple services. BESS models have been improved to better represent operational characteristics or capture degradation effects. Different solution methods and optimization techniques have been proposed to improve the benefits and cost-effectiveness of BESSs, using deterministic approaches prevalently but with impressive progress in modeling and addressing uncertainties.

**Summary** Recent progress in BESS scheduling and sizing better supports planning and operational decision-making in different use cases, which is highly important to advance the deployment of BESSs. Additional research is required to properly model the trade-off between short-term benefits and service life with multiple degradation effects explicitly considered in the decision-making process. Advanced methods are to be developed for effectively determining optimal BESS sizes that maximize overall benefits within a varying lifetime considering diversified system conditions, as well as uncertainties at planning and operational stages.

**Keywords** Battery degradation · Bundling grid services · Energy storage · Modeling · Optimal dispatch · Sizing · Stochastic optimization

## Introduction

Battery energy storage systems (BESSs) are flexible and scalable, and can respond instantaneously to unpredictable variations in demand and generation. They can provide a variety of services for bulk energy, ancillary, transmission, distribution, and customer energy management [1, 2]. The development and deployment of grid-connected BESSs have been gathering momentum, especially with the increasing penetration of renewable generation. As the technology has advanced [3], many demonstrations and deployments have been realized [4], and the regulatory structure is emerging [5]. For example, the Federal Energy Regulatory Commission (FERC) issued Order 755 in 2011, requiring ISO/RTO markets to compensate resources that can provide faster-ramping frequency regulation. As a result, 75% of large-scale battery storage power capacity in the U.S. provided frequency regulation in 2018. In February 2018, FERC issued Order 841 to further remove barriers that had prevented the efficient deployment of battery storage resources [6]. Clearly, developing less expensive and safer storage devices with longer cycle life is of great importance. There are quite a number of

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facilities demonstrating the technical feasibility of storage technologies, but few of these are truly cost-effective commercial ventures. Value streams must be identified and appropriately monetized. Considering the cost of a battery at current market rates, it will become necessary to capture multiple value streams simultaneously for a project to be financially viable.

Optimal dispatch and sizing considering Bundling services is the key to maximize benefits and enhance cost-effectiveness of BESSs. Economic benefits of a BESS highly depend on its operational characteristics and physical capability. Charging control could be extremely complicated due to the competition among various services for limited power and energy capacity, not only on a time step but also intertemporally more-energy discharged in the current hour, less is available for future hours. In addition, battery charging and discharging profiles have a direct impact on the battery degradation and loss of life. Frequent charging/discharging helps increase short-term benefits but accelerates degradation. Optimal strategies are needed to maximize total economic benefits within the battery lifetime, considering multiple degradation effects in the decision-making process. The problem becomes even more complicated when a BESS needs to be optimally sized with an objective to not only maximize the net benefits but also consider resilience performance. When incorporating uncertainties into BESS scheduling and sizing in addition to capturing diversified system conditions, these problems become extremely challenging to solve due to the complexity of uncertainty models and/or increased size of the optimization problem.

Many studies have been dedicated to this topic during the last few years. BESS models with different levels of complexity and fidelity are proposed and used. Problem formulation and solution methods largely depend on applications to be considered. This paper presents taxonomies for classifying modeling and solution methods for grid-connected BESSs, reviews existing studies in the context of the taxonomies, and discusses open issues and promising research directions.

## Modeling Methods

Technical characteristics and physical capability need to be appropriately modeled when scheduling, evaluating, or sizing a BESS for grid applications. For example, the rated power capacity of a BESS limits its ability to interact instantaneously with the grid. The energy capacity limits its capability to shift energy over time. The charging and discharging profiles have a direct impact on loss of life and degradation in performance, affecting strategies of using a BESS for grid services over its service life. Note that in addition to battery storage, a BESS also includes other elements, such as monitor and control, protection, thermal management, and power conversion systems. In BESS scheduling and evaluation studies, black- or grey-box models at the system level are generally preferred over individual component models to avoid unnecessary details, maintain modeling simplicity, and improve computational efficiency.

**Table 1** Existing studies grouped by BESS modeling methods

| | | Degradation effects | | |
|---|---|---|---|---|
| | | No | Loss-of-life | Full model |
| Operational Characteristics | Simplified | [7–30] | [31–43] | [44–46] |
| | High-fidelity | [47–50] | [51] | [52] |

A BESS can be represented as a dynamical system with two kinds of state variables to capture temporal interdependency of charging/discharging operations:

- State of charge (SOC) or energy state is a state variable that is used to describe the fast dynamics of present energy level.
- Several state of health (SOH) or degradation state variables are used to describe the slow dynamics of capacity loss associated with battery aging.

Modeling methods for representing operational characteristics and capturing degradation effects are summarized and classified as follows. Existing studies are grouped by BESS modeling method in Table 1.

## Operational Models

BESS operational models describe how a BESS can be operated using charging/discharging power and SOC. SOC is defined as the ratio of energy level to energy capacity (the usable energy from a fully charged BESS). The SOC dynamics characterize how the charging and discharging power affects future SOC. A BESS's charging/discharging power is limited by the rated power capacity and could also depend on SOC. BESS operational models can be classified into two types that are described as follows.

### Simplified Linear Systems

Most existing BESS scheduling and evaluation studies are based on a scalar linear system that resembles a simplified dynamics of energy state parameterized by static charging and discharging power limits, energy or SOC limits, and constant efficiencies. These models are also characterized by static power and energy capabilities that are independent of SOC. Some studies are based on a constant round-trip efficiency (RTE) model to capture electrical and other losses, such as [11, 24, 39]. However, the same RTE with different one-way efficiencies may lead to different optimal operating schedules. More importantly, by using an RTE only, one cannot accurately estimate SOC during charging or discharging and therefore could obtain an operating schedule that cannot be followed. Modeling one-way efficiencies is straightforward using conditional expressions as shown in studies such as [15, 35, 43]. Nevertheless, the conditional expressions cannot be directly integrated into standard mathematical programming. One common method to work around this is to introduce two non-negative auxiliary variables representing charging and discharging power and thereby capture losses associated with charging and discharge separately. Simultaneous charging and discharging lead to "fictitious" consumption of energy in a BESS with non-ideal efficiencies. Such kind of solutions are physically unrealizable. To address this problem, studies such as [13, 14, 38] introduce binary variables to avoid charging and discharging at the same time. An alternative method is to add complementarity constraints where the product of charging and discharging power at any time must be equal to zero, as shown in [22]. Note that a solution with simultaneous charging and discharging is not optimal for many practical applications because it causes unnecessary losses [19, 23]. In those cases, binary variables and complementarity constraints can be ignored, as adopted in many studies such as [8, 9, 44]. In cases where simultaneous charging and discharging could be an optimal solution, relaxation of complementarity constraints can be used [18, 53].

### High-Fidelity Systems

The simplified scalar linear model is easy to use but subject to several disadvantages and limitations. First, the power capability generally depends on SOC, but is completely ignored in the simplified models. In addition, the rate of change of SOC depends on not only charging/discharging power but also SOC. Furthermore, the charging/discharging efficiency also varies with SOC and power, whereas constant efficiencies are assumed in the simplified models. Several studies are dedicated to building generalized high-fidelity models into BESS scheduling and evaluation. The high-fidelity models can be a set of lookup tables or analytical expressions, as reported in [47–50, 52]. Such types of models can be constructed using manufacturer's specifications, test data, or existing empirical models. Regression techniques are commonly used to generate lookup tables or determine modeling parameters [50]. Note that depending on the characteristics of BESSs, high-fidelity models can be linear systems that well represent varying efficiencies, varying power capability, and SOC change rate as functions of power and SOC. These high-fidelity models help improve accuracy but increase computational burden and complexity when non-linearity is introduced.

## Degradation Models

Battery life is a measure of battery performance and longevity, which can be quantified in two ways: calendar and cycle life. Calendar life is the elapsed time before a battery becomes unusable whether it is in active use or inactive. It reflects a battery's inherent degradation over time. Cycle life is defined as the number of cycles a battery can perform before its nominal capacity falls below a certain percentage of its initial rated capacity. It depends on several factors such as depth of charge, discharging rate, and ambient temperature. Many existing studies for BESS scheduling and evaluation assume fixed lifespan to capture calendar aging, without explicitly modeling cycle aging. As a result, the value of a BESS may be overestimated when the battery needs to be retired earlier than its calendar life due to accelerated cycle aging. Degradation models describe how different operations affect the aging of cycle life, energy capacity, and resistance of a BESS. Most scheduling and evaluation studies that involve degradation models are based on simplified loss-of-life calculation. There are few studies that employ models to fully capture aging effects, including degradation in performance. Two types of degradation models are summarized as follows.

### Loss-of-life Models

The cycle life of a battery can be measured using either (a) total amount of energy in kilowatt hours that can flow throughout it or (b) the number of times it can be cycled before it needs to be replaced. The loss-of-life calculation depends on multiple factors, such as number of cycles, depth of cycles, and amount of energy charged and discharged. When capturing loss of life associated with different charging and discharging operations, almost all existing studies introduce an aging or degradation cost to transform the long-term installation cost to the short-term operational cost. In practice, irregular charging-discharging cycles make it difficult to count the number of life cycles and the corresponding energy throughput. Approximation methods are typically used. Given the lifetime throughput energy, the degradation cost per kilowatt hour of discharged energy can be estimated [34, 35]. Alternatively, given the number of cycles to failure at different depth of discharge (DOD), the corresponding degradation cost per cycle can be calculated [32, 43]. Aging cost can also be approximated as a piecewise linear function of charging/discharging power [31, 39], DOD [38, 40, 42], or both [35].

### Full Degradation Models

In addition to loss of life, charging and discharging operations over time also slowly impact the performance of a BESS, including reduced capacity and increased resistance, and thereby affect how a BESS will be used in future years and the corresponding benefits. The fading capacity and growing loss could significantly affect BESS scheduling strategies and evaluation results, but have not been well considered in charging control in existing studies. Some studies such as [44, 46] explicitly model dynamics of energy capacity to more accurately calculate degradation cost or limit the number of cycles within the calendar life. Other works such as [45] evaluate BESS capacity degradation via a post-processing step. An existing degradation-cost-based dispatch strategy can prevent charging/discharging operations with benefits less than the cost associated with loss of life, but does not necessarily maximize the total benefits over a BESS's useful lifetime. In other words, the degradation effects are not appropriately modeled to capture the reduced benefits in future years as an opportunity cost of cycling a BESS to maximize short-term benefits.

## Use Cases and Optimization Methods

The benefits from a BESS depend on how it is scheduled and dispatched to provide different services. The operational flexibility and degradation models describe feasible charging and discharging operations. Charging control needs to be designed to optimally use a BESS to maximize the total benefits from multiple grid services in both operational scheduling and long-term planning studies. Requirements and rules could be very different from one service to another. Objective functions and constraints need to be designed to properly model each service in different use cases. In addition, it is also necessary to capture the coupling among different services and their dependence on scheduled operation and capability to deviate from the scheduled baseline. Due to the temporal interdependency of BESS operations, multi-period optimization is almost a must. The problem formulation and solution methods largely depend on the nature of the problem. This section summarizes different use cases, problem types, solution methods, and optimization techniques in existing BESS scheduling, evaluation, and sizing studies. Table 2 groups these studies by problem type, number of applications, and solution method.

### Use Cases

While a BEES can provide Bundling grid and end-user services, many studies focus on a single application, such as [13, 51, 55] on energy arbitrage or energy cost reduction, [15, 34] on microgrid cost reduction, and [56] on frequency regulation. Considering the cost of batteries at current market rates, value streams from multiple applications are extremely important for a BESS project to be financially viable. Scheduling and evaluation of a BESS to capture stacked value streams has been a focus during the past few years. Energy arbitrage and frequency regulation are the two applications that are often considered simultaneously for grid-scale BESSs in existing studies such as [11, 37, 39]. As for behind-the-meter services, energy and demand charge reduction are commonly considered together [16, 20]. There are also studies that consider three or more services at the same time such as [9, 24, 31]. Several papers such as [27, 29, 41] are dedicated to the use of BESSs to simultaneously generate economic benefits and improve system resilience.

### Problem Types

From the perspective of time frame, existing studies can be classified into two groups:

– short-term operation (scheduling and dispatch)
– long-term planning (evaluation and sizing)

In operational scheduling studies such as [22, 38, 43, 47], model predictive control (MPC) problems are formulated over a short period of time, typically a day, to make charging/discharging decisions at each time step. This type of studies focus on BESS scheduling and dispatch methods, without any cost-benefit analysis over a long-term or battery life. Nevertheless, these methods can be used to repeatedly

**Table 2** Existing studies grouped by problem type, number of applications, and solution method

| | | Mathematical programming | | Other methods | |
|---|---|---|---|---|---|
| | | Deterministic | Stochastic | Deterministic | Stochastic |
| Operational Scheduling | Single application | [18, 32, 34] | [13, 22, 38] | [12, 19, 21] | [35, 43, 51] |
| | Multiple applications | [7, 23, 31, 46, 47] | [17, 24, 40] | [48, 49] | [25, 37] |
| Evaluation or Sizing | Single application | [14, 44] | [10, 36] | [33, 42] | [26, 28, 54] |
| | Multiple applications | [9, 11, 15, 16, 39] | [27, 29] | [20, 30, 48, 50] | [41, 45] |

schedule and simulate BESS hourly and daily operations over one or multiple representative years and thereby to estimate the present value of net benefits. Such a strategy is popular in many BESS evaluation studies, such as [9, 11, 39, 50]. Some other evaluation studies such as [11, 16] formulate the value assessment problem as an optimization by explicitly modeling BESS operations over a longer period (such as a month or year) in which diversified loading conditions and varying prices are captured.

While rated capacity and maximum charging are given in optimal scheduling and evaluation studies, sizing problems aim to identify the optimal BESS sizes to maximize the net benefits, considering the trade-off between benefits and cost. Optimal dispatch and/or charging/discharging control rules are generally involved to capture how the net-benefits vary with BESS size. These problems are generally more challenging to solve. To simplify the problem, simplified linear operation models are commonly used. In addition, degradation effects are not considered, or simply represented by degradation cost functions. To further simplify the problem, many sizing studies such as [14, 15, 44] only consider a short time frame or a few operation snapshots instead of a large number of diversified system operating conditions.

## Solution Methods

Value from a BESS depends on how it is used. It is desirable to find the best way to charge and discharge a BESS and thereby maximize the economic benefits from one or multiple applications. Optimization problems need to be formulated and solved based on BESS operational characteristics and degradation models while capturing the coupling among different applications. There are different approaches for optimally scheduling and sizing a BESS.

Most existing studies are based on mathematical programming methods, where the scheduling and sizing problems are formulated as standard programming problems (e.g., linear and convex programming) and then solved using off-the-shelf solvers. While almost all of these problems involve non-linear terms and logical expressions, optimization modeling techniques such as piecewise linear approximation, convex relaxation, and Big-M method can be used to generate their linear or convex equivalents or approximation. Linear programming (LP) is the most popular method that is used in many existing studies such as [9, 39, 44, 46]. Often, binary variables are introduced to represent generator on/off and battery charging/discharging status as well as the selection of options in different use cases, resulting in mixed-integer LP problems, such as the ones formulated in [14, 29, 38]. There are also studies based on convex optimization such as quadratic programming in [7], second-order cone programming [18], and conic programming [22].

Dynamic programming (DP) and reinforcement learning (RL) are also used for BESS scheduling and evaluation, especially when non-linear characteristics and constraints are involved. While the original engineering problems are described by continuous variables, DP and RL find approximate solutions in the discrete space. In these methods, BESS scheduling and evaluation problems are formulated as a Markov decision process. At each time step, given the current SOC, a BESS is charged/discharged according to a control policy and transits into a new SOC. The goal is to find a charging control policy that maximizes the cumulative benefits. Examples that are based on DP algorithms include [35, 49, 50]. To solve the curses of dimensionality of DP, approximated dynamic programming (ADP) algorithms have been proposed in [26, 28] for energy storage scheduling problems. While DP algorithms are model-based, RL can be seen as model-free or sample-based. Several RL algorithms have been developed for BESS scheduling [43, 51].

MPC is a standard method used to perform iterative and finite-horizon optimal dispatch of a BESS. One main advantage of MPC is that the model prediction allows to formulate system constraints explicitly in the optimal control policy design. At each time step, one solves a finite-horizon optimal dispatch problem online and updates system states. The iterative scheduling and dispatch process helps implicitly address uncertainties to some degree. Such a strategy has been employed in many studies, such as [9, 47, 48].

As for BESS sizing, one popular method is to formulate standard mathematical programming problems in which BESS energy and power capacity are treated as decision variables and the net benefits become the objective function to be maximized [14, 16, 44]. Bilevel optimization is an another approach for optimal sizing [30, 54], where the lower-level evaluation of a given size of BESS is embedded within the upper-level size searching problem. Searching algorithms such as gradient-based methods, particle swarm optimization, and genetic algorithm are often used at the upper level. Analytical approaches have also been proposed for BESS sizing in existing studies, such as [20, 42], based on an objective quantitative analysis of cost and benefits. Such kinds of methods identify key factors that affect optimal sizing and directly link the optimal sizes to input parameters.

Note that a large body of literature is based on deterministic methods using historical or representative system data, without explicitly modeling and addressing uncertainties associated with system load, renewable generation, and prices. In practice, scheduling and sizing decisions need to be made under uncertainties. Stochastic programming [24, 43], chance-constrained optimization [36, 40], ADP [26, 28], and robust optimization [17, 38] are popular methods for handling uncertainties in BESS scheduling and sizing problems. Reference [57] provides stochastic optimization canonical modeling framework and four fundamental classes of policies that encompass all the competing solution approaches. In addition to centralized approaches where a single control center gathers information from and provides control signals to the entire system, a number of distributed alternatives have been proposed for BESS operational scheduling [12, 19, 21]. In these algorithms, each coordination agent only maintains a set of variables and updates them through information exchange with a few neighbors.

## Discussion

Most existing studies focus on formulating BESS scheduling, evaluation, and sizing problems into standard mathematical programming through innovative linearization or relaxation methods. Simplified BESS models are commonly used. Optimal charging/discharging methods based on more accurate non-linear models are studied less often. Modeling methods to fully capture degradation effects are underexplored. How to explicitly build high-fidelity models and degradation effects into sizing process remains an open question. Even with simplified BESS models, sizing problems are computationally intensive and difficult to solve. This is why many sizing studies only consider a short time frame or a few operation snapshots that cannot fully represent diversified system operating conditions.

While centralized deterministic methods are prevalent, promising methods have been developed in recent years to make decisions in a distributed manner or to address uncertainties, especially for operational scheduling. While distributed control can help to overcome disadvantages of centralized control, additional efforts are required to develop more robust and efficient algorithms. Incorporating uncertainty at both the long-term planning stage and the short-term operational stage into evaluation and sizing would enhance the understanding of practically achievable BESS benefits, is yet to be developed. This would require computationally efficient multi-stage stochastic optimal sizing methods with uncertainties at different stages properly modelled.

One important problem that is largely ignored in the literature is how to optimally distribute battery cycle life over years. Degradation cost associated with loss of battery life is well considered in the existing literature. The optimal dispatch is determined by maximizing the difference between the revenue and the corresponding degradation cost within a day or a year. One main disadvantage of such kinds of methods is that they do not necessarily maximize the total benefits over a BESS's useful lifetime. For example, using these methods, a BESS may be cycled in some hours even though the returned revenue is just slightly higher than the degradation cost. The battery life could be saved for future more profitable operations. In other words, the degradation-cost-based dispatch methods fail to model the temporal interdependency of the use of a BESS over its useful lifetime and tends to overuse a BESS in early years, leading to suboptimal solutions. It seems that coupling SOC and SOH dynamics need to be modeled for maximize the benefits from a BESS. In addition, strategies and rules need to be developed to guide operational scheduling considering the loss of potential gain from high-value services in future years.

## Conclusions

In this paper, we provided an overview and critical review of existing modeling and optimization methods for BESS scheduling, evaluation, and sizing. Existing models for describing BESS operational characteristics and degradation effects were summarized, classified, and compared. The advantages and shortcomings of different modeling methods were highlighted. In addition, existing studies were grouped based on problem type, number of applications, and solution method. Key solution methods and optimization techniques were summarized. Finally, we discussed open issues and promising research directions.

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### Declarations

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