

# Energy-Storage Modeling: State-of-the-Art and Future Research Directions

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**Abstract**—Given its physical characteristics and the range of services that it can provide, energy storage raises unique modeling challenges. This paper summarizes capabilities that operational, planning, and resource-adequacy models that include energy storage should have and surveys gaps in extant models. Existing models that represent energy storage differ in fidelity of representing the balance of the power system and energy-storage applications. Modeling results are sensitive to these differences. The importance of capturing chronology can raise challenges in energy-storage modeling. Some models ‘decouple’ individual

operating periods from one another, allowing for natural decomposition and rendering the models relatively computationally tractable. Energy storage complicates such a modeling approach. Improving the representation of the balance of the system can have major effects in capturing energy-storage costs and benefits.

**Index Terms**—Energy storage, power system operations, power system expansion planning, power system economics, modeling

## I. INTRODUCTION

**T**HIS paper surveys needs in energy-storage modeling. This guidance is needed because energy storage represents modeling challenges that do not apply to most other power-system assets. These challenges arise from the physical characteristics of energy storage and range of services that it can provide. Existing models have a subset of our desirable capabilities, leaving gaps that can be filled with further research. We have a specific aim of informing the research community on these needs. The important issue of translating research advances into commercial software tools and industry dissemination is beyond our scope.

We examine operational, planning, and resource-adequacy modeling. A defining characteristic of operational models is that they capture the operation of a power system with a fixed asset mix. Planning models optimize the mix of resources to add to or remove from a power system. Resource-adequacy models focus on meeting system-reliability targets.

The remainder of this paper is organized as follows. Section II discusses contexts for energy-storage use. Section III provides an overview of challenges in energy-storage modeling and model desirables, which pertain to most of the model types that we survey. Section IV discusses energy-storage valuation. Section V surveys the state-of-the-art in energy-storage modeling and discusses gaps that are specific to each model type. Section VI concludes.

## II. CONTEXTS FOR ENERGY-STORAGE USE AND MODELING

We identify three possible energy-storage users, their potential objectives, services that energy storage can provide,

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and pertinent model types. Planners and operators minimize the cost or maximize the reliability of a power system. Such entities may compare energy storage to other resources as part of a least-cost plan *via* planning tools, including capacity-expansion, resource-adequacy, and production-cost (PCM) models. A wholesale-market participant may seek to maximize profit, which can be evaluated using a price-taking model (using historic or forecasted prices), a PCM (estimating future prices), or a strategic-behavior model (*e.g.*, capturing price-making behavior). Behind-the-meter (BTM) customers aim to minimize their retail costs, which can be estimated using a price-taking model with retail tariffs. There are also hybrid combinations, *e.g.*, a BTM customer may share energy storage with an aggregator, which uses part of the capacity in the wholesale market. Such a use of energy storage would yield a combined objective of minimizing costs and maximizing revenue. Energy-storage applications that are not market-priced require a comparison to cost-of-service alternatives.

In addition, policymakers, regulators, or market designers may model energy storage. For instance, a PCM could examine proposed energy-storage projects or a strategic-behavior model could analyze potential market or policy reforms.

### III. CHALLENGES AND DESIRABLES IN ENERGY-STORAGE MODELING

#### A. Generic Modeling Considerations

We begin with generic modeling issues that are not unique to energy storage. Validation against actual outcomes, which is not possible for all model types, is one consideration. Validation can be conducted reflectively, *e.g.*, ensuring that a model captures the rules, constraints, and financial settlements of the power system or market in question. If possible, comparing simulated results to an actual energy-storage project with similar characteristics can be valuable [1].

Cross-model comparison can illustrate the value of different model formulations, which raise context-specific trade-offs between fidelity and tractability [2]–[4]. Individual resources included in a system-wide model may be represented with limited details relative to stand-alone modeling of those resources. Another consideration is selecting a model that is well suited to the study question. Model detail depends also on available time (*e.g.*, operational versus planning applications).

#### B. Multi-Timeframe Modeling

Energy-storage technologies have a range of power and energy (duration) capacities and response rates [1]. Markets operate and clear with different temporal horizons and resolutions. These properties and the range of services that it can provide may require modeling energy storage across multiple timeframes. Multi-timeframe modeling remains an outstanding challenge, which could be addressed, *e.g.*, using an integrated multi-scale model or by decomposing the problem with a suite of models. A related challenge is to bridge the gap between the timescales of markets and energy-storage operations.

<sup>1</sup><http://www.energystorageexchange.org/>

#### C. Energy-Storage Model ‘Desirables’

1) *Representing Energy-Storage Capabilities:* A model should capture technical energy-storage capabilities, so long as the benefit of detail outweighs the cost of inclusion. Some energy-storage technologies may entail modeling power electronics, including dc/ac conversion and control of real- or reactive-power. The minimum of energy-storage modeling is:

$$s_t = (1 - \eta^s)s_{t-1} + \Delta^t p_t^c / \eta^c - \Delta^t \eta^d p_t^d, \forall t \quad (1)$$

$$s^{\min} \leq s_t \leq s^{\max}, \forall t \quad (2)$$

$$0 \leq p_t^c \leq p^{c,\max}, \forall t \quad (3)$$

$$0 \leq p_t^d \leq p^{d,\max}, \forall t. \quad (4)$$

Equalities [1] calculate,  $\forall t$ , time- $t$  state of energy (SOE) [2]  $s_t$ , in terms of time- $(t - 1)$  SOE and time- $t$  charging and discharging,  $p_t^c$  and  $p_t^d$ , respectively.  $\eta^s$ ,  $\eta^c$ , and  $\eta^d$  represent the use-independent energy-loss rate and charging and discharging efficiencies, respectively.  $\Delta^t$  is the time-step duration and converts power into energy. Inequalities [2]–[4] impose SOE, charging, and discharging limits, respectively.

Constraints [1]–[4] have a computationally simple structure and capture basic facets of energy-storage operations, but may be limited therein. The following surveys some modeling issues, the relative impact of which may depend on the technology and model focus, and should be examined in-detail.

a) *Dependency of Power on SOE:* Power and SOE can be related, which is neglected in [3]–[4] and most models [5].

b) *Dependency of Efficiency on Current:* Efficiencies are constant in [1], whereas they can depend on charging and discharging currents and rates [6]. This means that  $\eta^c$  and  $\eta^d$  depend on  $p_t^c$  and  $p_t^d$ , which is not captured in [1].

c) *Power Range:* Some technologies can operate in a continuous range between maximum charge and discharge rates whereas others may have minimum-operating points [7]. A mixed-integer formulation or discontinuous feasible region may be needed to capture the latter in [3]–[4] [8].

d) *Capacity-Recovery Effect:* This battery-specific effect occurs when discharging to minimum voltage, especially at a fast rate, after which the voltage recovers and further discharging is possible [9]. This effect is not investigated fully.

e) *Degradation:* Many energy-storage technologies degrade with each cycle. Rainflow-counting algorithms [10] are a state-of-the-art degradation-characterization approach. These algorithms are highly non-linear, and embedding them into a model yields a non-linear optimization, which raises computational issues. Some energy-storage technologies are subject to age-related degradation, which may have highly non-linear relationships with their SOE and temperature profiles [11].

Linear and mixed-integer approximations of degradation models are used commonly [12]–[17]. Another approach is to add cycling limits [18]–[20] or to conduct depth-of-discharge control [21]. These approaches are heuristic and rely on proper parameter selection. The development of more robust approaches to manage degradation, which balance fidelity and tractability of the degradation characterization, is needed.

<sup>2</sup>SOE denotes stored energy (Wh). ‘State of charge’ (SOC) indicates electrical charge (Ah). SOE is the product of SOC and voltage. Voltage can depend on SOC, which would yield a nontrivial relationship with SOE.

f) *Parasitics*: Energy-storage use may entail parasitic loads (e.g., heating or cooling of the storage medium), which may have temporal variance (e.g., peak during periods of highest energy-storage use) [22], [23].

2) *Balance of the Power System*: Energy storage derives value from impacting the balance of the power system. Thus, improvements in representing the balance of the power system may be more beneficial in improving energy-storage representation relative to energy-storage-specific modeling [24], [25]. Examples of non-energy-storage modeling choices include uncertainty characterization and temporal resolution (capturing the flexibility value of energy storage) and spatial resolution and transmission modeling (capturing spatio-temporal energy shifting and provision of transmission deferral and voltage and reactive-power support by energy storage) [26].

3) *Uncertainty Characterization*: Uncertainty can have outsized impacts on energy storage due to the technology's physical characteristics and energy-limited nature [27]. A deterministic model can overstate energy-storage value by assuming that pertinent data are known *a priori* [28]. Continuously deployed reserve products, e.g., frequency reserves, are important, as changes in bias toward upward or downward deployment can affect energy-storage operations and revenue. Risk preferences may be an important consideration.

Approaches to handling uncertainty include stochastic, robust, and chance-constrained optimization [8], [29]–[42]. However, these techniques introduce tractability and scaling issues, which may require model decomposition, relaxation, approximation, or heuristics [34], [40], [42]–[45].

4) *Market and Financial-Settlement Rules*: Most markets have resource-participation rules, which models should aim to capture. For example, energy-storage qualification in capacity mechanisms varies between markets. Simplifications include how resources participate or schedule in markets, how their operations are optimized, and financial settlements. A related issue is that many models focus on estimating the system value of energy storage without considering remuneration [15], [16], [33], [35], [36], [38]. In some cases energy storage can be socially beneficial but operate at a loss [46].

In some cases energy-storage operators find differences between forecast and actual results and market-operating strategies [1]. Developing models to analyze market rules and remuneration schemes would be beneficial. Such development is complicated by the diversity of wholesale market rules, which requires tailoring models to each case.

5) *Computational Complexity*: Computational complexity is related to the mathematical structure of a model. Linear and convex models can be solved relatively efficiently whereas other model structures may require significant effort. Thus, heuristic methods are used sometimes to approximate solutions before employing formal optimization [13], [47], [48]. Further development of efficient approaches to solving energy-storage models is needed, especially as other modeling gaps that we highlight are addressed (and increase model complexity).

#### IV. ENERGY-STORAGE VALUATION

Energy-storage valuation is a common use of energy-storage models. Energy-storage value streams and business models

depend on location and owner [49]. Services from front-of-the-meter energy storage include energy arbitrage, ancillary services (AS), resource adequacy, and asset deferral [37]. BTM energy storage can be used for tariff management, demand response, power quality, and (potentially) front-of-the-meter services [50]. Front-of-the-meter services from BTM energy storage may require an intermediary or aggregator. Energy storage also can provide societal benefits, e.g., reducing power-system emissions or enabling higher penetrations of renewable energy [51], [52], or can impose external costs [53]–[55].

Flexibility and modularity is an energy-storage benefit that can be difficult to capture. For example, ‘wires’ transmission and distribution projects are available in discrete sizes, which may require a large investment in anticipation of uncertain future demand. An energy-storage solution can be sized flexibly and additional energy-storage modules can be added as more capacity is needed. Moreover, many energy-storage technologies can be transported elsewhere once a transmission or distribution upgrade is deployed [56].

#### A. Market and Regulatory Structures

Given many potential applications, there is interest in value stacking or multi-use applications, wherein energy storage is used for multiple services [57]. Multi-use applications raise market and regulatory issues, due to potential monetization barriers [51]. For example, a utility that participates in a wholesale electricity market may capture transmission- and distribution-deferral benefits as part of its planning. By offering excess energy-storage capacity into the wholesale market, its energy-arbitrage and AS benefits can be captured as well.

However, some jurisdictions bar regulated utilities from owning assets that participate in wholesale markets [57]. Another potential barrier is services being procured in different markets, in which energy storage cannot participate simultaneously. Another issue is regulators tying cost recovery to the ownership structure of energy storage.

Multi-use applications also may raise operational constraints. An example framework for multi-use applications of energy storage<sup>3</sup> prioritizes some services (e.g., asset deferral), meaning that energy storage cannot provide services that conflict with its ability to fulfill prioritized-application obligations. This proposal raises additional concerns around double-counting of services, inasmuch as energy storage should receive an incremental payment for a second service only if it is distinct from another service that it is providing.

Proposed solutions to these barriers include contracting, tradeable capacity rights, capacity-sharing algorithms, and hybrid resource-ownership models [57]–[61]. Steps that are employed to mitigate such barriers should be captured in energy-storage models, with the *caveat* that markets and regulation are evolving quickly. Regulators are removing barriers to the participation of energy storage in wholesale markets.<sup>4</sup> As market rules and tariffs are modified to facilitate energy-storage participation, questions regarding the relative merits

<sup>3</sup>cf. docket number R.15-03-011 for further details.

<sup>4</sup>cf. Federal Energy Regulatory Commission docket numbers RM16-23-000 and AD16-20-000 for an example.

and efficiency of these designs will arise. The modeling methodologies that we survey (especially strategic-behavior models) could support market-rule development.

### B. Energy-Storage Costs

Energy-storage capital cost depends on technology and capacity. The contribution to total cost of the storage medium relative to other components (*e.g.*, power electronics, control systems, and casing) may be small for some technologies [62].

Operation and maintenance (O&M) cost depends on the device’s lifetime (through depreciation) and operating profile. Except for component replacement, O&M cost tend to be relatively low. Some applications yield ‘aggressive’ cycling profiles that can result in faster cycle-life degradation and component replacement. End-of-life costs (*e.g.*, component recycling) may introduce additional costs and design challenges.

Cost projections of energy storage vary widely [63] and are available from a variety of sources<sup>5</sup>. Despite the availability of public cost data, more robust estimates of long-run performance and component-replacement costs of energy storage is of importance, particularly for planning modeling.

## V. EXISTING MODELING TOOLS AND GAP ANALYSIS

### A. Price-Taking Models

Price-taking models estimate the value of energy storage providing market-priced services. These models assume that energy storage is sufficiently small to have no impact on prices, the market, or power system. This assumption yields a simplified (often linear [37]) model, allowing for objective-function maximization without needing to represent the balance of the power system. Dynamic and mixed-integer formulations are used as well [15], [64]. Pricing-taking models appear widely in the literature, due to their simplicity [29], [65].

1) *General Model Description*: Profit maximization is a common objective and price-taking models can include technical and regulatory constraints [66], [67]. These models estimate the value of providing any system services with prices against which energy-storage operation can be optimized and can represent multi-use applications [66], [68], [69].

A generic price-taking model:

$$\max \sum_t [\text{revenue}_t - \text{operational cost}_t] \quad (5)$$

$$\text{s.t. device constraints} \quad (6)$$

$$\text{external constraints} \quad (7)$$

$$\text{market-design constraints,} \quad (8)$$

maximizes operating profit over a fixed time horizon with discrete time steps, which are indexed by  $t$ .

#### 2) State-of-the-Art:

a) *Revenue*: Objective function (5) captures revenue based on prices for services. The revenue terms in (5) can vary depending on the services that are modeled. For example, some markets provide performance, mileage, and capacity payments for frequency regulation [41] and (5) should reflect these if modeling such a market.

<sup>5</sup>*e.g.*, <https://atb.nrel.gov/>

b) *Operational Cost*: Operational cost in (5) can depend on market transactions (*e.g.*, cost of charging energy), fuel costs (*e.g.*, natural gas used by diabatic compressed-air energy storage), degradation costs [70], [71], and other factors. Degradation costs are borne in the future and should be discounted to compute the net present value of energy storage [13], [14], [17], [72]. Energy losses, which are inherent in energy-storage use, require a minimum price difference between charging and discharging energy to yield positive profit.

c) *Device Constraints*: Device constraints (6) represent technical characteristics and limitations of energy storage in providing services. The bare minimum of device constraints include (1)–(4). Other complicating factors can include ramp and response rates, capacity changes (*e.g.*, due to degradation), and minimum-power levels when charging or discharging.

d) *External Constraints*: Constraints (7) can include use-specific externally imposed restrictions on energy storage. For instance, there may be minimum-SOE constraints if energy storage provides backup energy to a distribution feeder or distribution deferral [72], [73].

e) *Market-Design Constraints*: Wholesale markets may impose market-participation requirements (*e.g.*, a minimum offer size or discharge duration). Such requirements may be particularly pertinent for certain services (*e.g.*, capacity products). Another example is differences in how SOE management is conducted by market operators [74].

f) *Temporal Resolution and Horizon*: Typically, the temporal granularity meets that of the market that is being analyzed (*e.g.*, hourly for day-ahead and sub-hourly for real-time markets). The time horizon can depend on the applications that are under consideration (*e.g.*, a day-long model for energy arbitrage in a day-ahead market as opposed to diurnal and seasonal modeling of a reservoir hydroelectric system). A fixed optimization horizon can yield myopic decision making (*e.g.*, fully discharged energy storage at the end of the model horizon). Some models that are limited to a single market cycle have an ending target SOE to mitigate myopic behavior [75]. This approach is heuristic and sensitive to selecting a reasonable ending SOE, which may be dynamic. For instance, the target SOE may depend on weather and load conditions that are forecasted several days into the future.

g) *Uncertainty Characterization*: Stochastic, robust, and dynamic optimization are used to represent uncertainty [32], [34], [37], [39], [41]. Simulation- or scenario-based approaches, *e.g.*, optimization with a forecast and conducting *ex post* calculations using actual data, are employed also [28].

#### 3) Gaps and Research Needs:

a) *Price-Taking Assumption*: The price-taking assumption is a major limitation. The operation of a sufficient volume of energy storage can impact market or system conditions [76]. Moreover, energy storage must compete with other resources and may not be selected for dispatch. Thus, price-taking models may yield suboptimal decisions and over-estimate asset values. The price-taking assumption can be relaxed, *e.g.*, by using PCMs or strategic-behavior models. However, these modeling frameworks can be considerably more complex than price-taking counterparts. Simple extensions to price-taking models that can capture better the impacts of energy storage

on market and system outcomes are needed [28].

b) *Temporal Resolution and Horizon*: The market and application(s) that are modeled may suggest a natural time resolution and horizon. However, the frequency of market clearing may differ from the frequency with which provision of a service impacts energy storage. For instance, a frequency-regulation market may clear hourly despite impacting energy storage on a sub-minute basis. Thus, modeling the provision of frequency regulation at an hourly time resolution may entail approximating the resultant operation of energy storage [72].

c) *Resource Aggregation*: Energy-storage modeling is considering aggregations with other assets [66], [68], [69], [77]–[85]. Modeling can be simplified by approximating an aggregation as a single component that is subject to additional uncertainties, but refinements are needed. Hybrid systems may impose additional constraints, e.g., arising from the shared inverter of a system consisting of energy storage and solar panels that are coupled on the dc side of the inverter [86].

## B. Very-Short-Run Models

Some power-system needs (e.g., arresting frequency excursions and mitigating transients and harmonics) occur on extremely short time-scales. The proliferation of renewable energy and associated loss of synchronous inertia are expected to change these needs, which energy storage could meet, given the fast response time of some technologies [87], [88]. Very-short-run models represent the provision of such services.

1) *General Model Description*: Very-short-run and price-taking models have structural similarities. A typical difference between the two model types is that the latter are optimizations (e.g., formulated to maximize profit) whereas the former tend to be simulations (e.g., to ensure that a set of resources can provide the necessary services). In some instances, very-short-run models can be formulated as optimizations, for instance to maximize a performance criterion. The choice between optimization and simulation can be governed by whether particular services are market-remunerated or not, e.g., there are few markets that remunerate the provision of primary frequency reserves, making a financial objective function meaningless [89]–[91]. Some models assume that energy storage provides very-short-run services, in conjunction with other services (e.g., energy or AS) [18]–[21], [37], [92]–[100].

2) *State-of-the-Art*: A key distinction between price-taking and very-short-run models is that the latter focus on granular representation of energy-storage operations (e.g., capturing transients or dynamics). The operating profile can be random (e.g., following a frequency-reserve signal). Thus, SOE management, energy-storage sizing, and technology selection are primary concerns [101], [102]. Poor SOE management could lead to operating-profile non-compliance, profit over-estimates, or an energy-storage asset being disallowed from providing such services. Deterministic SOE-estimation, assuming a known operating profile, is used frequently [18], [95], [96], [98], [99], [103], [104], and may have difficulty in estimating the actual SOE. Some models represent uncertainty in operating profiles, e.g., through scenarios generated from historical data or assumed probability distributions, robust op-

timization, Markov-decision processes, or persistence forecasts [20], [21], [37], [80], [82]–[84], [94], [97], [100], [101].

Models that neglect uncertain operating profiles may not estimate SOE accurately, requiring adjustments to fulfill commitments. Thus, one may focus on developing operating strategies that avoid non-compliance in providing very-short-run services. Non-compliance can be avoided by re-establishing SOE periodically to a set point by transacting energy [18], [37], [94], [96], [100]. Another approach is to use SOE-dependent operational profiles, which establish threshold SOE values, beyond which energy storage provides only one of discharging and charging [77], [84], [92], [93], [105]. When SOE is between the thresholds, the energy storage follows the operating profile normally. Another approach is to offer a predefined quantity of energy-storage capacity for very-short-run services [21], [79], [81], [101], [103], [104].

3) *Gaps and Research Needs*:

a) *Non-Compliance Penalties*: Poor SOE management can result in energy storage not following an operating profile and non-compliance penalties, which is considered in a limited number of models [82]. Further analysis of penalties and their impacts on energy-storage operation and profit is needed.

b) *SOE Recourse*: An important capability that is lacking is consideration of operational recourse, whereby the actual SOE is used to adjust the subsequent operational schedule. Rolling-horizon optimization could allow models to mitigate SOE uncertainties better. A related capability is to quantify the reliability of energy-storage providing very-short-run services.

## C. Production-Cost Models

PCMs capture operational costs of a power system by optimizing the dispatch of its resources. This optimization accommodates technical, economic, regulatory, and policy factors and constraints. PCMs also can be used to design and evaluate the performance of future power systems, e.g., analyzing high renewable-energy penetrations [106], [107] or as part of system planning [108].

Incorporating it into a PCM captures the impact of energy storage on the balance of the power system, thereby relaxing the price-taking assumption of price-taking models. As such, the imputed value of energy storage is sensitive to how the power system is represented [109]. PCMs assess the impact of energy storage from a ‘system’ perspective (e.g., by a vertically integrated utility or in a centrally committed market) [33], [35], [36]. PCMs neglect market and resource-ownership considerations, although prices and revenues can be examined [110].

1) *General Model Description*: Most PCMs have cost-minimization or welfare-maximization as their objectives. In principle, a PCM can capture the use of energy storage for any service that it represents.

A generic welfare-maximizing PCM:

$$\max \text{ social welfare} \quad (9)$$

$$\text{s.t. power-system constraints} \quad (10)$$

$$\text{asset constraints,} \quad (11)$$

assumes a finite time horizon with discrete time steps.

## 2) State-of-the-Art:

a) *Objective Function:* Incorporating energy storage into a PCM may not require explicit adjustment of (9), because (9) accounts for the cost of producing energy that is charged into energy storage. One case in which (9) requires adjustment is the treatment of energy-storage degradation, which can be represented through a cost term.

b) *Power-System Constraints:* Power-system constraints that can be captured depend on the mathematical structure of a PCM. Linear formulations can capture economic-dispatch decisions and linearized power-flow constraints [35]. Mixed-integer formulations can represent transmission switching and other non-convexities. Power flows can be represented using more complex convex conic relaxations of power-flow constraints or non-linear and non-convex formulations of Kirchhoff's Laws [111].

System constraints in a PCM impact energy storage, inasmuch as they determine the services that energy storage can be captured as providing. For instance, linearized power-flow constraints can be limited in capturing energy storage providing reactive-power and voltage services. Nonlinear or convexified power-flow constraints may capture these benefits better [66]. Similarly, the representation of AS and reserves in a PCM impact whether energy storage's ability to provide these services is captured [36].

c) *Asset Constraints:* Mathematical structure determines asset constraints that can be captured by a PCM, which impact energy storage in two ways. One impact is that other power-system assets may have operational inflexibilities that energy storage can mitigate. Second, mathematical structures may differ in their ability to capture the energy-storage operations. Mixed-integer PCMs can represent unit commitments [33], [35], [36]. Thus, such models can capture benefits of energy storage reducing generator cycling, which would not appear in linear formulations [46].

Linear PCMs can capture basic energy-storage features (cf. Section III-C1), but can overestimate energy-storage value [15]. Nonlinear convex or mixed-integer refinements can capture cycling effects on degradation and efficiency losses, but at greater computational cost [15], [17].

d) *Temporal Resolution and Horizon:* Often production-cost modeling entails solving a chronological sequence of problems with fixed horizons. For instance, a day-long unit-commitment model with hourly resolution can be solved in a daily rolling-horizon fashion, as these are the time resolution and horizon that are common practice [33], [35], [36].

A given time resolution and horizon can yield myopic decision making and may not capture the time scales at which the operation of energy storage is impacted. Moreover, energy storage may have flexibility benefits that may not be captured in a model with coarse temporal granularity [15].

e) *Uncertainty Characterization:* Explicit representation of uncertainty features in some PCMs. Many energy-storage technologies are operationally flexible and may have an outsized role in helping to mitigate these uncertainties, which may not be captured in deterministic formulations. Hence, energy storage may benefit from representing uncertainty in a modeling exercise [35].

## 3) Gaps and Research Needs:

a) *Uncertainty Characterization:* Some PCMs that represent uncertainty overassume the availability of information in modeling recourse decisions [112], [113]. A common modeling approach assumes that day-ahead decisions are made with uncertain real-time conditions, which is followed by a set of real-time recourse decisions which have all uncertainties revealed. Such a model structure neglects the gradual revelation of uncertainty. Other important intertemporal dynamics include the actual deployment of reserves, which influences energy-storage SOE and its subsequent ability to provide energy and other services [72]. Development of models that represent better these types of dynamics would provide more robust estimates of the flexibility value of energy storage.

b) *Spatial Resolution:* For tractability, many PCMs use linearized power-flow constraints to represent only the transmission network. Non-linear power-flow models that capture voltage and reactive power may reveal additional energy-storage benefits [66]. The importance of capturing interactions between transmission and distribution networks is increasing. Extending PCMs to capture the distribution system may reveal additional energy-storage benefits that current models do not show.

c) *Computational Considerations:* Energy storage can increase the computational cost of PCMs, making efficient formulations and solution algorithms important. Much of the extant work in this vein focuses on efficient uncertainty representation [33], [35], [36], [38]. Work to model other features (beyond uncertainty) efficiently is needed.

## D. Strategic-Behavior Models

Strategic-behavior models relax two assumptions of price-taking and production-cost modeling. Strategic-behavior models do not assume that energy storage has only a marginal impact on market and system conditions, nor do they assume that a central planner co-optimizes the system. Rather, strategic-behavior models allow agents behave in a self-interested or price-making manner, which may yield decisions that are not cost-minimizing or welfare-maximizing [114].

A strategic-behavior model could be used by an agent to determine how to maximize the value of a privately owned energy-storage asset. However, these models tend to be limited in representing system and market details tractably. As such, it is more common to use these models to understand how strategic behavior may impact market and system outcomes or to inform policy, regulatory, or market-design decisions. For instance, energy-storage can be welfare-diminishing in certain circumstances [53], [55], [115]. This model type is used more often to study energy-storage operations *vis-à-vis* investment.

1) *General Model Description:* Strategic-behavior models can have a variety of structural features, meaning that there is no generic formulation, as in (5)–(8) and (9)–(11). A common feature of strategic-behavior models is that they compute an equilibrium (e.g., partial, Nash, or generalized Nash). An equilibrium has the defining feature that the strategic agents are making decisions that are individually optimal, in light of decisions that are taken by other strategic agents and the

operation of the system and market. This defining property of an equilibrium is important, as it captures self-interested behavior on the part of market participants.

One approach to model strategic behavior employs a multi-level structure. For instance, the upper level may represent profit-maximizing (e.g., investment, operational, or offering) behavior by market participants whereas the lower level represents market clearing (e.g., by a welfare-maximizing market operator) [74], [116]–[120]. Another approach avoids multi-level modeling by assuming a stylized (e.g., a Nash-Cournot paradigm) or competitive market-clearing model [53]–[55].

## 2) State-of-the-Art:

a) *Strategic Agents:* Which and how many agents are assumed to behave strategically varies. At one extreme are models that assume only one strategic player (e.g., an energy-storage owner) [53], [74], [117], [118]. Such models compute partial equilibria, inasmuch as the strategic player optimizes its behavior with fixed behavior for the others. This assumption may overstate strategic behavior, because in practice other agents can react to the strategic player.

At the other extreme are models that assume multiple strategic players (including non-energy-storage agents) [54], [55], [116]. Such models compute Nash or generalized Nash equilibria, depending on whether the agents' strategy spaces are coupled (e.g., through joint constraints).

b) *Decision Sequence:* Modeling sequential decisions captures one decision maker responding to another, but can increase computational complexity. A common approach to avoiding sequential decisions is to assume a simultaneous-move interaction, e.g., agents behaving *à la* Bertrand or Nash-Cournot models [53], [55]. Simultaneous decisions require solving multiple optimization problems (i.e., for each strategic agent) simultaneously. Equilibrium computation can be straightforward if the problems are convex, in which case equilibria can be found from necessary and sufficient optimality conditions of the individual problems.

Sequential interactions, conversely, require modeling multi-level optimization problems. A common approach to solving multi-level problems tractably is to replace lower-level problems with optimality conditions [54], [116]–[120].

## 3) Gaps and Research Needs:

a) *Computational Considerations:* Many of the gaps in strategic-behavior modeling are computational and are not energy-storage specific. Energy storage and modeling the evolution of its SOE exacerbates these challenges, because time periods become coupled. Absent energy storage, strategic-behavior models often can be decomposed across time. Thus, strategic-behavior models with energy storage are limited in representing uncertainty, multiple time periods, and a spatial network [117]. Developing modeling, solution, and decomposition techniques that can exploit uncertainty, temporal, or spatial structures to capture these features is needed.

b) *Equilibrium Computation:* As with many economic games, strategic-behavior models can have multiple equilibria. Algorithms that are available today rarely are able to guarantee that all equilibria can be found [121]. This raises the possibility that a strategic-behavior model that is used for market,

regulatory, and policy analysis does not identify equilibrium behavior that may occur in practice.

c) *Optimality Conditions:* Especially if representing sequential decisions, strategic-behavior models rely typically on replacing optimization problems with optimality conditions [122]. An issue with this solution technique is that optimality conditions of many classes of optimization problems are non-convex. This non-convexity can limit the use of this approach to modeling settings with very few sequential decisions. Moreover, the use of optimality conditions requires model structures that yield necessary and sufficient optimality conditions, which restricts constraint types that may be used [123]. Developing decomposition and parallel-computing techniques for solving strategic models of energy-storage operation is important.

## E. Capacity-Expansion and Portfolio-Planning Models

We classify three types of capacity-expansion and portfolio-planning models. First, screening tools, which combine a system's load-duration curve with technology costs to optimize a resource mix [124], [125], are excluded from our survey because they are limited in capturing power-system characteristics. A second set of approaches includes comparing benefits and costs of a candidate asset, e.g., as an added step of analysis after operational modeling of the asset, or employing strategic-behavior or equilibrium models. The model types that we survey in Sections V-A–V-D fall into this category. The third approach that we survey here models capacity expansion from the perspective of a central planner, by optimizing the resource mix subject to system-operation and -reliability constraints.

1) *General Model Description:* Most capacity-expansion models maximize electricity-sector social welfare or minimize its cost. Investments and operations are considered together in such models. A generic cost-minimizing model takes the form:

$$\min \sum_t [\text{investment cost}_t + \text{operational cost}_t]$$

s.t. investment constraints (e.g., budget and resource limits)  
operating constraints (e.g., load balance, power flow, generator limits);

and capacity-investment and operational decisions are represented over mid- to long-term optimization horizons. Differences in capacity-expansion models include: geographic resolution and scope, temporal resolution and horizon, asset resolution (e.g., aggregated or individual assets), sectoral resolution (e.g., electricity only or multiple energy carriers), foresight and uncertainty representation, perspective (e.g., central planner or merchant developer), and operational representation (e.g., unit commitment, power flow, and operating reserves). We do not provide a detailed survey of differences and capabilities of capacity-expansion models, referring interested readers to other works [126]–[130]. Many of these characteristics of a capacity-expansion model interact (e.g., operating-reserve representation can be interrelated with geographic and temporal resolution, geographic scope, and transmission representation).

How energy storage is included in system planning depends on model scale, scope, and application. For example, models with a broad geographic scope rarely include the distribution

system. Models that are used for policy analysis may focus on high-level costs and benefits of energy storage rather than detailed impacts [131], [132]. Some national-scale models include diurnal energy storage in only recent releases (e.g., 2018 was the first year in which battery energy storage was included in Annual Energy Outlook<sup>6</sup>).

Depending on the attributes that are emphasized in a particular model, energy storage can serve three primary applications: energy, capacity, and AS<sup>7</sup>. For example, the value of energy storage providing energy and AS can depend on the representation of dispatch and renewable-energy curtailment. Many capacity-planning models rely on a reduced-form dispatch with representative operating periods [127], [130], [131], [133], [134]. Operating-stage chronology can be limited or non-existent, which can complicate energy-storage modeling [135], [136]. To improve tractability, unit commitment is neglected in many capacity-expansion models [129], [137], [138]. The capacity value of energy storage in these models is often static, reflecting the difficulty in estimating dynamically how capacity values change with the resource mix [139].

Other factors that can affect energy-storage economics are the representations or assumptions of technology-improvement rates, resource or siting constraints, and policy (e.g., treatment of energy storage charging with renewable energy) [140]. More nuanced features, such as battery chemistries or non-electric energy-storage technologies, are ignored often.

For computational reasons, most capacity-expansion models are linear [141]–[144]. Mixed-integer formulations can capture more complex interactions, e.g., profit-driven investment decisions [145], [146] and unit commitments at the operating stage [147]. There are differences in modeling capacity expansion with energy storage from the perspectives of system operators and individual investors [148].

## 2) State-of-the-Art:

a) *Unit Commitment:* Energy storage can reduce the on-and-off cycling of other units, which can be a net benefit depending on its degradation [46], [149], [150]. Capturing this benefit depends on the representation of operational decisions in capacity-expansion models [151], [152].

b) *Model Resolution:* Some models consider a limited set of energy-storage technologies (e.g., National Energy Modeling System considers only diurnal energy storage with four hours of energy capacity [153]) whereas others allow for endogenous energy-storage sizing [138]. State-of-the-art models represent hourly or sub-hourly operating decisions. Flexibility in model resolution is becoming a more common feature, which allows for exploration of tradeoffs between model resolution and tractability [154].

c) *Capacity Value:* Some capacity-expansion models determine energy-storage capacity value endogenously through interactions between load patterns, transmission, and resource mix [139], [155], [156]. Other models employ out-of-optimization approaches to make these assessments [129] or capture capacity needs through load-growth scenarios [157].

d) *Transmission:* Oftentimes transmission constraints are represented in capacity-expansion models using pipes-and-bubbles [40], [158] or linearizations of Kirchhoff’s laws [43], [157]. The latter may require binary variables to capture disjunctive power-flow constraints if a line is built or not [159].

e) *Renewable-Resource Representation:* Energy storage can mitigate the impacts of uncertain and variable real-time renewable-energy availability [160] and renewable-energy curtailment [161], [162]. These renewable-energy impacts are driven by generator, transmission, and demand flexibility [163]–[166]. Thus, capturing synergies between energy storage and renewable resources in a capacity-expansion model is governed by how the balance of the system is modeled.

f) *Distributed and BTM Resources:* Distributed and BTM energy storage often are modeled on an *ad hoc* basis, by comparing energy storage to other solutions. Some models can optimize the use of distributed or BTM energy storage for multiple applications, including distribution deferral [73], voltage control [52], service reliability [56], [102], [167], [168], and customer-tariff management [50].

g) *Model Perspective:* Existing models capture central planners’, individual investors’, or co-ordinated perspectives. Central-planning models can be large-scale, but simple relative to other perspectives that may yield equilibrium constraints or problems [146], [169].

## 3) Gaps and Research Needs:

a) *Uncertainty Representation:* Many planning models that represent uncertainty do so using a multi-scale approach [40]. ‘Strategic’ uncertainties (e.g., long-term load growth or policy, technology, or fuel-cost changes) are represented explicitly whereas operational uncertainties (e.g., wind- or solar-availability or load patterns) are captured using representative operating periods. This modeling paradigm assumes no interim uncertainty in the operating stage (e.g., between when unit commitments are determined and real time) and can be contrasted with operational models that can capture interim uncertainty. Thus, this approach to representing uncertainty may underestimate the flexibility needs of the power system.

b) *Unit Commitment:* Many models parameterize unit-commitment decisions for sake of tractability whereas others are relaxing this, with associated scaling issues [137]. Convexification approaches can be used to represent unit commitment tractably [42]. Further work is needed to capture the net (of cycle-life loss and technology degradation) benefits of energy storage *vis-à-vis* resource cycling.

c) *Capacity Value:* There is growing recognition that increased variable generation and energy-limited resources require a departure from using planning-reserve margins and capacity values when evaluating resource adequacy [170]. It is unclear how well approximations of these requirements in capacity-expansion models are functioning [156], [171], [172]. Section V-F surveys this topic in greater detail.

d) *Transmission:* Linearized power-flow equations may yield infeasible transmission-expansion plans [173]. As such, computationally efficient means (e.g., second-order conic relaxations) of representing power flows with greater fidelity are needed to capture more accurately the transmission-deferral benefits of energy storage [174].

<sup>6</sup><https://www.eia.gov/outlooks/archive/aeo18/>

<sup>7</sup>Transmission deferral is captured to the extent that transmission is modeled. We do not consider transmission deferral to be a separate application because transmission is used to meet energy, capacity, and AS needs.



## F. Resource-Adequacy Models

Resource-adequacy models estimate the need for capacity to meet system-reliability targets, by assessing the reliability impacts of resources [175]. Most of these models focus on the bulk-power-system but neglect transmission-system reliability. Distribution-system studies receive less attention.

1) *General Model Description*: Resource-adequacy metrics include loss of load probability, loss of load expectation (LOLE), and expected unserved energy (EUE) [176].<sup>8</sup> Metrics for a resource's system-reliability contribution (e.g., its capacity value) include effective load carrying capability (ELCC), equivalent firm power (or capacity), and equivalent conventional power (or capacity). There is an important distinction between these metrics. LOLE, EUE, etc. measure power-system resource adequacy whereas ELCC etc. measure the reliability contribution of an individual resource.

A planning-reserve margin, which requires ascribing capacity values to resources, is a simple approach to resource-adequacy assessment. Probabilistic resource-adequacy models capture random events impacting energy-supply shortages [177]. Analytic methods, which capture different system states (e.g., simulating component failures with Bernoulli trials), are common probabilistic approaches [176]. Analytic methods require considering an exponential (in the number of components) number of system states and capturing chronology can be intractable. These difficulties motivate the use of Monte Carlo methods, which approximate analytic methods by analyzing a randomly simulated set of system states.

Energy storage has two technical characteristics—its dependence on the power system for charging energy and energy-limited nature—that complicate its resource-adequacy modeling. The resource-adequacy contribution of energy storage depends on having stored energy available when the system is at risk of unserved load [178]. Its operation may leave energy storage with insufficient stored energy to alleviate a loss-of-load event or its SOE may be depleted during a prolonged event. The services that energy storage provides may limit its resource-adequacy contribution. For example, using energy storage for frequency reserves may require that it reduces its SOE so that it has sufficient 'head room' to provide downward reserves. Thus, there are important and random intertemporal interdependencies in the SOE of energy storage. As such, methods that cannot represent chronology are of limited value in resource-adequacy modeling of energy storage.

Needing to charge energy storage can make its resource-adequacy contribution location-dependent. Energy storage at a location with a weak or unreliable transmission connection can be limited in its ability to charge and provide a local resource-adequacy benefit. Assuming reliable fuel supply, a generation resource would not raise such concerns.

### 2) State-of-the-Art:

a) *Planning-Reserve Margins*: Planning-reserve margins require ascribing capacity values to resources and techniques that are used include capacity-factor [179] and load-based approximations [180]. These approaches are simple and regu-

lators and market operators use them or propose their use to include energy storage in resource-adequacy modeling [139].

b) *Analytic Methods*: Energy storage can be captured in analytic methods by adjusting system loads based on assumed operating patterns. Such an approach neglects possibly dynamic or stochastic energy-storage operations (e.g., reacting to a loss-of-load event). There are works that represent stochastic or dynamic energy-storage operations, many of which rely on strong assumptions that may be untenable. One approach expresses the SOE of energy storage as a function of demand and its initial SOE, assuming that energy storage has unlimited energy capacity [181]. Another approach uses dynamic optimization to model energy-storage operations, but assumes that energy storage is operated to maximize arbitrage value without considering possible future loss-of-load events [171]. A third approach uses non-sequential simulation, assuming that energy storage always can be charged fully overnight [182].

c) *Monte Carlo Methods*: Sequential and non-sequential Monte Carlo methods can be applied to resource-adequacy modeling [177]. The latter are limited in representing the time evolution of energy-storage SOE, however. Sequential Monte Carlo simulation is applied to energy-storage case studies and consider other factors such as renewable resources, different energy-storage-deployment and -dispatch strategies, and network reliability [172], [183]–[187].

### 3) Gaps and Research Needs:

a) *Uncertainty Representation*: Typically, analytic and Monte Carlo methods account for uncertain loss-of-load events. An important research gap is developing tools that can account explicitly for these and other uncertainties (e.g., market prices) on the operation of energy storage, its SOE, and energy that is available to mitigate a loss-of-load event.

b) *Operational Representation*: Most resource-adequacy models neglect operating decisions, which may understate the operational-flexibility benefits of energy storage [188]. Operational decisions have added importance for energy storage, as they impact the SOE and energy that is available to mitigate a supply shortage. An added consideration is the timing of when uncertain information is revealed [171]. Another gap is models that capture multi-use applications [189].

c) *Network Representation*: The capacity value of energy storage can be location-dependent. Novel uses of energy storage, especially at the distribution level, can add complexities. These issues are not examined in the extant literature.

d) *Resource and Load Mix*: The resource-adequacy contribution of energy storage depends on the penetration of energy storage [190]–[192] and other resources [139], [193], load patterns [171], and whether it is hybridized [194], [195]. Methods that can provide robust resource-adequacy assessments that account for these factors are needed.

e) *Reliability Metrics*: Other aspects of power-system reliability include faults and dynamic-security considerations [196]. Methodologies that can assess the value of energy storage in helping to address such reliability issues are needed.

## VI. CONCLUSIONS

Energy-storage modeling presents challenges that may not apply to other power-system assets. One set of challenges stem

<sup>8</sup>Expected unserved energy also is referred to as expected energy not served (EENS) and expected energy unserved (EUE).

from unique energy-storage characteristics, which can complicate capturing the services that energy storage can provide. Another complication is that capturing energy-storage value depends upon other aspects of the power system being modeled with sufficient fidelity. In addition to optimizing energy-storage operation or investment by an owner or investor, these models can be used by stakeholders (*e.g.*, policymakers and regulators) to study the impacts of market and policy choices on energy storage and its use in power systems.

This paper surveys the state-of-the-art in energy-storage modeling and suggests directions in which existing models can be improved. Our aim is to guide future research and model development. Many of the modeling needs that we discuss do not pertain directly to energy-storage representation. Rather, modeling other power-system elements and services better can have an impact on capturing the full range of energy-storage benefits. A key takeaway from our work is that there is not a ‘one-size-fits-all’ approach to modeling energy storage. Depending upon the technology, decision maker’s perspective, and questions answered by a particular exercise, the value of modeling approaches and advances may differ.

#### REFERENCES

[1] M. Della Penna, M. Yeung, and D. Fribush, *Energy Storage End Uses: Energy Storage for Market Operations*, Pacific Gas and Electric Company, San Francisco, CA, 13 September 2016.

[2] M. G. Hoffman, M. C. W. Kintner-Meyer, A. Sadovsky, and J. G. DeSteele, “Analysis Tools for Sizing and Placement of Energy Storage in Grid Applications: A Literature Review,” Pacific Northwest National Laboratory, Tech. Rep. PNNL-19703, September 2010.

[3] J. Eichman, P. Denholm, J. Jorgenson, and U. Helman, “Operational Benefits of Meeting California’s Energy Storage Targets,” National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-5400-65061, December 2015.

[4] T. Mai, J. Bistline, Y. Sun, W. Cole, C. Marcy, C. Namovicz, and D. Young, “The role of input assumptions and model structures in projections of variable renewable energy: A multi-model perspective of the U.S. electricity system,” *Energy Economics*, vol. 76, pp. 313–324, October 2018.

[5] H. Pandžić and V. Bobanac, “An Accurate Charging Model of Battery Energy Storage,” *IEEE Transactions on Power Systems*, vol. 34, pp. 1416–1426, March 2019.

[6] N. Xue, W. Du, J. R. A. Martins, and W. Shyy, “Lithium-Ion Batteries: Thermomechanics, Performance, and Design Optimization,” in *Handbook of Clean Energy Systems*, L. F. Cabeza, R. Sioshansi, and J. Yan, Eds. West Sussex, United Kingdom: John Wiley & Sons Ltd, June 2015, vol. 5, Energy Storage, ch. 26, pp. 2849–2864.

[7] V. Koritarov, T. Veselka, J. Gasper, B. Bethke, A. Botterud, J. Wang, M. Mahalik, Z. Zhou, C. Milostan, J. Feltes, Y. Kazachov, T. Guo, G. Liu, B. Trouille, P. Donalek, K. King, E. Ela, B. Kirby, I. Krad, and V. Gevorgian, “Modeling and Analysis of Value of Advanced Pumped Storage Hydropower in the United States,” Argonne National Laboratory, Argonne, IL, Tech. Rep. ANL/DIS-14/7, June 2014.

[8] H. Ding, Z. Hu, and Y. Song, “Stochastic optimization of the daily operation of wind farm and pumped-hydro-storage plant,” *Renewable Energy*, vol. 48, pp. 571–578, December 2012.

[9] B. Homan, G. J. M. Smit, R. P. van Leeuwen, and M. V. ten Kortenaar, “A comprehensive model for battery State of Charge prediction,” in *2017 IEEE Manchester PowerTech*. Manchester, United Kingdom: Institute of Electrical and Electronics Engineers, 18–22 June 2017.

[10] L. L. Schluter, “Programmer’s Guide for LIFE2’s Rainflow Counting Algorithm,” Sandia National Laboratories, Albuquerque, NM, Tech. Rep. SAND90-2260, January 1991.

[11] C. Deline, W. Sekulic, D. Jenket, D. Jordan, N. DiOrio, and K. Smith, “Field-Aging Test Bed for Behind-the-Meter PV + Energy Storage,” National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/CP-5K00-74003, July 2019.

[12] M. A. Ortega-Vazquez, “Optimal scheduling of electric vehicle charging and vehicle-to-grid services at household level including battery degradation and price uncertainty,” *IET Generation, Transmission & Distribution*, vol. 8, pp. 1007–1016, June 2014.

[13] N. DiOrio, A. Dobos, S. Janzou, A. Nelson, and B. Lundstrom, “Technoeconomic Modeling of Battery Energy Storage in SAM,” National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-6A20-64641, September 2015.

[14] A. Cortés, G. Damato, and B. Kaun, “StorageVET™ V1.0 Software User Guide: User and Technical Documentation for the Storage Value Estimation Tool,” Electric Power Research Institute, Palo Alto, CA, Tech. Rep. 3002009357, December 2016.

[15] A. Sakti, K. G. Gallagher, N. Sepulveda, C. Uckun, C. Vergara, F. J. de Sisternes, D. W. Dees, and A. Botterud, “Enhanced representations of lithium-ion batteries in power systems models and their effect on the valuation of energy arbitrage applications,” *Journal of Power Sources*, vol. 342, pp. 279–291, 28 February 2017.

[16] B. Xu, J. Zhao, T. Zheng, E. Litvinov, and D. S. Kirschen, “Factoring the Cycle Aging Cost of Batteries Participating in Electricity Markets,” *IEEE Transactions on Power Systems*, vol. 33, pp. 2248–2259, March 2018.

[17] B. Foggo and N. Yu, “Improved Battery Storage Valuation Through Degradation Reduction,” *IEEE Transactions on Smart Grid*, vol. 9, pp. 5721–5732, November 2018.

[18] G. He, Q. Chen, C. Kang, P. Pinson, and Q. Xia, “Optimal Bidding Strategy of Battery Storage in Power Markets Considering Performance-Based Regulation and Battery Cycle Life,” *IEEE Transactions on Smart Grid*, vol. 7, pp. 2359–2367, September 2016.

[19] D.-I. Stroe, V. Knap, M. Swierczynski, A.-I. Stroe, and R. Teodorescu, “Operation of a Grid-Connected Lithium-Ion Battery Energy Storage System for Primary Frequency Regulation: A Battery Lifetime Perspective,” *IEEE Transactions on Industry Applications*, vol. 53, pp. 430–438, January-February 2017.

[20] Y. Shi, B. Xu, D. Wang, and B. Zhang, “Using Battery Storage for Peak Shaving and Frequency Regulation: Joint Optimization for Superlinear Gains,” *IEEE Transactions on Power Systems*, vol. 33, pp. 2882–2894, May 2018.

[21] M. Kazemi and H. Zareipour, “Long-term Scheduling of Battery Storage Systems in Energy and Regulation Markets Considering Battery’s Lifespan,” *IEEE Transactions on Smart Grid*, vol. 9, pp. 6840–6849, November 2018.

[22] W. Wang, Q. Luo, B. Li, X. Wei, L. Li, and Z. Yang, “Recent Progress in Redox Flow Battery Research and Development,” *Advanced Functional Materials*, vol. 23, pp. 970–986, 25 February 2013.

[23] X. Qiu, T. A. Nguyen, J. D. Guggenberger, M. L. Crow, and A. C. Elmore, “A Field Validated Model of a Vanadium Redox Flow Battery for Microgrids,” *IEEE Transactions on Smart Grid*, vol. 5, pp. 1592–1601, July 2014.

[24] F. J. de Sisternes, J. D. Jenkins, and A. Botterud, “The value of energy storage in decarbonizing the electricity sector,” *Applied Energy*, vol. 175, pp. 368–379, 1 August 2016.

[25] F. Cebulla and T. Fichter, “Merit order or unit-commitment: How does thermal power plant modeling affect storage demand in energy system models?” *Renewable Energy*, vol. 105, pp. 117–132, May 2017.

[26] R. Fernández-Blanco, Y. Dvorkin, B. Xu, Y. Wang, and D. S. Kirschen, “Optimal Energy Storage Siting and Sizing: A WECC Case Study,” *IEEE Transactions on Sustainable Energy*, vol. 8, pp. 733–743, April 2017.

[27] M. Chazarra, J. I. Pérez-Díaz, J. García-González, and A. Helseth, “Economic effects of forecasting inaccuracies in the automatic frequency restoration service for the day-ahead energy and reserve scheduling of pumped storage plants,” *Electric Power Systems Research*, vol. 174, p. 105850, September 2019.

[28] R. Sioshansi, P. Denholm, T. Jenkin, and J. Weiss, “Estimating the Value of Electricity Storage in PJM: Arbitrage and Some Welfare Effects,” *Energy Economics*, vol. 31, pp. 269–277, March 2009.

[29] A. Sandmo, “On the Theory of the Competitive Firm Under Price Uncertainty,” *The American Economic Review*, vol. 61, pp. 65–73, March 1971.

[30] S. A. Malcolm and S. A. Zenios, “Robust Optimization for Power Systems Capacity Expansion under Uncertainty,” *Journal of the Operational Research Society*, vol. 45, pp. 1040–1049, 1994.

[31] A. J. Conejo, F. J. Nogales, and J. M. Arroyo, “Price-Taker Bidding Strategy Under Price Uncertainty,” *IEEE Transactions on Power Systems*, vol. 17, pp. 1081–1088, November 2002.

[32] P. Mokrjan and M. Stephen, “A Stochastic Programming Framework for the Valuation of Electricity Storage,” in *26th USAEE/IAEE North*

- American Conference*. Ann Arbor, MI: International Association for Energy Economics, 24-27 September 2006.
- [33] R. Jiang, J. Wang, and Y. Guan, "Robust Unit Commitment With Wind Power and Pumped Storage Hydro," *IEEE Transactions on Power Systems*, vol. 27, pp. 800–810, May 2012.
- [34] J. Nascimento and W. B. Powell, "An Optimal Approximate Dynamic Programming Algorithm for Concave, Scalar Storage Problems With Vector-Valued Controls," *IEEE Transactions on Automatic Control*, vol. 58, pp. 2995–3010, December 2013.
- [35] N. Li, C. Uçkun, E. M. Constantinescu, J. R. Birge, K. W. Hedman, and A. Botterud, "Flexible Operation of Batteries in Power System Scheduling With Renewable Energy," *IEEE Transactions on Sustainable Energy*, vol. 7, pp. 685–696, April 2016.
- [36] K. Bruninx, Y. Dvorkin, E. Delarue, H. Pandžić, W. D'haeseleer, and D. S. Kirschen, "Coupling Pumped Hydro Energy Storage With Unit Commitment," *IEEE Transactions on Sustainable Energy*, vol. 7, pp. 786–796, April 2016.
- [37] M. Kazemi, H. Zareipour, N. Amjadi, W. D. Rosehart, and M. Ehsan, "Operation Scheduling of Battery Storage Systems in Joint Energy and Ancillary Services Markets," *IEEE Transactions on Sustainable Energy*, vol. 8, pp. 1726–1735, October 2017.
- [38] D. Bienstock, G. Muñoz, S. Yang, and C. Matke, "Robust linear control of storage in transmission systems, and extensions to robust network control problems," in *2017 IEEE 56th Annual Conference on Decision and Control*. Melbourne, Victoria, Australia: Institute of Electrical and Electronics Engineers, 12-15 December 2017, pp. 799–806.
- [39] D. Krishnamurthy, C. Uckun, Z. Zhou, P. R. Thimmapuram, and A. Botterud, "Energy Storage Arbitrage Under Day-Ahead and Real-Time Price Uncertainty," *IEEE Transactions on Power Systems*, vol. 33, pp. 84–93, January 2018.
- [40] Y. Liu, R. Sioshansi, and A. J. Conejo, "Multistage Stochastic Investment Planning with Multiscale Representation of Uncertainties and Decisions," *IEEE Transactions on Power Systems*, vol. 33, pp. 781–791, January 2018.
- [41] *StorageVET 2.0 User Guide: End User and Technical Documentation for the Storage Value Estimation Tool in Python*, Palo Alto, CA, May 2020, v1.0.2.
- [42] F. Pourahmadi, S. J. Kazempour, C. Ordoudis, P. Pinson, and S. H. Hosseini, "Distributionally Robust Chance-Constrained Generation Expansion Planning," *IEEE Transactions on Power Systems*, vol. 35, pp. 2888–2903, July 2020.
- [43] R. Domínguez, A. J. Conejo, and M. Carrión, "Toward Fully Renewable Electric Energy Systems," *IEEE Transactions on Power Systems*, vol. 30, pp. 316–326, January 2015.
- [44] I. Konstantelos and G. Strbac, "Valuation of Flexible Transmission Investment Options Under Uncertainty," *IEEE Transactions on Power Systems*, vol. 30, pp. 1047–1055, March 2015.
- [45] F. D. Muñoz and J.-P. Watson, "A scalable solution framework for stochastic transmission and generation planning problems," *Computational Management Science*, vol. 12, pp. 491–518, October 2015.
- [46] P. Denholm, J. Jorgenson, M. Hummon, T. Jenkin, D. Palchak, B. Kirby, O. Ma, and M. O'Malley, "The Value of Energy Storage for Grid Applications," National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-6A20-58465, May 2013.
- [47] M. Castillo-Cagigal, E. Caamaño-Martín, E. Matallanas, D. Masa-Bote, Á. Gutiérrez, F. M. Monasterio-Huelin, and J. Jiménez-Leube, "PV self-consumption optimization with storage and Active DSM for the residential sector," *Solar Energy*, vol. 85, pp. 2338–2348, September 2011.
- [48] D. Parra and M. K. Patel, "Effect of tariffs on the performance and economic benefits of PV-coupled battery systems," *Applied Energy*, vol. 164, pp. 175–187, 15 February 2016.
- [49] R. D. Masiello, B. Roberts, and T. Sloan, "Business Models for Deploying and Operating Energy Storage and Risk Mitigation Aspects," *Proceedings of the IEEE*, vol. 102, pp. 1052–1064, July 2014.
- [50] J. Jin and Y. Xu, "Optimal Storage Operation Under Demand Charge," *IEEE Transactions on Power Systems*, vol. 32, pp. 795–808, January 2017.
- [51] J. de Joode, D. Kingma, M. Lijesen, M. Mulder, and V. Shestalova, "Energy Policies and Risks on Energy Markets; A cost-benefit analysis," Centraal Planbureau, CPB Special Publication 51, March 2004.
- [52] Y. Yang, H. Li, A. Aichhorn, J. Zheng, and M. Greenleaf, "Sizing Strategy of Distributed Battery Storage System With High Penetration of Photovoltaic for Voltage Regulation and Peak Load Shaving," *IEEE Transactions on Smart Grid*, vol. 5, pp. 982–991, March 2014.
- [53] R. Sioshansi, "Welfare Impacts of Electricity Storage and the Implications of Ownership Structure," *The Energy Journal*, vol. 31, pp. 173–198, 2010.
- [54] —, "Increasing the Value of Wind with Energy Storage," *The Energy Journal*, vol. 32, pp. 1–30, 2011.
- [55] —, "When Energy Storage Reduces Social Welfare," *Energy Economics*, vol. 41, pp. 106–116, January 2014.
- [56] J. Kim and Y. Dvorkin, "Enhancing Distribution System Resilience with Mobile Energy Storage and Microgrids," *IEEE Transactions on Smart Grid*, vol. 10, pp. 4996–5006, September 2019.
- [57] R. Sioshansi, "Using Storage-Capacity Rights to Overcome the Cost-Recovery Hurdle for Energy Storage," *IEEE Transactions on Power Systems*, vol. 32, pp. 2028–2040, May 2017.
- [58] R. Sioshansi, P. Denholm, and T. Jenkin, "Market and Policy Barriers to Deployment of Energy Storage," *Economics of Energy & Environmental Policy*, vol. 1, pp. 47–63, March 2012.
- [59] J. A. Taylor, "Financial Storage Rights," *IEEE Transactions on Power Systems*, vol. 30, pp. 997–1005, March 2015.
- [60] K. Pandžić, H. Pandžić, and I. Kuzle, "Coordination of Regulated and Merchant Energy Storage Investments," *IEEE Transactions on Sustainable Energy*, vol. 9, pp. 1244–1254, July 2018.
- [61] X. Yan, C. Gu, H. Wyman-Pain, and F. Li, "Capacity Share Optimization for Multiservice Energy Storage Management Under Portfolio Theory," *IEEE Transactions on Industrial Electronics*, vol. 66, pp. 1598–1607, February 2019.
- [62] S. Schoenung, "Energy Storage Systems Cost Update," Sandia National Laboratories, Albuquerque, NM, Tech. Rep. SAND2011-2730, April 2011.
- [63] W. Cole and A. W. Frazier, "Cost Projections for Utility-Scale Battery Storage," National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-6A20-73222, June 2019.
- [64] P. Fatouros, I. Konstantelos, D. Papadaskalopoulos, and G. Strbac, "Stochastic Dual Dynamic Programming for Operation of DER Aggregators under Multidimensional Uncertainty," *IEEE Transactions on Sustainable Energy*, vol. 10, pp. 459–469, January 2019.
- [65] F. J. Diaz, J. Contreras, J. I. Munoz, and D. Pozo, "Optimal Scheduling of a Price-Taker Cascaded Reservoir System in a Pool-Based Electricity Market," *IEEE Transactions on Power Systems*, vol. 26, pp. 604–615, May 2011.
- [66] D. Gayme and U. Topcu, "Optimal Power Flow With Large-Scale Storage Integration," *IEEE Transactions on Power Systems*, vol. 28, pp. 709–717, May 2013.
- [67] D. Wu, C. Jin, P. Balducci, and M. Kintner-Meyer, "An Energy Storage Assessment: Using Optimal Control Strategies to Capture Multiple Services," in *2015 IEEE Power & Energy Society General Meeting*. Denver, CO, USA: Institute of Electrical and Electronics Engineers, 26-30 24 July 2015.
- [68] A. Cortés and S. Martínez, "On Distributed Reactive Power and Storage Control on Microgrids," *International Journal of Robust and Nonlinear Control*, vol. 26, pp. 3150–3169, 25 September 2016.
- [69] —, "A Projection-Based Decomposition Algorithm for Distributed Fast Computation of Control in Microgrids," *SIAM Journal on Control and Optimization*, vol. 56, pp. 583–609, 2018.
- [70] R. M. Spotnitz, "Simulation of capacity fade in lithium-ion batteries," *Journal of Power Sources*, vol. 113, pp. 72–80, 1 January 2003.
- [71] S. Succar and R. H. Williams, "Compressed Air Energy Storage Theory, Resources, And Applications For Wind Power," Princeton Environmental Institute, Tech. Rep., April 2008.
- [72] X. Xi and R. Sioshansi, "A Dynamic Programming Model of Energy Storage and Transformer Deployments to Relieve Distribution Constraints," *Computational Management Science*, vol. 13, pp. 119–146, January 2016.
- [73] A. Nourai, "Installation of the First Distributed Energy Storage System (DESS) at American Electric Power (AEP)," Sandia National Laboratories, Albuquerque, NM, Tech. Rep. SAND2007-3580, June 2007.
- [74] R. Sioshansi, "Optimized Offers for Cascaded Hydroelectric Generators in a Market with Centralized Dispatch," *IEEE Transactions on Power Systems*, vol. 30, pp. 773–783, March 2015.
- [75] F. Graves, T. Jenkin, and D. Murphy, "Opportunities for Electricity Storage in Deregulating Markets," *The Electricity Journal*, vol. 12, pp. 46–56, October 1999.
- [76] J. Arteaga and H. Zareipour, "A Price-maker / Price-taker model for the Operation of Battery Storage Systems in Electricity Markets," *IEEE Transactions on Smart Grid*, vol. 10, pp. 6912–6920, November 2019.
- [77] R. Hollinger, L. M. Diazgranados, F. Braam, T. Erge, G. Bopp, and B. Engel, "Distributed solar battery systems providing primary control

- reserve,” *IET Renewable Power Generation*, vol. 10, pp. 63–70, January 2016.
- [78] R. Sebastián, “Application of a battery energy storage for frequency regulation and peak shaving in a wind diesel power system,” *IET Generation, Transmission & Distribution*, vol. 10, pp. 764–770, February 2016.
- [79] A. V. Savkin, M. Khalid, and V. G. Agelidis, “A Constrained Monotonic Charging/Discharging Strategy for Optimal Capacity of Battery Energy Storage Supporting Wind Farms,” *IEEE Transactions on Sustainable Energy*, vol. 7, pp. 1224–1231, July 2016.
- [80] J. Chen and H. E. Garcia, “Economic optimization of operations for hybrid energy systems under variable markets,” *Applied Energy*, vol. 177, pp. 11–24, 1 September 2016.
- [81] J. Tan and Y. Zhang, “Coordinated Control Strategy of a Battery Energy Storage System to Support a Wind Power Plant Providing Multi-Timescale Frequency Ancillary Services,” *IEEE Transactions on Sustainable Energy*, vol. 8, pp. 1140–1153, July 2017.
- [82] G. He, Q. Chen, C. Kang, Q. Xia, and K. Poolla, “Cooperation of Wind Power and Battery Storage to Provide Frequency Regulation in Power Markets,” *IEEE Transactions on Power Systems*, vol. 32, pp. 3559–3568, September 2017.
- [83] H. Ding, P. Pinson, Z. Hu, J. Wang, and Y. Song, “Optimal Offering and Operating Strategy for a Large Wind-Storage System as a Price Maker,” *IEEE Transactions on Power Systems*, vol. 32, pp. 4904–4913, November 2017.
- [84] T. Chakraborty, D. Watson, and M. Rodgers, “Automatic Generation Control Using an Energy Storage System in a Wind Park,” *IEEE Transactions on Power Systems*, vol. 33, pp. 198–205, January 2018.
- [85] S. Varghese and R. Sioshansi, “The Price is Right? How Pricing and Incentive Mechanisms in California Incentivize Building Distributed Hybrid Solar and Energy-Storage Systems,” *Energy Policy*, vol. 138, p. 111242, March 2020.
- [86] J. Good and J. X. Johnson, “Impact of inverter loading ratio on solar photovoltaic system performance,” *Applied Energy*, vol. 177, pp. 475–486, 1 September 2016.
- [87] V. Knap, S. K. Chaudhary, D.-I. Stroe, M. Swierczynski, B.-I. Craciun, and R. Teodorescu, “Sizing of an Energy Storage System for Grid Inertial Response and Primary Frequency Reserve,” *IEEE Transactions on Power Systems*, vol. 31, pp. 3447–3456, September 2016.
- [88] H. Silva-Saravia, H. Pulgar-Painemal, and J. M. Mauricio, “Flywheel Energy Storage Model, Control and Location for Improving Stability: The Chilean Case,” *IEEE Transactions on Power Systems*, vol. 32, pp. 3111–3119, July 2017.
- [89] M. Koller, T. Borsche, A. Ulbig, and G. Andersson, “Review of grid applications with the Zurich 1 MW battery energy storage system,” *Electric Power Systems Research*, vol. 120, pp. 128–135, March 2015.
- [90] A. Zeh, M. Müller, M. Naumann, H. C. Hesse, A. Jossen, and R. Witzmann, “Fundamentals of Using Battery Energy Storage Systems to Provide Primary Control Reserves in Germany,” *Batteries*, vol. 2, pp. 1–21, September 2016.
- [91] M. Carrión, Y. Dvorkin, and H. Pandžić, “Primary Frequency Response in Capacity Expansion With Energy Storage,” *IEEE Transactions on Power Systems*, vol. 33, pp. 1824–1835, March 2018.
- [92] A. Oudalov, D. Chartouni, and C. Ohler, “Optimizing a Battery Energy Storage System for Primary Frequency Control,” *IEEE Transactions on Power Systems*, vol. 22, pp. 1259–1266, August 2007.
- [93] P. Mercier, R. Cherkaoui, and A. Oudalov, “Optimizing a Battery Energy Storage System for Frequency Control Application in an Isolated Power System,” *IEEE Transactions on Power Systems*, vol. 24, pp. 1469–1477, August 2009.
- [94] H. Akhavan-Hejazi and H. Mohsenian-Rad, “Optimal Operation of Independent Storage Systems in Energy and Reserve Markets With High Wind Penetration,” *IEEE Transactions on Smart Grid*, vol. 5, pp. 1088–1097, March 2014.
- [95] P. Zou, Q. Chen, Q. Xia, G. He, and C. Kang, “Evaluating the Contribution of Energy Storages to Support Large-Scale Renewable Generation in Joint Energy and Ancillary Service Markets,” *IEEE Transactions on Sustainable Energy*, vol. 7, pp. 808–818, April 2016.
- [96] A. Berrada, K. Loudiyi, and I. Zorkani, “Valuation of energy storage in energy and regulation markets,” *Energy*, vol. 115 Part 1, pp. 1109–1118, 15 November 2016.
- [97] T. Zhang, S. X. Chen, H. B. Gooi, and J. M. Maciejowski, “A Hierarchical EMS for Aggregated BESSs in Energy and Performance-Based Regulation Markets,” *IEEE Transactions on Power Systems*, vol. 32, pp. 1751–1760, May 2017.
- [98] K. Anderson and A. El Gamal, “Co-optimizing the value of storage in energy and regulation service markets,” *Energy Systems*, vol. 8, pp. 369–387, May 2017.
- [99] N. Yu and B. Foggo, “Stochastic valuation of energy storage in wholesale power markets,” *Energy Economics*, vol. 64, pp. 177–185, May 2017.
- [100] B. Cheng and W. B. Powell, “Co-Optimizing Battery Storage for the Frequency Regulation and Energy Arbitrage Using Multi-Scale Dynamic Programming,” *IEEE Transactions on Smart Grid*, vol. 9, pp. 1997–2005, May 2018.
- [101] D. Fooladivanda, C. Rosenberg, and S. Garg, “Energy Storage and Regulation: An Analysis,” *IEEE Transactions on Smart Grid*, vol. 7, pp. 1813–1823, July 2016.
- [102] S. Liu, X. Wang, and P. X. Liu, “A Stochastic Stability Enhancement Method of Grid-Connected Distributed Energy Storage Systems,” *IEEE Transactions on Smart Grid*, vol. 8, pp. 2062–2070, September 2017.
- [103] R. L. Fares, J. P. Meyers, and M. E. Webber, “A dynamic model-based estimate of the value of a vanadium redox flow battery for frequency regulation in Texas,” *Applied Energy*, vol. 113, pp. 189–198, January 2014.
- [104] F. Teng and G. Strbac, “Business cases for energy storage with multiple service provision,” *Journal of Modern Power Systems and Clean Energy*, vol. 4, pp. 615–625, October 2016.
- [105] K. Yang and A. Walid, “Outage-Storage Tradeoff in Frequency Regulation for Smart Grid With Renewables,” *IEEE Transactions on Smart Grid*, vol. 4, pp. 245–252, March 2013.
- [106] T. Mai, D. Sandor, R. Wiser, and T. R. Schneider, “Renewable Electricity Futures Study: Executive Summary,” National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-6A20-52409-ES, 2012.
- [107] A. Bloom, A. Townsend, D. Palchak, J. Novacheck, J. King, C. Barrows, E. Ibanez, M. O’Connell, G. Jordan, B. Roberts, C. Draxl, and K. Gruchalla, “Eastern Renewable Generation Integration Study,” National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-6A20-64472, August 2016.
- [108] R. H. Byrne, T. A. Nguyen, D. A. Copp, B. R. Chalamala, and I. Gyuk, “Energy Management and Optimization Methods for Grid Energy Storage Systems,” *IEEE Access*, vol. 6, pp. 13 231–13 260, 2018.
- [109] P. Denholm, Y.-H. Wan, M. Hummon, and M. Mehos, “An Analysis of Concentrating Solar Power with Thermal Energy Storage in a California 33% Renewable Scenario,” National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-6A20-58186, March 2013.
- [110] R. Sioshansi, R. P. O’Neill, and S. S. Oren, “Economic Consequences of Alternative Solution Methods for Centralized Unit Commitment in Day-Ahead Electricity Markets,” *IEEE Transactions on Power Systems*, vol. 23, pp. 344–352, May 2008.
- [111] C. Bingane, M. F. Anjos, and S. Le Digabel, “Tight-and-Cheap Conic Relaxation for the AC Optimal Power Flow Problem,” *IEEE Transactions on Power Systems*, vol. 33, pp. 7181–7188, November 2018.
- [112] W. B. Powell and S. Meisel, “Tutorial on Stochastic Optimization in Energy—Part I: Modeling and Policies,” *IEEE Transactions on Power Systems*, vol. 31, pp. 1459–1467, March 2016.
- [113] —, “Tutorial on Stochastic Optimization in Energy—Part II: An Energy Storage Illustration,” *IEEE Transactions on Power Systems*, vol. 31, pp. 1468–1475, March 2016.
- [114] E. Nasrolahpour, S. J. Kazempour, H. Zareipour, and W. D. Rosehart, “Strategic Sizing of Energy Storage Facilities in Electricity Markets,” *IEEE Transactions on Sustainable Energy*, vol. 7, pp. 1462–1472, October 2016.
- [115] A. S. Siddiqui, R. Sioshansi, and A. J. Conejo, “Merchant Storage Investment in a Restructured Electricity Industry,” *The Energy Journal*, vol. 40, pp. 129–163, 2019.
- [116] H. Mohsenian-Rad, “Coordinated Price-Maker Operation of Large Energy Storage Units in Nodal Energy Markets,” *IEEE Transactions on Power Systems*, vol. 31, pp. 786–797, January 2016.
- [117] K. Hartwig and I. Kockar, “Impact of Strategic Behavior and Ownership of Energy Storage on Provision of Flexibility,” *IEEE Transactions on Sustainable Energy*, vol. 7, pp. 744–754, April 2016.
- [118] E. Nasrolahpour, S. J. Kazempour, H. Zareipour, and W. D. Rosehart, “A Bilevel Model for Participation of a Storage System in Energy and Reserve Markets,” *IEEE Transactions on Sustainable Energy*, vol. 9, pp. 582–598, April 2018.
- [119] A. Shahmohammadi, R. Sioshansi, A. J. Conejo, and S. Afsharnia, “The Role of Energy Storage in Mitigating Ramping Inefficiencies

- Caused by Variable Renewable Generation,” *Energy Conversion and Management*, vol. 162, pp. 307–320, 15 April 2018.
- [120] —, “Market Equilibria and Interactions Between Strategic Generation, Wind, and Storage,” *Applied Energy*, vol. 220, pp. 876–892, 15 June 2018.
- [121] D. Pozo, E. Sauma, and J. Contreras, “Basic theoretical foundations and insights on bilevel models and their applications to power systems,” *Annals of Operations Research*, vol. 254, pp. 303–334, July 2017.
- [122] S. A. Gabriel, A. J. Conejo, J. D. Fuller, B. F. Hobbs, and C. Ruiz, Eds., *Complementarity Modeling in Energy Markets*, ser. International Series in Operations Research & Management Science. New York, New York: Springer-Verlag, 2013, vol. 189.
- [123] D. Huppmann and S. A. Siddiqui, “An exact solution method for binary equilibrium problems with compensation and the power market uplift problem,” *European Journal of Operational Research*, vol. 266, pp. 622–638, 16 April 2018.
- [124] A. J. Conejo, M. C. Caramanis, and J. A. Bloom, “An Efficient Algorithm for Optimal Reservoir Utilization in Probabilistic Production Costing,” *IEEE Transactions on Power Systems*, vol. 5, pp. 439–447, May 1990.
- [125] S. Stoft, *Power System Economics: Designing Markets for Electricity*. New York, New York: Wiley-Interscience, 2002.
- [126] S. Pfenninger, A. Hawkes, and J. Keirstead, “Energy systems modeling for twenty-first century energy challenges,” *Renewable and Sustainable Energy Reviews*, vol. 33, pp. 74–86, May 2014.
- [127] P. Sullivan, K. Eurek, and R. Margolis, “Advanced Methods for Incorporating Solar Energy Technologies into Electric Sector Capacity-expansion Models: Literature Review and Analysis,” National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-6A20-61185, July 2014.
- [128] D. Keles, P. Jochem, R. McKenna, M. Ruppert, and W. Fichtner, “Meeting the Modeling Needs of Future Energy Systems,” *Energy Technology*, vol. 5, pp. 1007–1025, July 2017.
- [129] W. Cole, B. Frew, T. Mai, Y. Sun, J. E. T. Bistline, G. J. Blanford, D. Young, C. Marcy, C. Namovicz, R. Edelman, B. Meroney, R. Sims, J. Stenhouse, and P. Donohoo-Vallett, “Variable Renewable Energy in Long-Term Planning Models: A Multi-Model Perspective,” National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-6A20-70528, November 2017.
- [130] N. Helistö, J. Kiviluoma, H. Holttinen, J. D. Lara, and B. Hodge, “Including operational aspects in the planning of power systems with large amounts of variable generation: A review of modeling approaches,” *WIREs Energy and Environment*, vol. 8, September/October 2019.
- [131] E. Hale, B. Stoll, and T. Mai, “Capturing the Impact of Storage and Other Flexible Technologies on Electric System Planning,” National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-6A20-65726, May 2016.
- [132] P. Denholm and R. Margolis, “Energy Storage Requirements for Achieving 50% Solar Photovoltaic Energy Penetration in California,” National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-6A20-66595, August 2016.
- [133] P. Nahmmacher, E. Schmid, L. Hirth, and B. Knopf, “Carpe diem: A novel approach to select representative days for long-term power system modeling,” *Energy*, vol. 112, pp. 430–442, 1 October 2016.
- [134] G. J. Blanford, J. H. Merrick, J. E. T. Bistline, and D. T. Young, “Simulating Annual Variation in Load, Wind, and Solar by Representative Hour Selection,” *The Energy Journal*, vol. 39, pp. 189–212, 2018.
- [135] L. Kotzur, P. Markewitz, M. Robinius, and D. Stolten, “Time series aggregation for energy system design: Modeling seasonal storage,” *Applied Energy*, vol. 213, pp. 123–135, 1 March 2018.
- [136] H. Teichgraber and A. R. Brandt, “Clustering methods to find representative periods for the optimization of energy systems: An initial framework and comparison,” *Applied Energy*, vol. 239, pp. 1283–1293, 1 April 2019.
- [137] T. Mai, C. Barrows, A. Lopez, E. Hale, M. Dyson, and K. Eurek, “Implications of Model Structure and Detail for Utility Planning: Scenario Case Studies Using the Resource Planning Model,” National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-6A20-63972, April 2015.
- [138] Electric Power Research Institute, “US-REGEN Model Documentation,” Electric Power Research Institute, Palo Alto, CA, Tech. Rep. 3002010956, April 2018.
- [139] P. Denholm, J. Nunemaker, P. Gagnon, and W. Cole, “The Potential for Battery Energy Storage to Provide Peaking Capacity in the United States,” National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-6A20-74184, June 2019.
- [140] C. Wadia, P. Albertus, and V. Srinivasan, “Resource constraints on the battery energy storage potential for grid and transportation applications,” *Journal of Power Sources*, vol. 196, pp. 1593–1598, 1 February 2011.
- [141] United States Environmental Protection Agency, “Documentation for EPA Base Case v.5.13 Using the Integrated Planning Model,” United States Environmental Protection Agency, Washington, D.C., EPA 450R13002, November 2013.
- [142] M. Beaudin, H. Zareipour, A. Schellenberg, and W. Rosehart, “Chapter 1 - Energy Storage for Mitigating the Variability of Renewable Electricity Sources,” in *Energy Storage for Smart Grids: Planning and Operation for Renewable and Variable Energy Resources (VERs)*, P. Du and N. Lu, Eds. Boston, Massachusetts: Academic Press, 2015, pp. 1–33.
- [143] H. Akhavan-Hejazi and H. Mohsenian-Rad, “Operation of Independent Large-Scale Battery-Storage Systems in Energy and Reserve Markets,” in *Energy Storage for Smart Grids: Planning and Operation for Renewable and Variable Energy Resources (VERs)*, P. Du and N. Lu, Eds. Boston, Massachusetts: Academic Press, 2015, ch. 11, pp. 295–320.
- [144] “The Electricity Market Module of the National Energy Modeling System: Model Documentation 2016,” United States Energy Information Administration, Washington, D.C., Tech. Rep., July 2017.
- [145] Y. Dvorkin, R. Fernández-Blanco, D. S. Kirschen, H. Pandžić, J.-P. Watson, and C. A. Silva-Monroy, “Ensuring Profitability of Energy Storage,” *IEEE Transactions on Power Systems*, vol. 32, pp. 611–623, January 2017.
- [146] D. Khastieva, I. Dimoukas, and M. Amelin, “Optimal Investment Planning of Bulk Energy Storage Systems,” *Sustainability*, vol. 10, pp. 1–23, March 2018.
- [147] D. Pudjianto, M. Aunedi, P. Djapic, and G. Strbac, “Whole-Systems Assessment of the Value of Energy Storage in Low-Carbon Electricity Systems,” *IEEE Transactions on Smart Grid*, vol. 5, pp. 1098–1109, March 2014.
- [148] M. R. Sheibani, G. R. Yousefi, M. A. Latify, and S. Hacıopian Dolatabadi, “Energy storage system expansion planning in power systems: a review,” *IET Renewable Power Generation*, vol. 12, pp. 1203–1221, 20 August 2018.
- [149] J. T. Alt, M. D. Anderson, and R. G. Jungst, “Assessment of Utility Side Cost Savings from Battery Energy Storage,” *IEEE Transactions on Power Systems*, vol. 12, pp. 1112–1120, August 1997.
- [150] R. Guédez, J. Spelling, and B. Laumert, “Reducing the Number of Turbine Starts in Concentrating Solar Power Plants Through the Integration of Thermal Energy Storage,” *Journal of Solar Energy Engineering*, vol. 137, pp. 1–8, February 2015.
- [151] B. Palmintier and M. Webster, “Impact of Unit Commitment Constraints on Generation Expansion Planning with Renewables,” in *2011 IEEE Power and Energy Society General Meeting*. Detroit, MI: Institute of Electrical and Electronics Engineers, 24–28 July 2011.
- [152] H. Daneshi and A. K. Srivastava, “Security-constrained unit commitment with wind generation and compressed air energy storage,” *IET Generation, Transmission & Distribution*, vol. 6, pp. 167–175, February 2012.
- [153] “The National Energy Modeling System: An Overview 2018,” United States Energy Information Administration, Washington, D.C., Tech. Rep., April 2019.
- [154] J. D. Jenkins and N. A. Sepulveda, “Enhanced Decision Support for a Changing Electricity Landscape: The GenX Configurable Electricity Resource Capacity Expansion Model,” 27 November 2017, an MIT Energy Initiative Working Paper Revision 1.0.
- [155] B. Frew, W. Cole, Y. Sun, J. Richards, and T. Mai, “8760-Based Method for Representing Variable Generation Capacity Value in Capacity Expansion Models,” National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/CP-6A20-68869, August 2017.
- [156] J. DeCarolis, K. Dulaney, H. Fell, C. Galik, J. Johnson, S. Kalland, N. Lu, D. Lubkeman, I. Panzarella, A. Proudlove, A. Rodrigo de Queiroz, W. Tang, A. Alrushoud, C. Gambino, Y. Meng, M. Liang, S. Liu, D. Mulcahy, D. Sodano, D. Soutendijk, and L. Sun, “Energy Storage Options for North Carolina,” NC State Energy Storage Team, Tech. Rep., February 2019.
- [157] L. Boffino, A. J. Conejo, R. Sioshansi, and G. Oggioni, “A Two-Stage Stochastic Optimization Planning Framework to Deeply Decarbonize Electric Power Systems,” *Energy Economics*, vol. 84, p. 104457, October 2019.
- [158] W. Short, “Regions in Energy Market Models,” National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-640-40506, February 2007.

[159] L. Bahiense, G. C. Oliveira, M. Pereira, and S. Granville, "A Mixed Integer Disjunctive Model for Transmission Network Expansion," *IEEE Transactions on Power Systems*, vol. 16, pp. 560–565, August 2001.

[160] M. Black and G. Strbac, "Value of storage in providing balancing services for electricity generation systems with high wind penetration," *Journal of Power Sources*, vol. 162, pp. 949–953, November 22 2006.

[161] W. A. Braff, J. M. Mueller, and J. E. Trancik, "Value of storage technologies for wind and solar energy," *Nature Climate Change*, vol. 6, pp. 964–969, October 2016.

[162] M. Arbabzadeh, R. Sioshansi, J. X. Johnson, and G. A. Keoleian, "The role of energy storage in deep decarbonization of electricity production," *Nature Communications*, vol. 10, pp. 1–11, 30 July 2019.

[163] *Study of Electric Transmission in Conjunction with Energy Storage Technology*, Lower Colorado River Authority, Austin, TX, August 2003, prepared for Texas State Energy Conservation Office.

[164] P. Denholm and R. M. Margolis, "Evaluating the limit of solar photovoltaics (PV) in traditional electric power systems," *Energy Policy*, vol. 35, pp. 2852–2861, 2007.

[165] R. Sioshansi and W. Short, "Evaluating the Impacts of Real-Time Pricing on the Usage of Wind Generation," *IEEE Transactions on Power Systems*, vol. 24, pp. 516–524, May 2009.

[166] P. Denholm, M. O'Connell, G. Brinkman, and J. Jorgenson, "Overgeneration from Solar Energy in California: A Field Guide to the Duck Chart," National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-6A20-65023, November 2015.

[167] S. Singla, Y. Ghiassi-Farrokhfal, and S. Keshav, "Using Storage to Minimize Carbon Footprint of Diesel Generators for Unreliable Grids," *IEEE Transactions on Sustainable Energy*, vol. 5, pp. 1270–1277, October 2014.

[168] X. Xi, R. Sioshansi, and V. Marano, "A Stochastic Dynamic Programming Model for Co-optimization of Distributed Energy Storage," *Energy Systems*, vol. 5, pp. 475–505, September 2014.

[169] S. Bhattacharjee, R. Sioshansi, and H. Zareipour, "Benefits of Strategically Sizing Wind-Integrated Energy Storage and Transmission," *IEEE Transactions on Power Systems*, vol. 36, pp. 1141–1151, March 2021.

[170] *2016 Probabilistic Assessment*, North American Electric Reliability Corporation, 3353 Peachtree Road, NE, Suite 600, North Tower, Atlanta, GA 30326, March 2017.

[171] R. Sioshansi, S. H. Madaeni, and P. Denholm, "A Dynamic Programming Approach to Estimate the Capacity Value of Energy Storage," *IEEE Transactions on Power Systems*, vol. 29, pp. 395–403, January 2014.

[172] Y. Zhou, P. Mancarella, and J. Mutale, "Framework for capacity credit assessment of electrical energy storage and demand response," *IET Generation, Transmission & Distribution*, vol. 10, pp. 2267–2276, 9 June 2016.

[173] R. Bent, C. Coffrin, R. R. E. Gumucio, and P. Van Hentenryck, "Transmission Network Expansion Planning: Bridging the Gap between AC heuristics and DC Approximations," in *2014 Power Systems Computation Conference*. Wroclaw, Poland: Institute of Electrical and Electronics Engineers, 18–22 August 2014.

[174] H. Xing, H. Cheng, L. Zhang, S. Zhang, and Y. Zhang, "Second-Order Cone model for Active Distribution Network Expansion Planning," in *2015 IEEE Power & Energy Society General Meeting*. Denver, CO: Institute of Electrical and Electronics Engineers, 26–30 July 2015.

[175] L. L. Garver, "Effective Load Carrying Capability of Generating Units," *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-85, pp. 910–919, August 1966.

[176] R. Billinton and R. N. Allan, *Reliability Evaluation of Power Systems*. Boston, Massachusetts: Pitman Advanced Publishing Program, 1984.

[177] R. Billinton and P. Wang, "Distribution System Reliability Cost/Worth Analysis Using Analytical and Sequential Simulation Techniques," *IEEE Transactions on Power Systems*, vol. 13, pp. 1245–1250, November 1998.

[178] P. Denholm and T. Mai, "Timescales of Energy Storage Needed for Reducing Renewable Energy Curtailment," National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-6A20-68960, September 2017.

[179] S. H. Madaeni, R. Sioshansi, and P. Denholm, "Estimating the Capacity Value of Concentrating Solar Power Plants with Thermal Energy Storage: A Case Study of the Southwestern United States," *IEEE Transactions on Power Systems*, vol. 28, pp. 1205–1215, May 2013.

[180] R. Perez, M. Taylor, T. Hoff, and J. P. Ross, "Reaching Consensus in the Definition of Photovoltaics Capacity Credit in the USA: A Practical Application of Satellite-Derived Solar Resource Data," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 1, pp. 28–33, March 2008.

[181] B. Klöckl and G. Papaefthymiou, "An effort to overcome the chronological modeling methods for energy storage devices," in *2005 International Conference on Future Power Systems*. Amsterdam, Netherlands: Institute of Electrical and Electronics Engineers, 18 November 2005.

[182] G. Edwards, S. Sheehy, C. J. Dent, and M. C. M. Troffaes, "Assessing the contribution of nightly rechargeable grid-scale storage to generation capacity adequacy," *Sustainable Energy, Grids and Networks*, vol. 12, pp. 69–81, December 2017.

[183] B. Bagen and R. Billinton, "Impacts of Energy Storage on Power System Reliability Performance," in *2005 Canadian Conference on Electrical and Computer Engineering*. Saskatoon, Saskatchewan, Canada: Institute of Electrical and Electronics Engineers, 1–4 May 2005, pp. 494–497.

[184] P. Hu, R. Karki, and R. Billinton, "Reliability evaluation of generating systems containing wind power and energy storage," *IET Generation, Transmission & Distribution*, vol. 3, pp. 783–791, August 2009.

[185] L. H. Koh, G. Z. Yong, W. Peng, and K. J. Tseng, "Impact of Energy Storage and Variability of PV on Power System Reliability," *Energy Procedia*, vol. 33, pp. 302–310, 2013.

[186] I. Konstantelos, P. Djapic, G. Strbac, P. Papadopoulos, and A. Laguna, "Contribution of energy storage and demand-side response to security of distribution networks," *CIRED - Open Access Proceedings Journal*, vol. 2017, pp. 1650–1654, October 2017.

[187] G. Stephen, "Probabilistic Resource Adequacy Suite (PRAS) v0.6 Model Documentation," National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-5C00-79698, May 2021.

[188] M. A. Mansouri and R. Sioshansi, "The Effect of Natural-Gas Prices on Power-System Reliability," *Current Sustainable/Renewable Energy Reports*, 2021, in press.

[189] R. Moreno, R. Moreira, and G. Strbac, "A MILP model for optimising multi-service portfolios of distributed energy storage," *Applied Energy*, vol. 137, pp. 554–566, 1 January 2015.

[190] B. Zhang, D. Stenclik, and W. Hall, "Calculating the Capacity Value and Resource Adequacy of Energy Storage on High Solar Grids," in *2018 Grid of the Future*, no. 2018-18. Reston, VA: Conseil International des Grands Réseaux Électriques, 28–31 October 2018.

[191] K. Parks, "Declining Capacity Credit for Energy Storage and Demand Response With Increased Penetration," *IEEE Transactions on Power Systems*, vol. 34, pp. 4542–4546, November 2019.

[192] K. Carden and N. Wintermantel, "Energy Storage Capacity Value on the CAISO System," Astrapé Consulting, Tech. Rep., 20 November 2019.

[193] D. Sodano, J. F. DeCarolis, A. Rodrigo de Queiroz, and J. X. Johnson, "The symbiotic relationship of solar power and energy storage in providing capacity value," *Renewable Energy*, vol. 177, pp. 823–832, November 2021.

[194] S. H. Madaeni, R. Sioshansi, and P. Denholm, "How Thermal Energy Storage Enhances the Economic Viability of Concentrating Solar Power," *Proceedings of the IEEE*, vol. 100, pp. 335–347, February 2012.

[195] R. Sioshansi and P. Denholm, "The Value of Concentrating Solar Power and Thermal Energy Storage," *IEEE Transactions on Sustainable Energy*, vol. 1, pp. 173–183, October 2010.

[196] A. M. Rei, A. M. Leite da Silva, J. L. Jardim, and J. C. O. Mello, "Static and Dynamic Aspects in Bulk Power System Reliability Evaluations," *IEEE Transactions on Power Systems*, vol. 15, pp. 189–195, February 2000.



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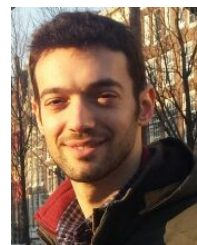
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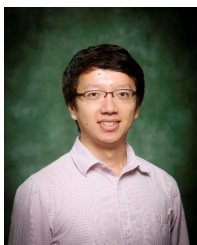
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