Annual Review of Environment and Resources

Modeling Costs and Benefits of Energy Storage Systems

Eric Hittinger[1,2] and Rebecca E. Ciez[3]

[1]L2EP–Laboratoire d'electrotechnique et d'electronique de puissance, Université de Lille, F-59000 Lille, France

[2]Department of Public Policy, Rochester, Rochester Institute of Technology, College of Liberal Arts, Rochester, New York 14623, USA; email: eshgpt@rit.edu

[3]Andlinger Center for Energy and the Environment, Princeton University, Princeton, New Jersey 08540, USA

Annu. Rev. Environ. Resour. 2020. 45:445–69

First published as a Review in Advance on May 4, 2020

The *Annual Review of Environment and Resources* is online at environ.annualreviews.org

https://doi.org/10.1146/annurev-environ-012320-082101

Keywords

electrical energy storage, cost analysis, future technology cost, systems modeling, electricity market policy

Abstract

In recent years, analytical tools and approaches to model the costs and benefits of energy storage have proliferated in parallel with the rapid growth in the energy storage market. Some analytical tools focus on the technologies themselves, with methods for projecting future energy storage technology costs and different cost metrics used to compare storage system designs. Other tools focus on the integration of storage into larger energy systems, including how to economically operate energy storage, estimate the air pollution and greenhouse gas emissions effects of storage, or understand how policy and market rules influence storage deployment and operation. Given the confluence of evolving technologies, policies, and systems, we highlight some key challenges for future energy storage models, including the use of imperfect information to make dispatch decisions for energy-limited storage technologies and estimating how different market structures will impact the deployment of additional energy storage.

Contents

INTRODUCTION

Energy storage is a broad term that describes various technologies designed to store energy for later useful application. Storage is often associated with either generation or consumption of energy, but storage is not a net producer of energy and is only a net consumer of energy due to system inefficiency. Although some forms of energy storage are historically quite common (gasoline, for example), in this review we limit the discussion to electricity energy storage[1]—technologies that consume electricity at one point in time in order to deliver electricity (or reduce its consumption) at a later point in time. For electricity, energy storage technologies take many forms. Electricity can be stored directly as a charge in a capacitor, in the form of mechanical potential or thermal energy, or electrochemically, with energy stored and released in chemical bonds. Energy can also be stored in the form of produced gases [e.g., hydrogen (1, 2)], but here we focus on closed-loop systems where electricity is both consumed and returned.

Electricity energy storage is not a new technology, but interest in energy storage has increased significantly in the past 15 years, driven by two factors that are somewhat interdependent: (*a*) an increased need for energy storage to complement deployed and projected variable wind and solar generation and (*b*) rapidly decreasing costs for various storage technologies, most prominently lithium-ion batteries. As a result of these two forces, the storage industry has experienced rapid growth in the past decade, with projections for the trend to continue for decades to come.

Frequency regulation: an electricity system service that involves high-frequency (second-to-second) adjustment of power output, used to balance supply and demand on short time scales

The nature of these new storage technologies, when combined with modern grid communication (smart grids), has also enabled a new set of applications for energy storage. Historically, energy storage in the form of pumped hydropower was used as a form of generation reserve, with the possibility of providing some frequency regulation or related balancing services. But the new generation of storage technologies, when embedded into a modernized grid, can provide a wide

[1] We continue to use the terms energy storage or storage, even though the topic is specifically electricity energy storage.

set of services for various customers. On the generation side, storage can provide peaking capacity, time-shifting of generation (energy arbitrage), and ancillary services such as frequency regulation or spinning reserve. For distribution companies, storage can help manage peak electricity demand or integrate distributed solar, and provide voltage or frequency support for weak parts of the system. For customers, storage can help improve reliability, increase self-consumption of solar or other local generation, and provide the ability to shift consumption to respond to electricity rate structures.

Spinning reserve: an electricity system service where a generator or other facility commits to supplying additional power output within 5–20 minutes if requested by the system operator

Attempts to understand the net benefits of energy storage technologies—the topic of this review article—have also been growing quickly in sophistication. Increased efforts toward quantifying the economic costs and benefits of energy storage in electricity systems, including emissions effects, have been driven by both the growing relevance of these analyses as well as the fundamental challenges involved in studying the topic, attracting and allowing for a broad set of research approaches to address different facets of the general question. There is a range of interesting economic questions relating to energy storage discussed below, including variations on "What are the current and future costs of energy storage technologies?", "What is the optimal way to operate energy storage (under a variety of assumptions and scenarios)?", "What is the optimal design of an energy storage device?", "What effect does revenue-maximizing storage have on electricity system emissions and how can that be reduced?", and "How do market rules or policy affect the operation or economics of energy storage?".

COSTS OF ENERGY STORAGE TECHNOLOGIES

When evaluating the costs of energy storage technologies, there are a few key parameters to consider. Unlike electricity generation technologies, where capital costs are normally rated based on the maximum power output (i.e., \$/W) with fuel costs contributing to the cost of energy produced (\$/Wh), in energy storage systems these costs both contribute to the installed capital cost of the system.

Beyond the capital costs of the technology, it is also important to consider the system lifetime (which is dictated by the irreversibilities and losses inherent in the system that accumulate over time, especially for electrochemical systems), the response time of the system, the rated power of the system, and the duration that a system can deliver the rated power. Efficiency is also a concern, particularly if electricity prices or air pollutant and greenhouse gas emissions from the electricity system are high, but as both cost and emissions associated with electricity generation decrease, efficiency plays a smaller role in the overall cost of delivering stored energy. Finally, operation and maintenance expenses also contribute to the overall cost of using storage technologies. Each of these factors contributes to the total cost of delivering electricity with storage, and we discuss several metrics commonly used to evaluate the costs of storage systems.

Technology Description

Of the mechanical energy storage technologies, pumped hydro has been the most widely adopted. Hydropower dams have acted as a form of electricity storage for a century, and pumped hydro has been used to balance large nuclear power plants, which operate best at constant power output levels (3). Using geographically favorable sites, water is pumped into an upper reservoir, and the potential energy of the pumped water can then be used to spin a turbine and generate electricity.

Other large-scale mechanical storage options include compressed air storage and thermal storage. Early compressed air systems rely on a natural gas turbine in conjunction with the compressed air. The efficiency of these turbines is then higher than conventional turbines because they do not have to generate compressed air for the combustion process, but these systems still rely on the combustion of fossil fuels (4). More recent research efforts and pilot projects have attempted to use the expansion of the compressed air alone to generate electricity, with successful pilot projects in Texas and Switzerland (5, 6). Thermal energy storage is most frequently paired with concentrated solar power systems, which heat a molten salt that is then stored and used to generate steam overnight (7). Concentrated solar systems are generally located in extremely sunny locations, but other methods, such as resistive heating, could be implemented to heat the energy storage medium independent of the concentrated solar array. Heat exchangers pass the thermal energy from the storage medium to boil water, which is then used to spin a turbine to generate electricity.

Compressed air energy storage (CAES): an energy storage technology that stores energy by compressing air into a chamber and recovers the energy by running the air through a turbine, normally in conjunction with natural gas combustion

Electrochemical energy storage technologies include batteries and fuel cells, and there are many varieties of both technologies. Unlike mechanical storage technologies, which all rely on turbines to spin magnetic generators, electrochemical storage technologies use chemical bonds as the storage mechanism (8). The positive and negative electrodes of batteries can be both solids and liquids. If electrodes are solids, a liquid electrolyte is necessary to facilitate ion transfer, as is the case in lead-acid batteries, which have been available for more than 150 years, and intercalation batteries such as lithium and sodium-ion cells, which are much newer. When both electrodes are liquids, there are typically membrane separators to prevent crossover between the reactants, as is the case in most flow battery configurations (9).

Drivers of Technology Costs

For large-scale mechanical storage systems, cost is influenced by geography. Pumped hydro systems require sites suitable for both a storage reservoir and sufficient elevation change to provide potential energy. As with pumped hydro, compressed air energy storage (CAES) has also been limited by the availability of natural resources to provide low-cost air storage. Common formations for underground storage include mined salt caverns and other porous rock formations (4). Above-ground storage options have been explored but are much more expensive than using existing underground storage facilities, and they have struggled to become commercially viable (10, 11). The size of the geographic resources, in conjunction with the size of the turbines installed, impacts the overall power:energy ratio of the system, but approximations of the system costs are listed in **Table 1**.

Unlike pumped hydro and compressed air systems, where the storage medium is effectively free, finding low-cost materials that retain heat is critical for thermal storage systems. Although heat can be stored directly as steam, the most common choice is molten salts, which can achieve higher temperatures (7, 19). Other sensible heat storage materials, such as concrete and sand, are extremely low cost and have been proposed but not widely implemented (7, 43–45). Metal hydrides, which have an exothermic reaction when hydrogen is added, have the potential to reach temperatures higher than existing salts but remain under research development (46).

Flywheel energy storage has been used in different forms for thousands of years, but most of their more recent applications have been high-speed flywheels, often paired with renewable electricity projects. The round-trip efficiency of these systems can be high, although self-discharge rates are also high enough to discourage long-duration storage of energy, as friction and other losses accumulate over time if the device is left with stored energy. Because of these losses, the cost per kWh of energy stored is high, and power-specific costs are relatively low. Although the technology saw early success as renewable electricity installations increased in the mid- to late 2000s, the industry has faced challenges from other technologies in recent years (9, 23, 47).

Traditionally, capacitors relied on dielectric materials to store a charge directly, but today electrochemical double-layer capacitors and pseudocapacitors are far more common. They rely on

Table 1 Storage technologies and performance parameters

Technology	Cost [$/kW]	Cost [$/kWh]	Round-trip efficiency	Charge/discharge rates	Cycles/product lifetime	System sizes	Key limitations
Pumped hydro	$1,000–$2,500 (12)	–	70–85% (13)	Rate specified by maximum rated power: 6–4,000,000 kW	20+ years (14)	6–4,000,000 kW/ 10^2–10^7 kWh (**https://www.sandia.gov/ess-ssl/global-energy-storage-database/**)	Geographically limited
Compressed air	$1,000–$2,800 (15)	–	With natural gas: Energy ratio: 0.8, <55% efficiency (16, 17) Adiabatic compression alone: 70–75% (5)	Charging: 0.25–0.65C Discharging: 0.04–0.5C (4, 6)	20–30 years (18)	110,000 kW/ 2,640,000 kWh 321,000 kW/ 642,000 kWh (4) 12,000 kWh (6)	Geographically limited, historically dependent on natural gas
Thermal storage	$1,250–$1,500 (19)	$20–$30 (19)	33% (19)	0.05–0.33C (**https://www.sandia.gov/ess-ssl/global-energy-storage-database/**)	25–40 years (20)	100–280,000 kW/ 1,000–1,100,000 kWh (**https://www.sandia.gov/ess-ssl/global-energy-storage-database/**)	Typically paired with concentrated solar
Flywheel	$250–$300	$1,000–$5,000 (9, 21, 22)	90–95% (21)	10–35C (21)	20+ years (23)	100–250 kW/3–25 kWh (21)	High energy costs, high self-discharge rate
Lithium-ion	$250–$500 (24)	$175–$225 (25, 26)	80–85% (27)	0.03–6C (**https://www.sandia.gov/ess-ssl/global-energy-storage-database/**)	10–20 years (27)	1–40,000 kW/ 10–120,000 kWh (**https://www.sandia.gov/ess-ssl/global-energy-storage-database/**)	Borrowed from vehicle applications with high power: energy ratio
Sodium-ion	$250–$500 (24)	$250–$300 (28, 29)	90–95% (30, 31)	0.05–0.8C (**https://www.sandia.gov/ess-ssl/global-energy-storage-database/**)	20+ years (31)	10–50,000 kW/ 20–300,000 kWh (**https://www.sandia.gov/ess-ssl/global-energy-storage-database/**)	Larger ion size results in more expansion/contraction of electrode materials than lithium-ion cells

(*Continued*)

Table 1 (*Continued*)

Technology	Cost [$/kW]	Cost [$/kWh]	Round-trip efficiency	Charge/discharge rates	Cycles/product lifetime	System sizes	Key limitations
Vanadium flow battery	$150–$400 (24)	$125 (32)	75–95% (32)	0.1–0.66C (**https://www.sandia.gov/ess-ssl/global-energy-storage-database/**)	20 years (33)	5–5,000 kW/40–10,000 kWh (**https://www.sandia.gov/ess-ssl/global-energy-storage-database/**)	Additional system hardware, high storage material cost
Iron flow battery	$150–$400 (24)	$7 (34)	≤70% (35, 36)	0.16C (**https://www.sandia.gov/ess-ssl/global-energy-storage-database/**)	20+ years (35)	10 kW/60 kWh (**https://www.sandia.gov/ess-ssl/global-energy-storage-database/**)	Additional system hardware; cycling maintenance may be necessary to manage uneven plating of metal electrode
ZnBr flow battery	$150–$400 (24)	$10 (37)	65–75% (**https://energystorage.org/why-energy-storage/technologies/solid-electrode-batteries/**)	0.16–0.5C (**https://www.sandia.gov/ess-ssl/global-energy-storage-database/**)	10 years (33, 38)	3–1,000 kW/50–6,000 kWh (**https://www.sandia.gov/ess-ssl/global-energy-storage-database/**)	
Lead acid	$250–$500 (24)	$100–$300 (39)	81% (40)	0.025–2C (**https://www.sandia.gov/ess-ssl/global-energy-storage-database/**)	5–10 years (40)	2–10,000 kW/7–10,500 kWh (**https://www.sandia.gov/ess-ssl/global-energy-storage-database/**)	Low energy density and specific capacity, battery useful life highly dependent on cycling behavior
Capacitors	$25–$50 (41)	$10,000–$20,000 (41)	75–95% (41)	2–720C (**https://www.sandia.gov/ess-ssl/global-energy-storage-database/**)	20+ years (42)	28–4,000 kW/3.5–150 kWh (**https://www.sandia.gov/ess-ssl/global-energy-storage-database/**)	Excellent power density and cycle life, but very low energy density, limit the duration of charging and discharging cycles without extreme cost

charged electrodes, typically made of carbon, to separate the ions within an electrolyte (48, 49). Because this separation happens at the surface of the electrodes (whether in contact with the electrolyte or with the other electrode), capacitors are excellent at providing high power density, but their energy storage capacity is limited. Increasing electrode thickness does not result in a higher amount of energy stored; thus, reducing the costs of both the electrolyte and the excess electrode material is important for minimizing system costs.

Although some battery technologies have been in use for more than 150 years, recent innovations have led to drastic improvements in technology and cost. Until recent technological improvements, lead-acid batteries were the most commonly adopted electrochemical storage technology, with relatively low capital cost, but they suffer from relatively low efficiency and useful life, retiring when they reach 80% of their initial storage capacity. The low cost and availability made them a common choice for off-grid microgrids and solar + storage systems, and backup power systems for applications such as cell phone towers, but they were too expensive to be broadly implemented at grid-scale (**https://www.sandia.gov/ess-ssl/global-energy-storage-database/**).

In contrast, lithium-ion battery costs have fallen dramatically since their commercial introduction in 1991 (50). Today's lithium-ion batteries offer higher energy density and specific energy than lead-acid batteries. Current areas of research focus on improving the storage capacity of the positive electrode materials (51, 52) and removing the carbon material from the negative electrode to have a lithium-metal battery, which would reduce the balance of cell hardware (53, 54). Improvements in electrolyte materials and battery management systems have extended the useful life of lithium-ion batteries, and it is possible to design systems that cycle the batteries until they are at 60% of their storage capacity. Lithium-ion batteries are nearly perfectly responsive, which is partially driven by the electric vehicle market, where power density is a highly valued attribute. Because power and energy density are coupled in battery cells, this means that commercially available lithium-ion batteries are expensive for longer-duration applications. Sodium-ion batteries rely on the same charging and discharging mechanisms as lithium-ion batteries and make use of materials that are even more abundant. However, negative electrode materials are somewhat limited because sodium ions are larger than lithium ions, which also increases the expansion and contraction of the electrode materials as the cell is charged and discharged repeatedly (55, 56). Estimating the balance of system costs for storage systems is an important but understudied area of research, with relatively few estimates of system hardware costs available (24, 57).

A challenge for both lead-acid and intercalation batteries is the coupling of energy and power within the battery system. Most designs have been adaptations of automotive batteries, which demand a higher power density than a long-duration storage application requires. Flow batteries, which have storage tanks for reactants and membrane separators, offer a pathway to decouple the power conversion and energy storage battery components. In practice, flow battery systems are typically targeted for 4–6-hour (or longer) applications, because the pumping or other circulatory systems limit their responsiveness and ability to provide high-value grid services (58, 59). Because the redox reactants are a substantial portion of the cost of flow batteries, many different combinations/reactions have been used as reactants in flow batteries, including zinc-bromine, iron (ferric/ferrous couples), chromium (chromic/chromous couple), and vanadium (vanadium/vanadium oxide) (60). Newer configurations make use of gravity and eliminate some or all of the pumps that force convection between the reactants to reduce balance of system costs, but they have not yet been widely commercialized (61, 62).

How Do We Estimate Future Costs?

Given the rapid change in energy storage technology costs and the role that energy storage may play in the future electricity grid, there is interest in predicting the future cost of these technologies, especially for batteries. Multiple methods have been applied to make these predictions, including using statistical analyses to identify learning rates over time, expert elicitations of future technology costs, and technical cost models of the technology inputs and manufacturing processes. The methods often vary by storage technology, with the most recent research focus on battery technologies that have seen rapid cost declines.

For many mature technologies, such as pumped hydro, both system costs and installations have been relatively stable in recent years, and studies examining costs over time have found that there is not a significant impact from learning-by-doing to further reduce costs (63). Costs are also highly site specific, with many of the most advantageous sites already selected. This is particularly true for countries such as the United States and Japan, which already have large pumped hydro facilities (**https://www.sandia.gov/ess-ssl/global-energy-storage-database/**). Many recent projects have been upgrades to pre-existing hydropower and pumped hydro facilities (3). Given the limited number of facilities, modeling of compressed air and thermal storage systems has been limited, and primarily consists of technical cost models using sensitivity analyses of capital costs, or substitutions of high-value materials to assess potential for future cost reductions (15, 20, 64, 65).

Much of the recent research into future energy storage technology costs has focused on the cost of lithium-ion batteries. Several models have made use of historical price and production data to try to extrapolate future cost reductions (50, 66, 67) or have conducted expert elicitations to identify future technology costs and potential drivers of future costs (68, 69).

Bottom-up technical cost models, which analyze a sample cell design to account for parameters such as cell dimensions, electrode thicknesses, and battery chemistry, have also been developed. For the sample cell design, these models then estimate the costs of manufacturing, including input material costs, equipment, labor, energy, and other expenses. Argonne National Lab's BatPaC model constructs numerous different pouch cells with different storage capacities and chemistries. The cost model relies on a cost estimate for a representative plant and scales manufacturing costs relative to this representative production volume depending on the desired production rate. Iterations of this model have been used to examine how reducing time-intensive manufacturing steps such as electrode wetting and cell formation can reduce overall cost (70). Other engineering models use discrete estimates of the cost of equipment, labor, and energy necessary to manufacture a specified annual production volume (71, 72). Beyond models, a common industry practice for estimating the cost floor for lithium-ion batteries is to consider the raw material costs—lithium carbonate, cobalt, nickel, manganese, etc.—for the electrodes and electrolyte materials compared to the specific capacity of the storage materials.

Studies for other battery chemistries are less prolific. Sodium-ion batteries are occasionally included in market-based learning rate models (63) or borrow from technical cost models of lithium-ion batteries, with substitutions for input material costs and electrode capacities (28). Similarly, some flow battery chemistries have been included in broader storage market analyses of learning rate (63). Others have conducted technical cost models of different flow battery chemistries, and numerous studies (73, 74), including a study by Darling et al. (24), have attempted to model the future cost of flow batteries by disaggregating and estimating the costs of system components and comparing them to lithium-ion battery system costs.

Each of these types of model has strengths and weaknesses: Learning rate models can effectively capture market trends but do not provide much information about the drivers of those costs. Expert elicitation studies can identify research trends and policy trends, but experts are not always consistent when estimating the costs of components and systems for storage technologies, and identification of research areas is dependent on the selected experts. Technical cost models can effectively model existing manufacturing processes, cell designs, and battery chemistries but will not be able to predict changes to new cell chemistries that are discovered in future research.

SYSTEM COST METRICS

With the many different performance parameters/technology characteristics and associated costs for different storage technologies, modeling storage costs often necessitates the use of a common cost metric that can be applied for the analysis. Although most studies make use of such a metric, there is no universally agreed upon standard or formula used to calculate the costs of electricity storage, given that different metrics highlight different features of storage cost and operation.

Metrics from engineering economics are often employed, including the net present value of a storage system, the internal rate of return of storage systems, and the breakeven period. Breakeven calculations are especially common when considering distributed systems such as microgrids or behind-the-meter storage, where there is a clear alternative to the storage technology (e.g., diesel generators for microgrids, purchasing grid electricity for behind-the-meter systems).

Frequently, analyses will make use of a levelized cost metric, although there are many different variations of this metric (75, 76). The most encompassing metric is the levelized cost of electricity (LCOE). In this calculation, the cost of electricity includes any capital expenses associated with electricity generation for direct consumption ($c_{cap,\,gen}$), capital expenses for electricity generation that goes to storage ($c_{cap,\,gen2stor}$), capital expenses for storage technologies ($c_{cap,\,stor}$), fuel (p_{fuel}) or purchased electricity (p_{elec}) costs (accounting for efficiency losses of the generator, η_{gen}, and round-trip efficiency losses of storage charge and discharge, η_{RTE}), and operating expenses ($c_{O+M,\,gen}$, $c_{O+M,\,gen2stor}$, $c_{O+M,\,stor}$). Costs can be discounted (using discount rate r) to determine the net present value and then divided by the discounted amount of electricity delivered over the system lifetime ($e_{delivered}$ in Equation 2) to calculate LCOE (Equation 4). An alternative method that produces the same result is to annualize all costs based on their useful lifetime (T) with the capital recovery factor (Equation 1) and then divide by annual energy delivered (Equation 5). The energy delivered for the LCOE includes energy that is generated or purchased from the grid and consumed directly ($e_{gen,\,consumed}$, $e_{grid,\,consumed}$) or that is stored and used later ($e_{gen,\,stor}$, $e_{grid,\,stor}$). Because the LCOE metric includes the costs of fuel and electricity purchased to meet all of the system demand and to charge storage devices, the LCOE is highly variable in response to local electricity or fuel prices. For this reason, some analysts prefer to use the levelized cost of storage (LCOS), which explicitly focuses on the costs associated with the electricity stored ($e_{delievered,\,stor}$ in Equation 3). When calculating the LCOS (Equations 6 and 7), the expenses include the capital costs of storage ($c_{cap,\,stor}$) and additional generation capacity necessary to account for the electricity lost during the storage cycle ($c_{cap,\,gen2stor}$), operation and maintenance expenses ($c_{O+M,\,\mathrm{stor}}$, $c_{O+M,\,gen2stor}$), and the fuel and electricity necessary to account for the electricity lost during the storage cycle. Because the LCOS accounts for only the additional electricity necessary to cover efficiency losses, the LCOS is less sensitive to local electricity or fuel prices. Although these are broad formulas for calculating levelized costs, they are by no means universally applied using these exact formulas. Some calculations omit operation and maintenance expenses, and others include salvage rates or decommissioning costs.

Regardless of the exact formula used, a key distinction to draw when calculating the LCOE or LCOS is that the cost is also determined by demand for the electricity or stored energy. Although a storage system might be technically able to cycle continuously for all hours of the year, demand is driven by consumption patterns. For storage technologies, this means that even if a system is sized to provide longer-duration storage, actual cycling behavior can mean that the charging and discharging cycles often use just a fraction of the installed capacity, limiting the electricity delivered by the system and increasing levelized cost:

$$CRF = \frac{r(1+r)^{T-1}}{(1+r)^{T}-1}, \tag{1.}$$

$$e_{delivered} = e_{gen,consumed} + e_{gen,stor} + e_{grid,consumed} + e_{grid,stor}, \tag{2.}$$

$$e_{delivered,stor} = e_{gen,stor} + e_{grid,stor}, \tag{3.}$$

$$LCOE_{NPV} = \frac{\begin{array}{l}\sum_{t=0}^{T} \Big(c_{cap,stor}(t) + c_{cap,gen}(t) + c_{cap,gen2\,stor}(t) + c_{O+M,stor}(t) + c_{O+M,gen}(t) + c_{O+M,gen2\,stor}(t) \\ \quad + \frac{p_{fuel}}{\eta_{gen}}\left(e_{gen,consumed}(t) + \frac{1}{\eta_{RTE}} e_{gen,stor}(t)\right) + p_{elec}\left(e_{grid\,consumed}(t) + \frac{1}{\eta_{RTE}} e_{grid,stor}(t)\right)\Big) \Big/ (1+r)^{t}\end{array}}{\sum_{t=0}^{T} e_{delivered}(t)/(1+r)^{t}}, \tag{4.}$$

$$LCOE_{ANNUALIZED} = \frac{\begin{array}{l}(c_{cap,stor} + c_{cap,gen} + c_{cap,gen2stor})CRF + (c_{O+M,stor} + c_{O+M,gen} + c_{O+M,gen2stor}) \\ \quad + \frac{p_{fuel}}{\eta_{gen}}\left(e_{gen,consumed} + \frac{1}{\eta_{RTE}} e_{gen,stor}\right) + p_{elec}\left(e_{grid\,consumed} + \frac{1}{\eta_{RTE}} e_{grid,stor}\right)\end{array}}{e_{delivered}}, \tag{5.}$$

$$LCOS_{NPV} = \frac{\begin{array}{l}\sum_{t=0}^{T} \Big(c_{cap,stor}(t) + c_{cap,gen2\,stor}(t) + c_{O+M,stor}(t) + c_{O+M,gen2\,stor}(t) \\ \quad + \left(\frac{1}{\eta_{RTE}} - 1\right)\left(\frac{p_{fuel}}{\eta_{gen}} e_{gen,stor}(t) + p_{elec} e_{grid,stor}(t)\right)\Big) \Big/ (1+r)^{t}\end{array}}{\sum_{t=0}^{T} e_{delivered,stor}(t)/(1+r)^{t}}, \tag{6.}$$

$$LCOS_{ANNUALIZED} = \frac{(c_{cap,stor} + c_{cap,gen2stor})CRF + (c_{O+M,stor} + c_{O+M,gen2stor}) + \left(\frac{1}{\eta_{RTE}} - 1\right)\left(\frac{p_{fuel}}{\eta_{gen}} e_{gen,stor} + p_{elec} e_{grid,stor}\right)}{e_{delivered,stor}}. \tag{7.}$$

Some have attempted to clarify this point by distinguishing between the LCOE and levelized cost of shaped energy (77). One limitation of current levelized system cost metrics is the uncertainty around system retirement costs, which are usually not included. Whereas some storage technologies, such as lead-acid batteries, can be decommissioned and recycled profitably or refurbished to extend their lifetime (pumped hydro systems), disposal options for newer technologies are not yet defined. For lithium-ion systems, decommissioning system components could prove to be expensive, although recycling of both battery materials and other hardware components could provide some value (78, 79).

MODELING APPROACHES FOR ENERGY STORAGE ECONOMICS

Questions about the economics of energy storage often rely on determining how that storage would or should operate. Although true for other technologies, analysis of optimal storage operation often reaches levels of complexity beyond that required for wind turbines or natural gas power plants. Much of the cutting edge research into energy storage economics is focused on determining the operation of storage: how storage should make decisions under uncertainty, how storage should divide efforts between different services, or how storage should strategically bid into markets in locations where it has sufficient scale to affect prices. The importance of storage operation is also evident in the growing number of private companies created to sell proprietary storage dispatch software to storage owners (80). The reader should know that, in parallel with the publicly available research described in this review, private entities are developing their own intellectual property in the form of algorithms intended to maximize the value of storage for their customers. For both the public and private spheres, the frontier of storage economics research is intently focused on understanding optimal storage operation under different scenarios and conditions. For this reason, we dedicate an entire section to methods for the modeling of storage operation.

The operation of energy storage has a fundamental difference from other electricity technologies that makes the modeling of storage both more challenging and more interesting. This difference is that energy storage is an energy-limited technology, meaning that it cannot operate continuously in any mode or service unless that mode or service happens to be energy neutral. Although that distinction may seem minor, it means that the decision of what to do with a storage device right now depends on what it has done in the past and what you plan to do with it in the future, adding a temporal dependence to any reasonably sophisticated storage analysis. This concept is not strictly new to electricity modeling—operational and economic implications of ramping limitations and start-up constraints of power plants is a topic of current investigation in electricity system dispatch modeling (81). However, the intertemporal dependence that is central to good energy storage models is often neglected or treated in simplified ways for most electricity system modeling because those dynamics are of lesser importance for traditional generation technologies, whereas they are central to the operation of storage.

Hypothetically, the issue of intertemporal reliance could be overcome with sufficiently large storage so that energy constraints were not important. But that strategy runs contrary to the concepts of storage economics: Normally, the economic questions that we ask of storage are either "What is the minimum amount of storage I need for some purpose?" or "What is the maximum amount of value or service that I can extract from a given storage device?", and the question of constraints cannot be avoided in either case. Moreover, despite the complication of temporal interaction, storage modeling does enjoy the benefit of simple operation in other ways. Most storage technologies are, effectively, perfectly responsive—able to meet rapidly changing control signals for charging and discharging (9). Electrochemical technologies and flywheels are the most straightforward, with charge and discharge limits as the primary constraint. Pumped hydropower is similar, although hydrological constraints may dictate when and how the storage can operate, depending on the dam location. Standard CAES designs use combustion of natural gas as a heat source to heat the expanding air and thus have some economic and operational dependence on natural gas availability.

In addition to the constraints described above, all energy storage technologies have losses, which can be divided into two primary categories: cycling losses and self-discharge. Cycling losses are an unavoidable consequence of the second law of thermodynamics, when combined with practical storage designs. In short, storage will never be able to deliver the same amount of energy that was used to charge it. These losses are usually described using a round-trip efficiency figure for the technology, which may be set as a constant for modeling purposes or vary as a function of other parameters in more sophisticated analyses. Likewise, the attribution of the losses to charging or discharging (or both) can have minor effects on storage modeling. Self-discharge occurs whether or not the storage is being cycled. Although all forms of storage experience some self-discharge, it is often small enough to be trivial for modeling purposes. However, in some technologies, such as friction losses in flywheels or heat dissipation in thermal energy storage, self-discharge can be of similar scale or larger than cycling losses.

Models of energy storage operation are designed to determine or approximate the optimal storage operation under a given scenario. Although there are analyses of storage operation that do not explicitly state this goal, the advancement of a specific algorithm implicitly suggests that the output of that algorithm is optimal (or at least good) under some scenario or set of constraints. The decision criteria for energy storage is also relatively simple: At each point in time, how much energy should go into or out from the storage device? However, answering this question can require sophisticated models that account for the intertemporal nature of storage operation, uncertainty about the future, and even strategic action in the game-theoretic sense. In this work, we divide storage operation models into four approximate categories of increasing sophistication: atemporal models, perfect information models, imperfect information models, and strategic operation models.

Perfect information model: a storage model that uses or assumes perfect information about future conditions, allowing a sufficiently complex model to identify the indisputably optimal operational pattern

Linear programming (LP): a broad category of optimization algorithms often used in energy systems analysis; LP models can efficiently identify a globally optimal solution to problems when correctly formulated within methodological constraints

Atemporal Models

The simplest form of storage model is one that neglects the temporal aspect of energy storage, which is justified in cases where the storage operation is predictable enough that it does not need to be calculated. In these cases, some typical operational pattern is assumed, and the system effects or economics are calculated directly. For example, Poullikkas (82) examines the economics of different solar thermal systems in Cyprus, including differing amounts of thermal storage. In this case, the thermal storage is operationally modeled as variable hours of output from the solar plant, from 5 hours (no storage) up to 24 hours. Atanacio et al. (83) provide another example, investigating the effect that adding flywheel energy storage for frequency regulation would have on grid emissions. Although the modeling effort for the generation fleet was sophisticated, the addition of flywheel energy storage was modeled as a decrease in the frequency regulation requirement for the system. This effectively assumed that the flywheels would operate continuously to provide this service, a fair assumption given the performance characteristics of the technology. In both examples, the energy in and out of the storage device is not explicitly tracked, and there is no algorithm used to decide when to operate storage.

Perfect Information Models

Most storage models track time series data about important storage operational parameters, such as charge/discharge of the storage and state-of-charge, and use some form of algorithm to make decisions about when to charge and discharge. The problem is easier when knowledge about future conditions is known to the algorithm with certainty, and these models are often known as perfect information models. The presence of perfect information is not trivial in the modeling sense because it allows for algorithms that can find the indisputably optimal strategy. The obvious issue with perfect information assumptions is that reality rarely provides perfect information about future events and instead forces electricity system participants to strategize under uncertainty. However, results from perfect information models can be useful because they provide an upper bound on the operational and economic capabilities of energy storage and, in some scenarios, produce results that are not far from an imperfect information scenario (where actual revenue may reach 85% or more of maximum theoretical revenue) (84, 85).

A common way to solve for optimal storage operation under perfect information is through linear programming (LP), where a range of approaches with the same logical basis have been applied. As in other fields, the challenge of LP approaches is normally in formulating the problem in a way that meets the constraints of the method. LP models of energy storage have achieved increasing complexity as the field has progressed, integrating greater numbers of services, storage parameters, or operational constraints. Drury et al. (16) provide a straightforward application by creating and applying a model of CAES storage, co-optimizing its operation between energy and reserve services using an LP approach. Moreno et al. (86) provide one of the more sophisticated perfect information models, which determines the optimal operation of distributed storage resources providing multiple services (arbitrage, frequency regulation, spinning reserve, and network congestion reduction) while providing appropriate compensation. The mixed integer linear programming (MILP) approach they develop even includes both active and reactive power needs and delivery.

Connolly et al. (87) describe an alternative algorithm utilizing perfect information to maximize arbitrage revenue, wherein an iterative process finds high price/low price temporal pairs, checks whether energy can be moved from one to the other, then commits to the transfer, and returns to the start of the cycle by searching for another pair. The algorithm stops when it can no longer find any transfer of energy that is both profitable and permitted by the storage constraints. When implemented correctly, this method gives the same result as the more standard LP method but may be an easier basis for expanding the analysis into other services or uncertainties. As an example, Staffell & Rustomji (88) extend the method to include reserve services by blocking out periods when storage is offering reserve services from the energy arbitrage search. They also include uncertainty about future prices by replacing all future energy prices with seasonally averaged prices from the previous year. This effectively means that the algorithm perfectly solves the problem of storage operation, but with price inputs that are generally (but not exactly) correct. Another algorithm with the benefit of conceptual and algorithmic simplicity is "backwards induction," as applied by Cho & Kleit (89) to determining the operation of energy storage that can provide both energy and spinning reserve services. In this method, calculations are performed backwards in time, starting at the end of some period (a day, for example), and the value of having energy in the storage in one hour is taken as the value of holding it in the prior hour. Working backwards, the value of using the energy at any time step is compared with the value of holding it for a later time step.

Imperfect Information Models

In reality, most of the economic opportunities for energy storage involve uncertain knowledge of future conditions, in the form of electricity prices, renewable energy generation, electricity demand, or other factors. It then makes sense that we need to develop algorithms for storage operation that respect this uncertainty about the future, both because they will give more realistic results and because any algorithm that is used to control actual storage devices does not have access to future information, except by proxy (i.e., day-ahead prices or forecasts). The approaches used to operate storage under uncertain futures differ, but generally apply algorithms of varying sophistication to determine the optimal storage operation now, given some fixed expectation about future states, with the calculations rerun at a predefined frequency. The characterization of future states can take on many forms depending on the problem examined, and is generally less standardized than perfect information approaches, but often takes the form of forecasting demand patterns, price patterns, or renewable energy production based on prior data and applying a logical (although not always strictly optimal) decision algorithm.

A simple imperfect information algorithm for storage operating in an energy market is to set a buy price, below which storage will charge as much as possible, and sell price, above which storage will sell as much as possible (neither charging or discharging when the price is between these points) (90). The buy and sell prices are set on the basis of optimal values from historical price data. Although the buy and sell price points may be fixed throughout the year, a more sophisticated approach can vary them based on seasonal/weekly/daily cycles and/or current state of charge of the storage. Zafirakis et al. (91) apply several different storage algorithms to energy arbitrage in various European electricity markets. They borrow a moving average method from finance and also use several different methods to generate price forecasts against which they optimize storage operation, including (*a*) using historical data to find daily and weekly long-term price patterns, (*b*) forecasting that the following day/week will match the same day/week from the prior year, and (*c*) forecasting that the following day/week will match the prior day/week. An alternative strategy for forecasting future electricity prices on a rolling basis is to use day-ahead or hour-ahead prices as reasonable forecasts to determine storage operation in markets where these are available (85, 92).

Strategic Operation Models

The most sophisticated storage models are those that consider the effect that storage operation would have on the market itself, attempting to come up with an operational strategy that maximizes profits (or some other goal) after accounting for market effects and/or strategic action of other participants. This type of price maker model may be required when the scale of storage considered is large relative to the electricity system or in cases where market participants have a direct economic incentive to take strategic action. We divide this type of model into two categories: algorithms that consider a single decision maker co-optimizing storage operation with that of other resources and those that consider strategic action from competing decision makers in a market.

Goteti et al. (93) provide an example of the first category, by adding nonmarginal amounts of energy storage to an electricity grid modeled with a traditional dispatch model. In order to account for the effect that storage has on the dispatch of other resources, they use an iterative method: They calculate hourly prices without storage, then determine the optimal storage operation under those prices and add storage operation to the dispatch model, which is then rerun, producing new time-varying prices. A new dispatch is calculated for storage based on these new prices and averaged into storage operation from prior iterations, eventually converging to a solution. Krishnan & Das (94) provide a more detailed model, including locational analysis (using the IEEE 24-bus system) to determine both the optimal deployment of energy storage and its operation. The strategy in this analysis starts with a relatively traditional unit commitment/dispatch model that includes energy storage as a participant and then uses a higher-level search algorithm to test the value of very large amounts of energy storage at each node. This allows the algorithm to identify the highest-value locations, and the scale of storage is determined by examining the amount that the storage device is actually used. Dvorkin et al. (95) have a similar goal, but use a MILP formulation to determine the location, size, and profitability of energy storage. Lueken & Apt (96) create a reduced form unit commitment model of the PJM Interconnect to investigate the operation and profitability of price-making storage, and Sioshansi et al. (84) present a similar analysis with a different approach. Chen et al. (97) develop a genetic algorithm search method to simultaneously search for the optimal amount and operation of energy storage in a microgrid.

Modeling the strategic interaction between competitors using a game theoretical model that also includes operation (and potentially investment decisions) is challenging and normally results in models that are highly computationally intensive. Nasrolahpour et al. (98) use a Benders decomposition method on a LP framework to examine a storage owner's optimal strategy for storage investment and operation. Sioshansi (99) uses a mathematical approach to study the economic behavior of generators and storage owners in a competitive market with and without market power. He finds that new storage improves overall welfare in a competitive market but can decrease welfare in some cases where firms have sufficient market power.

ECONOMIC ANALYSES OF ENERGY STORAGE

This section provides a review of the questions that have been asked about energy storage economics. We attempt to provide a sense of the breadth of existing research, organizing the section into different analytical themes, as well as provide relevant details on the approach and conclusions from the literature.

The most common and straightforward category of storage economic analysis is work that considers the revenue, benefits, net benefits, or cost-effectiveness of storage for a specific application. Examples include Walawalkar et al. (100), who investigate the economics of sodium-sulfur batteries and flywheels in New York State, finding that the electricity prices at the time would render them profitable. Greenblatt et al. (18) compare the economics of CAES to gas turbines for managing wind power variability. Das et al. (101) investigate the benefits of a CAES plant from both private and system perspectives, and include co-optimization between energy and ancillary services on an IEEE 24-bus system. Braff et al. (102) consider the addition of storage to wind and solar plants, comparing the cost of storage to the direct revenue benefits to the owner, identifying the optimal amount of storage as storage cost changes. Similar applications (the value of adding storage to wind) have been studied using different approaches (103–105). Cleary et al. (106) use a PLEXOS-based model to examine the benefit that CAES would have for reduced curtailment and generator cycling in Ireland under continued expansion of wind generation, concluding that there are net system benefits in a scenario with significant expansion of wind.

An active and growing area of research for energy storage is investigation of the stacked benefits that storage can provide and development of algorithms that allow storage to co-optimize between different services. The general challenge in this space is that provision of one service (energy arbitrage, for example) cuts into the amount of other services that can be provided, because of the limitation in energy capacity. This means that the total revenue that storage can achieve from a group of services is less than the total if storage provides each service individually. Hence, algorithm development must use some combination of advanced methods and defensible assumptions and heuristics to co-optimize across different services. Berrada et al. (107) provide a detailed review of past efforts and develop a perfect information model that co-optimizes storage offers into the day-ahead energy, real-time energy, and frequency regulation markets. Hu et al. (108) offer an alternative approach for customer-sited storage that offers regulation and spinning reserve services into the wholesale market while also managing local renewable energy self-consumption and time-of-use prices. A Brattle analysis of storage in California concludes that the stacked benefits of storage are about three times as large as the single largest value stream (generation capacity savings) (109).

A focus on energy storage in capacity expansion models can provide insight into how storage technologies contribute to long-term shifts in the design, operation, and economics of the electrical grid. Go et al. (110) use a MILP capacity expansion model to deploy generation, transmission, and storage to meet a renewable portfolio standard constraint, finding that co-optimizing all three technologies can provide greater benefits than a focus on generation and transmission. Strbac et al. (111) summarize a body of work investigating the value of energy storage in helping to achieve UK decarbonization plans , and de Sisternes et al. (112) provide a similar analysis for the United States.

A separate thread of energy storage research involves understanding the value of storage for distributed applications (57), normally considering storage at commercial or residential sites (113). Storage economics can be quite different in this application because of the gap between utility rate structures and wholesale prices, and potential complementarities with local production (such as rooftop solar) and demand (114, 115). Various analyses provide different perspectives on the question of optimal storage size and operation for electricity customers, including responding to demand response rate structures (116), as well as general formulations to the problem (117). Luthander et al. (118) consider how residential storage can complement residential solar when both resources can be shared among a cluster of neighboring houses. They find that PV self-consumption of the cluster increases by 15% when operated as a group rather than individual homes and that shared storage increases it by 5% more than individual storage. Hao et al. (119) consider the economics of residential thermal loads (air conditioning, water heater, refrigerator) that can act as energy storage and find that their economics compete favorably with existing distributed storage technologies. Weis & Ilinca (120) investigate the value of storage in improving wind-diesel microgrids in remote Canadian areas.

Another stream of relevant research involves deeper investigation into the effects of more realistic but more complex modeling of storage or other components. Wankmüller et al. (121) apply two different models of battery degradation to batteries performing energy arbitrage. They find that this more realistic modeling of degradation reduces profits by 12–46%, but that this figure can be improved by including a cycling cost function in the storage operational model. Hittinger et al. (40) propose a more detailed microgrid battery model that includes efficiency that varies with temperature and charge rate, and capacity fade that is integrated into the operational model. Sarker et al. (122) develop a MILP framework for optimal storage dispatch that accounts for variable charge rates, variable efficiency, and battery degradation to assess the degree to which these real-life effects shift optimal storage operation.

ENVIRONMENTAL ANALYSES OF ENERGY STORAGE

The relationship between energy storage and electricity system emissions is complex and depends on the features of the electricity system into which storage is embedded. As a result, a growing body of literature has been focused on applying techno-economic models of energy storage to estimate the emissions effects of storage operation and understand how it is affected by different factors. Early research introduced the concepts that would be expanded later on, such as Denholm & Holloway's (123) 2005 analysis showing that storage charged with coal power has higher emissions of SO_2 and NO_x than a new Clean Air Act-compliant peaker plant. Arbabzadeh et al. (124) laid out further conceptual grounding of the relationship between storage and emissions in their "Twelve Principles for Green Energy Storage in Grid Applications," which describes design, operation, and system integration considerations.

Analyses estimating the effect of storage on emissions have been completed from various perspectives, including different storage applications (wholesale versus distributed), emissions modeling approaches (based on measured data versus modeled data), and time frames (present-day versus future effects). The general conclusion of this body of work is that present-day storage tends to produce a small increase in electricity system emissions, but that effect will reverse in the future as storage interacts positively with increased amounts of wind and solar. There are two primary methods used for estimating the emissions effects of storage operation. In the first, historical emissions data are used to estimate the time-varying marginal emissions rate of an electricity grid—this is the emissions rate of the marginal generator and gives the expected change in emissions resulting from small changes in supply or demand of electricity. When coupled with an economic model that gives the operation of storage, marginal emissions rates can be used to estimate the emissions effect of that operation. The marginal emissions method can give accurate and highly resolved estimates of emissions effects but becomes less appropriate as storage is considered at large scale or for future grids with a different generation mix. To understand these scenarios, electricity system dispatch models of various types are employed, with emissions rates assigned to different generators. Although the level of sophistication varies—different treatment of transmission and ramping limits, different treatment of emissions disaggregated at the plant level or varying as a function of power output, different treatment of ancillary services or reserve margins—the basic concept is to run the same electricity system model with and without energy storage and investigate the differences in terms of total emissions, generator construction/operation, and economics.

In a 2013 analysis of wholesale storage in Texas, Carson & Novan (125) use a simple two-period model of storage operation and historic emissions data to estimate marginal emissions rates and find that storage is expected to increase CO_2 and SO_2 emissions while decreasing NO_x. Considering present-day wholesale markets, Hittinger & Azevedo (126) used historic electricity prices and marginal emissions data to show that bulk energy storage would consistently increase US electricity system CO_2 emissions (with SO_2 and NO_x emissions generally increasing) if operated to maximize revenue. In follow-on works, alternative operational strategies for storage were identified that could reduce or eliminate storage-induced emissions at low cost (127), and the storage-induced emissions were compared against the relatively small amount of wind and solar required to offset them (128).

For distributed storage using a marginal emissions approach, Fares & Webber (129) used household-level consumption and solar production data to determine that sending solar energy back into the grid is more environmentally beneficial than storing the energy in household storage devices, mainly due to efficiency losses. Babacan et al. (130) study the operation of distributed storage in three different operational modes across 16 US utilities and conclude that storage can be used for reducing CO_2 emissions or reducing the customer's bill, but rarely both at the same time. Fisher & Apt (131) consider aggregator-controlled distributed storage and use a sophisticated battery model (including co-optimizing multiple revenue streams such as arbitrage, reduction of demand charges, frequency regulation, and spinning reserve) to come to similar conclusions: Profit-maximizing storage increases system emissions, but this effect can be reduced by thoughtful tariff design.

Using electricity system models rather than historical data gives up some precision but allows researchers to answer a broader set of questions, especially those relating to large-scale storage deployments on future grids with significantly different generation mixes. Lueken & Apt (96) developed a model of the PJM network to study the nonmarginal effects of 20 GW of new storage and found that adding storage modestly increased greenhouse gas emissions. Lin et al. (132) use 9-bus and 30-bus test systems to study the effect of new storage that offers power system reserves with and without emission caps for coal generators. With the emissions cap, storage works excessively and increases emissions from other fuels. Without the coal emissions cap, storage may still increase emissions due to reserve capacity—storage space that is not filled by renewable energy. Craig et al. (133) investigate the effect of adding storage to the Texas electricity grid as it pursues decarbonization goals out to the year 2045, concluding that new storage does increase emissions today but that this may reverse as soon as the year 2025. Goteti et al.'s (93) analysis pursues a similar question for Midcontinent Independent System Operator (MISO) using different methods and comes to the conclusion that storage will begin to decrease emissions after an additional 20 GW of wind/solar is installed across MISO.

INTERACTION OF STORAGE ECONOMICS WITH MARKET RULES AND POLICIES

A smaller but important field of research involves quantitative investigation of the relationship between government policy or market rules and storage operation and economics. The energy storage community has long-recognized policy and market barriers for energy storage (134, 135). As an asset class, it does not fall cleanly into existing categories, awkwardly acting as both generation and consumption as well as bridging wholesale and distribution utility markets. Although the qualitative importance of market rules for storage is understood, the necessary analytical support has lagged.

Cleary et al. (136) use a PLEXOS-based model of the Irish electricity grid to study how changing market rules might affect the economics of CAES to complement wind generation. The change to an Integrated Single Electricity Market in Ireland internalized the cost of wind forecast uncertainty to wind generators where it was previously considered a system cost spread across all participants. They find that the addition of storage under the new market conditions should benefit consumers by lowering average electricity prices, but slightly increases the payback period of wind generators. Byrne et al. (137) consider the revenue to a flywheel energy storage plant (modeled after an existing plant) in PJM after implementation of Federal Energy Regulatory Commission

Orders 755 and 784, which direct system operators to offer pay-for-performance and compensate participants for speed and accuracy of response. Paine et al. (138) create a detailed pumped hydro storage model and apply it to a revenue maximization problem under the market rules of MISO and ISO New England. They find that the market rules from ISO New England reward storage differently, resulting in almost twice the revenue and eliciting different operational patterns from the same profit-maximizing storage.

CHALLENGES AND OUTSTANDING ISSUES IN STORAGE ECONOMICS

Although the field of energy storage economics has grown quickly, there are promising avenues for further development. We highlight several in this section, and we apologize to future readers if there are important research directions that we did not foresee.

The most obvious outstanding issue to practitioners of storage economic analysis may be the lack of standardization and challenge of general applicability of storage models. As the reader has seen throughout this article, there are many methods that have been applied to questions of storage economics, with each case study prompting a new analytical tool. Although this body of literature demonstrates the breadth of insight in the field and provides many options for new work, it also demonstrates a lack of high-level organization and may suggest that storage economics is still in a phase focused on methodological development rather than methodological refinement or comparison. At the same time, users of storage models are currently at a disadvantage because there are few "off the shelf" storage models available (outside of the world of dispatch software purchased for an actual storage deployment). Two important exceptions are the Electric Power Research Institute's Storage Valuation Estimation Tool, a perfect information model that can analyze the operation and economics of grid-scale energy storage (**https://www.storagevet.com/**), and HOMER, a now-commercial microgrid design and optimization tool originally developed at the National Renewable Energy Laboratory (**https://www.homerenergy.com/**). Although these tools are a good start, they do not provide the broad selection of relatively straightforward tools that are available for related systems, such as electricity dispatch models. Hence, comparing and developing standardized methods that can be broadly applied is a valuable direction for new work.

Although the analytical space for development of perfect information models is well-established, imperfect information modeling has a plethora of good ideas without a strong grounding in theory or well-demonstrated superiority to other methods. Work in this field often develops a new method and shows that it is superior to standard methods for some particular problem, but we do not have any kind of universal theory to describe which methods are superior for particular problems and why. We propose that there is opportunity for important contributions in this space, potentially in conjunction with modern machine learning developments.

A third area where new research could contribute to practical questions is in analysis of the interaction between market or policy design and storage valuation and operation. Although there has been work on this general topic, there are important questions at the retail and wholesale levels about how market rules affect storage economics and operation decisions and how new storage will affect markets in response. For example, how should utilities design rate structures in a way that motivates storage owners to generate system benefits without allowing those customers to take unfair advantage? On the wholesale level, how do different market designs, such as energy-only versus capacity markets, the allocation of responsibility for ancillary services, and the design of those services affect the quantity of storage that can be expected and the way that it will be operated? How, in response, will new storage affect prices in different energy services and the addition or retirement of other generators? Analyses that answer these questions generally fall between the body of work that examines the economics of specific storage applications and that which examines the value of storage in capacity expansion modeling.

SUMMARY POINTS

1. Storage modeling approaches have proliferated over the past 15 years, and there are now a wide variety of identified models and concepts.
2. Storage operation models can be roughly grouped, in increasing complexity, into four categories: atemporal, perfect information, imperfect information, and strategic operation.
3. Economic analyses of storage most commonly test the costs, benefits, net benefits, or cost-effectiveness of providing a specific service.
4. Estimating the emissions effects of storage adoption or operation uses two main methods: marginal emissions rates or electricity system models.
5. Progress in storage economics may rely on synthesis and evaluation of existing ideas and methods to provide generally applicable tools.

FUTURE ISSUES

1. Decommissioning procedures and second life applications are still open questions for electrochemical systems.
2. Storage modeling methods are limited to particular applications, making easily used and broadly applicable tools of great value.
3. A deeper understanding of the relative merits of different imperfect information models is needed, potentially with the help of modern machine learning approaches.
4. A greater understanding of how market design and policies impact storage investment and operation is needed.

DISCLOSURE STATEMENT

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

ACKNOWLEDGMENTS

R.E.C. acknowledges support from the Andlinger Center for Energy and the Environment.

LITERATURE CITED

1. Michalski J, Bünger U, Crotogino F, Donadei S, Schneider G-S, et al. 2017. Hydrogen generation by electrolysis and storage in salt caverns: potentials, economics and systems aspects with regard to the German energy transition. *Int. J. Hydrogen Energy* 42(19):13427–43
2. Greenblatt JB, Miller DJ, Ager JW, Houle FA, Sharp ID. 2018. The technical and energetic challenges of separating (photo)electrochemical carbon dioxide reduction products. *Joule* 2(3):381–420

3. Deane JP, Ó Gallachóir BP, McKeogh EJ. 2010. Techno-economic review of existing and new pumped hydro energy storage plant. *Renew. Sustain. Energy Rev.* 14(4):1293–302
4. Budt M, Wolf D, Span R, Yan J. 2016. A review on compressed air energy storage: basic principles, past milestones and recent developments. *Appl. Energy* 170:250–68
5. Marcus D. 2011. *Fuel-free geologic compressed air energy storage from renewable power*. Pap. 582-11-13126-3225, Gen. Compress., TX. **https://www.tceq.texas.gov/assets/public/implementation/air/terp/ntig/prog_rpts/GC_Task1.pdf**
6. Geissbühler L, Becattini V, Zanganeh G, Zavattoni S, Barbato M, et al. 2018. Pilot-scale demonstration of advanced adiabatic compressed air energy storage, Part 1: Plant description and tests with sensible thermal-energy storage. *J. Energy Storage* 17:129–39
7. Liu M, Tay NHS, Bell S, Belusko M, Jacob R, et al. 2016. Review on concentrating solar power plants and new developments in high temperature thermal energy storage technologies. *Renew. Sustain. Energy Rev.* 53:1411–32
8. Gür TM. 2018. Review of electrical energy storage technologies, materials and systems: challenges and prospects for large-scale grid storage. *Energy Environ. Sci.* 11(10):2696–767
9. Luo X, Wang J, Dooner M, Clarke J. 2015. Overview of current development in electrical energy storage technologies and the application potential in power system operation. *Appl. Energy* 137:511–36
10. St. John J. 2015. SustainX to merge with General Compression, abandon above-ground CAES ambitions. *Greentech Media*, March 31. **https://www.greentechmedia.com/articles/read/sustainx-to-merge-with-general-compression-abandon-above-ground-caes-ambiti#gs.stszv3**
11. Spector J. 2017. LightSail energy enters "hibernation" as quest for game-changing energy storage runs out of cash. *Greentech Media*, Dec. 19. **https://www.greentechmedia.com/articles/read/lightsail-energy-cheap-compressed-air-storage-hibernation#gs.stqw1o**
12. Steffen B. 2012. Prospects for pumped-hydro storage in Germany. *Energy Policy* 45:420–29
13. Barbour E, Wilson IAG, Radcliffe J, Ding Y, Li Y. 2016. A review of pumped hydro energy storage development in significant international electricity markets. *Renew. Sustain. Energy Rev.* 61:421–32
14. International Renewable Energy Agency (IRENA). 2017. *Electricity Storage and Renewables: Costs and Markets to 2030*. Abu Dhabi, UAE: IRENA. **https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2017/Oct/IRENA_Electricity_Storage_Costs_2017.pdf**
15. McGrail BP, Davidson CL, Bacon DH, Chamness MA, Reidel SP, et al. 2013. *Techno-economic performance evaluation of compressed air energy storage in the Pacific Northwest*. Pap. PNNL-22235, Pac. Northwest Natl. Lab., Richland, WA. **https://caes.pnnl.gov/pdf/PNNL-22235.pdf**
16. Drury E, Denholm P, Sioshansi R. 2011. The value of compressed air energy storage in energy and reserve markets. *Energy* 36(8):4959–73
17. US Energy Information Administration (EIA). 2019. *Average Operating Heat Rate for Selected Energy Sources*. Washington, DC: EIA. **https://www.eia.gov/electricity/annual/html/epa_08_01.html**
18. Greenblatt JB, Succar S, Denkenberger DC, Williams RH, Socolow RH. 2007. Baseload wind energy: modeling the competition between gas turbines and compressed air energy storage for supplemental generation. *Energy Policy* 35(3):1474–92
19. González-Roubaud E, Pérez-Osorio D, Prieto C. 2017. Review of commercial thermal energy storage in concentrated solar power plants: steam versus molten salts. *Renew. Sustain. Energy Rev.* 80:133–48
20. Parrado C, Marzo A, Fuentealba E, Fernández AG. 2016. 2050 LCOE improvement using new molten salts for thermal energy storage in CSP plants. *Renew. Sustain. Energy Rev.* 57:505–14
21. Chen H, Cong TN, Yang W, Tan C, Li Y, Ding Y. 2009. Progress in electrical energy storage system: a critical review. *Prog. Nat. Sci.* 19(3):291–312
22. Farret FA, Godoy Simões M. 2006. *Integration of Alternative Sources of Energy*. Hoboken, NJ: Wiley
23. Hadjipaschalis I, Poullikkas A, Efthimiou V. 2009. Overview of current and future energy storage technologies for electric power applications. *Renew. Sustain. Energy Rev.* 13(6):1513–22
24. Darling RM, Gallagher KG, Kowalski JA, Ha S, Brushett FR. 2014. Pathways to low-cost electrochemical energy storage: a comparison of aqueous and nonaqueous flow batteries. *Energy Environ. Sci.* 7(11):3459–77

25. Goldie-Scot L. 2019. A behind the scenes take on lithium-ion battery prices. *Bloomberg New Energy Finance*, March 5. **https://about.bnef.com/blog/behind-scenes-take-lithium-ion-battery-prices/**
26. Ciez RE, Whitacre JF. 2017. Comparison between cylindrical and prismatic li-ion cell costs using a process based cost model. *J. Power Sourc.* 340:273–81
27. Cole W, Will Frazier A. 2019. *Cost Projections for Utility-Scale Battery Storage*. Tech. Rep. NREL/TP-6A20–73222, NREL, Golden, CO. **https://www.nrel.gov/docs/fy19osti/73222.pdf**
28. Vaalma C, Buchholz D, Weil M, Passerini S. 2018. A cost and resource analysis of sodium-ion batteries. *Nat. Rev. Mater.* 3:18013
29. Peters JF, Peña Cruz A, Weil M. 2019. Exploring the economic potential of sodium-ion batteries. *Batteries* 5(1):10
30. Whitacre JF, Wiley T, Shanbhag S, Wenzhuo Y, Mohamed A, et al. 2012. An aqueous electrolyte, sodium ion functional, large format energy storage device for stationary applications. *J. Power Sourc.* 213:255–64
31. Hwang J-Y, Myung S-T, Sun Y-K. 2017. Sodium-ion batteries: present and future. *Chem. Soc. Rev.* 46(12):3529–614
32. Zeng YK, Zhao TS, An L, Zhou XL, Wei L. 2015. A comparative study of all-vanadium and iron-chromium redox flow batteries for large-scale energy storage. *J. Power Sourc.* 300:438–43
33. Skyllas-Kazacos M, Chakrabarti MH, Hajimolana SA, Mjalli FS, Saleem M. 2011. Progress in flow battery research and development. *J. Electrochem. Soc.* 158(8):R55–79
34. Tucker MC, Phillips A, Weber AZ. 2015. All-iron redox flow battery tailored for off-grid portable applications. *ChemSusChem*. 8(23):3996–4004
35. Advanced Research Projects Agency-Energy (ARPA-E). 2016. *New Iron Flow Battery Design for Flow Batteries*. Washington, DC: ARPA-E. **https://arpa-e.energy.gov/sites/default/files/EnergyStorageSystems_SBIR_ExternalProjectImpactSheet_FINAL.pdf**
36. Selverston S, Nagelli E, Wainright JS, Savinell RF. 2019. All-iron hybrid flow batteries with in-tank rebalancing. *J. Electrochem. Soc.* 166(10):A1725–31
37. Biswas S, Senju A, Mohr R, Hodson T, Karthikeyan N, et al. 2017. Minimal architecture zinc-bromine battery for low cost electrochemical energy storage. *Energy Environ. Sci.* 10(1):114–20
38 Leung P, Li X, de León CP, Berlouis L, John Low CT, Walsh FC. 2012. Progress in redox flow batteries, remaining challenges and their applications in energy storage. *RSC Adv*. 2(27):10125–56
39 Hu X, Zou C, Zhang C, Li Y. 2017. Technological developments in batteries: a survey of principal roles, types, and management needs. *IEEE Power Energ. Mag.* 15(5):20–31
40 Hittinger E, Wiley T, Kluza J, Whitacre J. 2015. Evaluating the value of batteries in microgrid electricity systems using an improved Energy Systems Model. *Energy Convers. Manag.* 89:458–72
41 Miller JR, Burke AF. 2008. Electrochemical capacitors: challenges and opportunities for real-world applications. *Electrochem. Soc. Interface* 17:53–57
42 Burke A. 2007. R&D considerations for the performance and application of electrochemical capacitors. *Electrochim. Acta* 53(3):1083–91
43. John E, Hale M, Selvam P. 2013. Concrete as a thermal energy storage medium for thermocline solar energy storage systems. *Solar Energy* 96:194–204
44. Li G. 2016. Sensible heat thermal storage energy and exergy performance evaluations. *Renew. Sustain. Energy Rev.* 53:897–923
45. Salomoni VA, Majorana CE, Giannuzzi GM, Miliozzi A, Di Maggio R, et al. 2014. Thermal storage of sensible heat using concrete modules in solar power plants. *Solar Energy* 103:303–15
46. Ward PA, Corgnale C, Teprovich JA, Motyka T, Hardy B, et al. 2016. Technical challenges and future direction for high-efficiency metal hydride thermal energy storage systems. *Appl. Phys. A* 122(4):462
47. Abboud RG, Battle B. 2018. RGA Investments, LLC acquires Beacon Power, LLC. *RGA Labs*, May 1. **http://www.rgalabs.com/BeaconPressRelease2018May01.pdf**
48. Hall PJ, Mirzaeian M, Isobel Fletcher S, Sillars FB, Rennie AJR, et al. 2010. Energy storage in electrochemical capacitors: designing functional materials to improve performance. *Energy Environ. Sci.* 3(9):1238–51
49. Miller JR, Simon P. 2008. Materials science. Electrochemical capacitors for energy management. *Science* 321(5889):651–52

50. Nykvist B, Nilsson M. 2015. Rapidly falling costs of battery packs for electric vehicles. *Nat. Clim. Change* 5:329–32
51. Schipper F, Erickson EM, Erk C, Shin J-Y, Chesneau FF, Aurbach D. 2016. Review—recent advances and remaining challenges for lithium ion battery cathodes. *J. Electrochem. Soc.* 164(1):A6220–28
52. Nitta N, Yushin G. 2014. High-capacity anode materials for lithium-ion batteries: choice of elements and structures for active particles. *Particle* 31:317–36
53. Albertus P, Babinec S, Litzelman S, Newman A. 2017. Status and challenges in enabling the lithium metal electrode for high-energy and low-cost rechargeable batteries. *Nat. Energy* 3(1):16–21
54. Howell D, Cunningham B, Duong T, Faguy P. 2016. *Overview of the DOE VTO Advanced Battery R&D Program*. Washington, DC: US Dep. Energy. **http://energy.gov/sites/prod/files/2016/06/f32/es000_howell_2016_o_web.pdf**
55. Luo W, Shen F, Bommier C, Zhu H, Ji X, Hu L. 2016. Na-ion battery anodes: materials and electrochemistry. *Acc. Chem. Res.* 49(2):231–40
56. Whitacre JF, Shanbhag S, Mohamed A, Polonsky A, Carlisle K, et al. 2015. A polyionic, large-format energy storage device using an aqueous electrolyte and thick-format composite $NaTi_2(PO_4)_3$/activated carbon negative electrodes. *Energy Technol.* 3(1):20–31
57. O'Shaughnessy E, Cutler D, Ardani K, Margolis R. 2018. Solar plus: a review of the end-user economics of solar PV integration with storage and load control in residential buildings. *Appl. Energy* 228:2165–75
58. Fisher M, Apt J, Whitacre JF. 2019. Can flow batteries scale in the behind-the-meter commercial and industrial market? A techno-economic comparison of storage technologies in California. *J. Power Sourc.* 420:1–8
59. Soloveichik GL. 2015. Flow batteries: current status and trends. *Chem. Rev.* 115(20):11533–58
60. Park M, Ryu J, Wang W, Cho J. 2016. Material design and engineering of next-generation flow-battery technologies. *Nat. Rev. Mater.* 2(1):16080
61. Chen X, Hopkins BJ, Helal A, Fan FY, Smith KC, et al. 2016. A low-dissipation, pumpless, gravity-induced flow battery. *Energy Environ. Sci.* 9(5):1760–70
62. Biswas S, Senju A, Mohr R, Hodson T, Karthikeyan N, et al. 2017. Minimal architecture zinc-bromine battery for low cost electrochemical energy storage. *Energy Environ. Sci.* 10(1):114–20
63. Schmidt O, Hawkes A, Gambhir A, Staffell I. 2017. The future cost of electrical energy storage based on experience rates. *Nat. Energy* 6(8):17110
64. Klumpp F. 2016. Comparison of pumped hydro, hydrogen storage and compressed air energy storage for integrating high shares of renewable energies—potential, cost-comparison and ranking. *J. Energy Storage* 8:119–28
65. Manickam K, Mistry P, Walker G, Grant D, Buckley CE, et al. 2019. Future perspectives of thermal energy storage with metal hydrides. *Int. J. Hydrogen Energy* 44(15):7738–45
66. Mayer T, Kreyenberg D, Wind J, Braun F. 2012. Feasibility study of 2020 target costs for PEM fuel cells and lithium-ion batteries: a two-factor experience curve approach. *Int. J. Hydrogen Energy* 37(19):14463–74
67. Kittner N, Lill F, Kammen DM. 2017. Energy storage deployment and innovation for the clean energy transition. *Nat. Energy* 2:17125
68. Few S, Schmidt O, Offer GJ, Brandon N, Nelson J, Gambhir A. 2018. Prospective improvements in cost and cycle life of off-grid lithium-ion battery packs: an analysis informed by expert elicitations. *Energy Policy* 114:578–90
69. Sakti A, Azevedo IML, Fuchs ERH, Michalek JJ, Gallagher KG, Whitacre JF. 2017. Consistency and robustness of forecasting for emerging technologies: the case of Li-ion batteries for electric vehicles. *Energy Policy* 106:415–26
70. Wood DL, Li J, Daniel C. 2015. Prospects for reducing the processing cost of lithium ion batteries. *J. Power Sourc.* 275:234–42
71. Sakti A, Michalek JJ, Fuchs ERH, Whitacre JF. 2015. A techno-economic analysis and optimization of Li-ion batteries for light-duty passenger vehicle electrification. *J. Power Sourc.* 273:966–80
72. Ciez RE, Whitacre JF. 2017. Comparison between cylindrical and prismatic lithium-ion cell costs using a process based cost model. *J. Power Sourc.* 340:273–81

73. Mellentine J. 2011. *Performance characterization and cost assessment of an iron hybrid flow battery*. PhD Thesis, Univ. Iceland, Univ. Akureyri
74. Androsov A, Amarnath A, Scott M, Hu A. 2014. *Bromine-polysulfide redox-flow battery design: cost analysis*. PhD Thesis, Univ. Tenn.
75. Lai CS, McCulloch MD. 2017. Levelized cost of electricity for solar photovoltaic and electrical energy storage. *Appl. Energy* 190:191–203
76. Jülch V. 2016. Comparison of electricity storage options using levelized cost of storage (LCOS) method. *Appl. Energy* 183:1594–606
77. Ziegler MS, Mueller JM, Pereira GD, Song J, Ferrara M, et al. 2019. Storage requirements and costs of shaping renewable energy toward grid decarbonization. *Joule* 3:2134–53
78. Westlake B, Handa R, Sprau S, Kamath H, Weber J, Laaguidi I. 2017. *Recycling and disposal of battery-based grid energy storage systems*. Prod. ID 3002006911, EPRI, Palo Alto, CA. **https://www.epri.com/#/pages/product/000000003002006911/?lang=en-US**
79. Pellow MA, Ambrose H, Mulvaney D, Betita R, Shaw S. 2020. Research gaps in environmental life cycle assessments of lithium ion batteries for grid-scale stationary energy storage systems: end-of-life options and other issues. *Sustain. Mater. Technol.* 23:e00120
80. Navigant Research. 2019. *Energy storage software: market trends, business models, and global market forecasts: 2019–2028*. Rep., Navig. Res., Chicago, IL. **https://www.navigantresearch.com/reports/energy-storage-software**
81. Liu Y, Wu L, Li J. 2019. Towards accurate modeling of dynamic startup/shutdown and ramping processes of thermal units in unit commitment problems. *Energy* 187:115891
82. Poullikkas A. 2009. Economic analysis of power generation from parabolic trough solar thermal plants for the Mediterranean region—a case study for the island of Cyprus. *Renew. Sustain. Energy Rev.* 13(9):2474–84
83. Atanacio M, Fioravanti R, Katzenstein W, Vu K. 2012. *Emission II study of advanced storage used for frequency regulation*. Sandia Neg. Proj. 96362, Dep. Energy, Sandia Natl. Lab., KEMA Inc., Albuquerque, NM. **https://www.sandia.gov/ess-ssl/docs/other/KEMA_Emission_II_Report_Advanced_Storage_Providing_Regulation_12-31-2012.pdf**
84. Sioshansi R, Denholm P, Jenkin T, Weiss J. 2009. Estimating the value of electricity storage in PJM: arbitrage and some welfare effects. *Energy Econ.* 31(2):269–77
85. Salles MBC, Huang J, Aziz MJ, Hogan WW. 2017. Potential arbitrage revenue of energy storage systems in PJM. *Energies* 10(8):1100
86. Moreno R, Moreira R, Strbac G. 2015. A MILP model for optimising multi-service portfolios of distributed energy storage. *Appl. Energy* 137:554–66
87. Connolly D, Lund H, Finn P, Mathiesen BV, Leahy M. 2011. Practical operation strategies for pumped hydroelectric energy storage (PHES) utilising electricity price arbitrage. *Energy Policy* 39(7):4189–96
88. Staffell I, Rustomji M. 2016. Maximising the value of electricity storage. *J. Energy Storage* 8:212–25
89. Cho J, Kleit AN. 2015. Energy storage systems in energy and ancillary markets: a backwards induction approach. *Appl. Energy* 147:176–83
90. Hittinger ES, Azevedo IML. 2015. Bulk energy storage increases United States electricity system emissions. *Environ. Sci. Technol.* 49(5):3203–10
91. Zafirakis D, Chalvatzis KJ, Baiocchi G, Daskalakis G. 2016. The value of arbitrage for energy storage: evidence from European electricity markets. *Appl. Energy* 184:971–86
92. McConnell D, Forcey T, Sandiford M. 2015. Estimating the value of electricity storage in an energy-only wholesale market. *Appl. Energy* 159:422–32
93. Goteti NS, Hittinger E, Williams E. 2019. How much wind and solar are needed to realize emissions benefits from storage? *Energy Syst.* 10(2):437–59
94. Krishnan V, Das T. 2015. Optimal allocation of energy storage in a co-optimized electricity market: Benefits assessment and deriving indicators for economic storage ventures. *Energy* 81:175–88
95. Dvorkin Y, Fernández-Blanco R, Kirschen DS, Pandžić H, Watson J, Silva-Monroy CA. 2017. Ensuring profitability of energy storage. *IEEE Trans. Power Syst.* 32(1):611–23
96. Lueken R, Apt J. 2014. The effects of bulk electricity storage on the PJM market. *Energy Syst.* 5(4):677–704

97. Chen C, Duan S, Cai T, Liu B, Hu G. 2011. Optimal allocation and economic analysis of energy storage system in microgrids. *IEEE Trans. Power Electron.* 26(10):2762–73
98. Nasrolahpour E, Kazempour SJ, Zareipour H, Rosehart WD. 2016. Strategic sizing of energy storage facilities in electricity markets. *IEEE Trans. Sustain. Energy* 7(4):1462–72
99. Sioshansi R. 2014. When energy storage reduces social welfare. *Energy Econ.* 41:106–16
100. Walawalkar R, Apt J, Mancini R. 2007. Economics of electric energy storage for energy arbitrage and regulation in New York. *Energy Policy* 35(4):2558–68
101. Das T, Krishnan V, McCalley JD. 2015. Assessing the benefits and economics of bulk energy storage technologies in the power grid. *Appl. Energy* 139:104–18
102. Braff WA, Mueller JM, Trancik JE. 2016. Value of storage technologies for wind and solar energy. *Nat. Clim. Change* 6(10):964–69
103. Sioshansi R. 2011. Increasing the value of wind with energy storage. *Energy J.* 32(2):1–29
104. Korpaas M, Holen AT, Hildrum R. 2003. Operation and sizing of energy storage for wind power plants in a market system. *Int. J. Electr. Power Energy Syst.* 25(8):599–606
105. Locatelli G, Palerma E, Mancini M. 2015. Assessing the economics of large energy storage plants with an optimisation methodology. *Energy* 83:15–28
106. Cleary B, Duffy A, OConnor A, Conlon M, Fthenakis V. 2015. Assessing the economic benefits of compressed air energy storage for mitigating wind curtailment. *IEEE Trans. Sustain. Energy* 6(3):1021–28
107. Berrada A, Loudiyi K, Zorkani I. 2016. Valuation of energy storage in energy and regulation markets. *Energy* 115:1109–18
108. Hu W, Wang P, Gooi HB. 2016. Assessing the economics of customer-sited multi-use energy storage. In *2016 IEEE Region 10 Conference (TENCON), Singapore*, pp. 651–54. Piscataway, NJ: IEEE
109. Hledik R, Leuken R, McIntyre C, Bishop H. 2017. *Stacked Benefits: Comprehensively Valuing Battery Storage in California*. Boston, MA: Brattle. **http://files.brattle.com/files/7208_stacked_benefits_-_final_report.pdf**
110. Go RS, Munoz FD, Watson J-P. 2016. Assessing the economic value of co-optimized grid-scale energy storage investments in supporting high renewable portfolio standards. *Appl. Energy* 183:902–13
111. Strbac G, Aunedi M, Konstantelos I, Moreira R, Teng F, et al. 2017. Opportunities for energy storage: assessing whole-system economic benefits of energy storage in future electricity systems. *IEEE Power Energy Mag.* 15(5):32–41
112. de Sisternes FJ, Jenkins JD, Botterud A. 2016. The value of energy storage in decarbonizing the electricity sector. *Appl. Energy* 175:368–79
113. Weniger J, Bergner J, Tjaden T, Quaschning V. 2014. *Economics of residential PV battery systems in the self-consumption age*. Paper presented at the 29th European Photovoltaic Solar Energy Conference and Exhibition, Sept. 22–26
114. Truong CN, Naumann M, Karl RC, Müller M, Jossen A, Hesse HC. 2016. Economics of residential photovoltaic battery systems in Germany: the case of Tesla's Powerwall. *Batteries* 2(2):14
115. Lam RK, Tran DH, Yeh H. 2015. Economics of residential energy arbitrage in California using a PV system with directly connected energy storage. In *2015 IEEE Green Energy and Systems Conference (IGESC)*, pp. 67–70. Piscataway, NJ: IEEE
116. Zheng M, Meinrenken CJ, Lackner KS. 2015. Smart households: dispatch strategies and economic analysis of distributed energy storage for residential peak shaving. *Appl. Energy* 147:246–57
117. Wu D, Kintner-Meyer M, Yang T, Balducci P. 2016. Economic analysis and optimal sizing for behind-the-meter battery storage. In *2016 IEEE Power and Energy Society General Meeting (PESGM)*, pp. 1–5. Piscataway, NJ: IEEE
118. Luthander R, Widén J, Munkhammar J, Lingfors D. 2016. Self-consumption enhancement and peak shaving of residential photovoltaics using storage and curtailment. *Energy* 112:221–31
119. Hao H, Sanandaji BM, Poolla K, Vincent TL. 2015. Potentials and economics of residential thermal loads providing regulation reserve. *Energy Policy* 79:115–26
120. Weis TM, Ilinca A. 2008. The utility of energy storage to improve the economics of wind-diesel power plants in Canada. *Renew. Energy* 33(7):1544–57

121. Wankmüller F, Thimmapuram PR, Gallagher KG, Botterud A. 2017. Impact of battery degradation on energy arbitrage revenue of grid-level energy storage. *J. Energy Storage* 10:56–66
122. Sarker MR, Murbach MD, Schwartz DT, Ortega-Vazquez MA. 2017. Optimal operation of a battery energy storage system: trade-off between grid economics and storage health. *Electric Power Syst. Res.* 152:342–49
123. Denholm P, Holloway T. 2005. Improved accounting of emissions from utility energy storage system operation. *Environ. Sci. Technol.* 39(23):9016–22
124. Arbabzadeh M, Johnson JX, Keoleian GA, Rasmussen PG, Thompson LT. 2016. Twelve principles for green energy storage in grid applications. *Environ. Sci. Technol.* 50(2):1046–55
125. Carson RT, Novan K. 2013. The private and social economics of bulk electricity storage. *J. Environ. Econ. Manag.* 66(3):404–23
126. Hittinger ES, Azevedo IML. 2015. Bulk energy storage increases United States electricity system emissions. *Environ. Sci. Technol.* 49(5):3203–10
127. Arciniegas LM, Hittinger E. 2018. Tradeoffs between revenue and emissions in energy storage operation. *Energy* 143:1–11
128. Hittinger E, Azevedo IML. 2017. Estimating the quantity of wind and solar required to displace storage-induced emissions. *Environ. Sci. Technol.* 51(21):12988–97
129. Fares RL, Webber ME. 2017. The impacts of storing solar energy in the home to reduce reliance on the utility. *Nat. Energy* 2(2):17001
130. Babacan O, Abdulla A, Hanna R, Kleissl J, Victor DG. 2018. Unintended effects of residential energy storage on emissions from the electric power system. *Environ. Sci. Technol.* 52:13600–608
131. Fisher MJ, Apt J. 2017. Emissions and economics of behind-the-meter electricity storage. *Environ. Sci. Technol.* 51(3):1094–101
132. Lin Y, Johnson JX, Mathieu JL. 2016. Emissions impacts of using energy storage for power system reserves. *Appl. Energy* 168:444–56
133. Craig MT, Jaramillo P, Hodge B-M. 2018. Carbon dioxide emissions effects of grid-scale electricity storage in a decarbonizing power system. *Environ. Res. Lett.* 13(1):014004
134. Sioshansi R, Denholm P, Jenkin T. 2012. Market and policy barriers to deployment of energy storage. *Econ. Energy Environ. Policy* 1(2):47–64
135. Kaufman S, Komor P, Langdon B, Vallett P. 2011. Electricity storage in regulated markets: getting the rules right. *Electr. J.* 24(6):63–71
136. Cleary B, Duffy A, O'Connor A, Conlon M. 2015. Assessing the future economic performance of wind generation in conjunction with compressed air energy storage in the new proposed Irish electricity market. *Econ. Bus. Lett.* 4(3):87–97
137. Byrne RH, Concepcion RJ, Silva-Monroy CA. 2016. Estimating potential revenue from electrical energy storage in PJM. *2016 IEEE Power and Energy Society General Meeting (PESGM)*, pp. 1–5. Piscataway, NJ: IEEE
138. Paine N, Homans FR, Pollak M, Bielicki JM, Wilson EJ. 2014. Why market rules matter: optimizing pumped hydroelectric storage when compensation rules differ. *Energy Econ.* 46:10–19