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King Abdullah Petroleum Studies and Research Center

The Value of Storage in Electricity Generation:

A Qualitative and Quantitative Review

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October 2020

Doi: 10.30573/KS--2020-DP23

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Key Points

This study conducts an extensive review of the literature on the valuation of storage, and focuses on the three primary methodologies employed — the levelized cost of storage (LCOS), production-cost models, and market-based models.

LCOS provides average break-even cost, the production-cost model estimates the savings attained by deploying storage, and the market-based approach views storage as if it were traded in a competitive market.

We argue that in the near-term, storage offers more value to vertically integrated utilities, which can fully realize the benefits of storage to achieve lower system-wide generation costs, than to investors in market environments.

In many ways, current trends in the deployment of storage resemble the initial stages of the proliferation of renewables. It is beneficial for policymakers and industry players to review the lessons offered by the emergence of earlier disruptive technologies in the electricity sector.

Summary

Electricity storage technology has many useful applications in the energy sector and can complement variable renewable power generation to achieve a low-carbon future. For policymakers, utilities, and investors, effective decisions in this context require an understanding of how to determine the monetary value of storage. This study conducts an extensive review of the literature on the valuation of storage, and focuses on the three primary methodologies employed — the levelized cost of storage (LCOS), production-cost models, and market-based models — which each produce different results. LCOS provides average break-even cost, the production-cost model estimates the savings attained by deploying storage, and the market-based approach views storage as if it were traded in a competitive market. We discuss the advantages and disadvantages of each method. Our analysis reveals that storage generates the most value in the form of reserve services. Given current market regulations, we argue that in the near-term, storage will be more valuable for vertically integrated utilities than in open market environments. Finally, we examine how current storage deployment efforts can benefit from the lessons offered by the uptake of renewable energy technology in the past two decades.

1. Introduction

Propelled by falling capital costs and increased environmental concerns, the share of renewable installations is rising steadily worldwide. While renewable technologies enjoy near-zero marginal cost and emit no carbon once deployed, solar and wind energy are non-dispatchable and variable. When renewables comprise a relatively small portion of total capacity, utilities can accommodate this with little difficulty. However, as the share of renewables rises, maintaining grid stability and reliability becomes more challenging (Mararakanye and Bekker 2019).

Electricity storage can enable wider and more aggressive deployment of renewables (Abrell, Rausch, and Streitberger 2019; Haas et al. 2018). Like the renewables sector, the battery industry has greatly increased cost efficiency, enabling much lower prices, a trend widely expected to continue (Cole and Frazier 2019). Battery systems have plummeted from about 1,000 United States (U.S.) dollars per kilowatthour ($/kWh) in 2010 to about $150–200/kWh in 2020. However, this is not yet price competitive across all geographies and applications.

In many ways, storage differs from thermal and renewable generation technologies. First, storage can be deployed at the generation, transmission, and distribution levels (Kyriakopoulos and Arabatzis 2016). Second, storage can be utilized across energy, capacity, and ancillary markets and can provide multiple services simultaneously. Third, storage cannot provide energy indefinitely: thermal and renewable generation can continue as long as a fuel or energy source is available, but battery systems typically store no more than four hours of reliable output in current utility applications (Li et al. 2019).

Despite the benefits storage offers, numerous regulatory, market, and technological challenges impede faster deployment. From a regulatory viewpoint, storage is difficult to manage because it can be applied across the entire electricity value chain. Current utilities do not have enough experience to deal with such a unique technology as current utilities and electricity markets have been functioning around legacy generators for decades (Debia, Pineau, and Siddiqui 2019). Nonetheless, some utilities and markets around the world have taken progressive steps and amended their regulations to allow storage to compete in providing services.

To effectively regulate storage and maximize its value, policymakers must understand what benefits it can provide and how these can impact the energy mix (Berrada, Loudiyi, and Zorkani 2016). Here, it is vital to distinguish *value* from simple cost or profitability; this aids regulators, utilities, and investors in better understanding the financial viability of storage projects (Alabdullatif, Gerding, and Perez-Diaz 2020; Gailani et al. 2020). Storage can provide numerous services in widely varying environments — from off-grid households to large utilities and open electricity markets. Accordingly, many studies have attempted to quantify its value. The literature includes different valuation methodologies that have produced a range of numerical results and other findings.

Because the valuation of a technology is crucial to its regulation, this work provides a thorough review of how the value of storage has been calculated in the literature. This paper answers two core research questions: (1) How does the literature determine the monetary value of the various services that storage provides? (2) What are the strengths and weaknesses of each method?

1. Introduction

The remainder of this paper comprises five sections. Section 2 provides an overview of the services that storage can provide at both utility and distributed scales. Section 3 describes the main valuation methods adopted in the literature, and Section 4 follows with a thorough quantitative review. Section 5 discusses the numerical findings and offers insights for future studies. This section also examines the strengths and weaknesses of the various valuation techniques. Finally, Section 6 concludes the paper and summarizes its main findings.

2. What Services Can Storage Provide

This paper reviews the literature of valuation methodologies for storage. Because storage can be deployed to serve widely varying applications at different scales, on or off the grid, a range of valuation techniques exists. Thus, an overview of the different services that storage can provide is a useful starting point.

Table 1 summarizes noteworthy storage applications and services, organized by grid connectivity and scale. It also provides the typical battery sizes/capacities for each. This highlights the numerous technical capabilities of electricity storage technologies and their potential impact across market segments.

Table 1. Summary of storage technology services.

Grid connection status	Scale	Service	Typical battery size in MW
On-grid	Utility	Energy and/or arbitrage	10-300
		Firm (peaking) capacity	10-300
		Frequency response	1-100
		Regulation reserve	1-100
		Contingency/(non)spinning reserves	10-100
		Load following – ramping	2-400
		Transmission and distribution benefits	10-100
		Black-start	-
		Value-stacking	-
	Distributed	Energy and/or arbitrage	0.01-0.2
		Peak-demand cost reduction	0.01-0.2
		Eliminate/minimize renewable energy curtailment	0.01-0.2
Off-grid	Microgrid[1]	Energy and/or arbitrage	0.025-1
		Reserves	0.025-1
		Frequency control	0.1-1
		Enhance diesel generator efficiency	0.025-1
		Eliminate/minimize renewable energy curtailment	0.025-1
	Single household	Energy	0.001-0.01
		Enhance diesel generator efficiency	0.001-0.01
		Eliminate/minimize renewable energy curtailment	0.001-0.01

Note: MW = megawatt.

[1] Micrograds may be connected to the main grid or entirely isolated. However, the former case is excluded because this essentially makes it utility scale, which is discussed separately.

2.1. On-grid applications of storage

Grid-connected services can be categorized as either utility (large) or distributed (small) scale. The latter includes the residential, commercial and industrial sectors (Fisher, Apt, and Whitacre 2019). For perspective, the famous Tesla Power Wall has a usable energy capacity of 13.5 kWh and can provide 5 kilowatts (kW) of continuous power (7 kW of peak). If many small-scale storage systems are connected, they can be treated as a single utility-scale system, which calls for a different valuation approach (Gissey et al. 2019). On the other hand, typical utility-scale storage projects range from 1 megawatt (MW) to 200 MW and can provide power for one to four hours.

2.1.1. Utility-scale storage applications

Energy and/or arbitrage: Electricity storage facilitates a form of arbitrage: earning a profit by charging storage devices (i.e., buying electricity) when energy prices are low and discharging them (i.e., selling electricity) when energy prices are high (Kadri and Raahemifar 2019). The terms 'energy' and 'arbitrage' are sometimes used interchangeably in the literature in utility-scale storage applications. For renewables, storage allows energy generated during periods of oversupply to be held for later sale or use (Hu et al. 2019; Queiroz, Lopes, and Martins 2020). Similarly, utilities can increase profits by dispatching stored energy during peak demand times. Without storage, they typically incur significant expenses by starting up additional generators, normally the least efficient ones in the mix, to satisfy excess demand.

Firm (peaking) capacity: System operators must ensure the availability of sufficient firm (dispatchable) generation capacity to meet projected peak demand (Gupta et al. 2020). Depending on a system's energy mix and load profiles, storage can provide a more cost-effective option for peaking capacity compared with prevailing technologies. As mentioned above, utilities normally meet peak demand using high-cost secondary generators.

Reserves: Reserves are among the most important and most valuable services that storage can perform within a power system. Also referred to as 'operating reserves' and/or 'ancillary services,' reserves help ensure grid stability and reliable delivery of power (Hummon et al. 2013). Grid operators require alternating current to be maintained at or near a determined frequency, generally 60 hertz (Hz) (or 50 Hz depending on the country). To prevent instability, generators must respond to major frequency deviations within seconds (Tang et al. 2019). Regulation (or primary) reserves refer to those ready to meet demand in a relatively short time frame (15 minutes to one hour) (Bignucolo et al. 2017). Contingency reserves, whether spinning or non-spinning, are allocated to respond in a slightly longer time frame (30 minutes to two hours). Ramping describes reserves capable of answering changes in demand over a multiple hour time frame (Hu et al. 2018). The 'duck curve' demand profile provides a classic example of why storage can be valuable in reserves, especially for ramping. It is important to note that the terminology, exact definitions, and durations related to reserves vary in the literature. For a detailed discussion, please refer to Ela, Milligan, and Kirby (2011).

Transmission and distribution benefits: Operators must invest in transmission and distribution (T&D) infrastructure, whether in the form of upgrades or entirely new T&D lines. Given that T&D investment requirements are excessively high, storage can help defer these expenses (Li et al. 2020) in a number of ways, including peak-shaving or relaxing congestion at constrained locations (Wogrin and Gayme 2015), especially when renewables account for a large share of the energy mix. Storage can also decrease transmission and distribution losses through optimized siting. At the distribution level particularly, storage can improve voltage profiles and decrease reactive power flow (Mehrjerdi and Hemmati 2019). In many networks, significant T&D congestion occurs only a few times a year. Rather than building additional T&D infrastructure that would be under-utilized, operators can deploy mobile energy storage as a practical and cost-effective solution (Kim and Dvorkin 2019) for sporadic and infrequent congestion incidents.

Black-start: In a black-start, a generator powers up using an on-site source, such as storage or a diesel generator, as opposed to drawing energy from the grid (Li et al. 2019). This may be necessary, for example, during system-wide failures.

Value stacking: Value stacking is the capability of a storage system to simultaneously provide more than one of the previously mentioned services (Nguyen, Copp, and Byrne 2019). This may require more capacity and result in more charging/discharging cycles of the storage device, reducing its lifetime. Hence, the financial implications and value gained from providing multiple services should be carefully assessed.

2.1.2. Distributed-scale storage applications

Energy and/or arbitrage: As discussed above, storage systems facilitate arbitrage and can increase the profits (or reduce costs) of electricity producers. At the distributed scale, this occurs when consumers are charged via time-of-use (TOU) pricing or similar mechanisms, for example. Storage also enables the energy generated by distributed-scale renewable installations to be retained for sale (if the utility allows sale back to the grid, such as through ‘net metering’) or use when prices are high.

Peak demand reduction: Utilities typically bill consumers according to their electricity consumption (i.e., volumetric billing). In many countries, they also add a fixed fee (sometimes called a ‘demand charge’) based on customers’ peak power usage during the billing period. Storage systems can reduce this expense by charging energy during periods of lower demand and discharging it when consumption rises. Financially, this can be assessed using the net present value (NPV) or payback period approach to determine whether demand charge reductions exceed the cost of installing and operating the storage (Tiemann et al. 2020). Generally, a specific storage capacity would be optimal for minimizing a consumer’s overall energy and storage cost.

Eliminate/reduce renewable energy curtailment: Whenever the output of distributed-scale solar photovoltaic (PV) (or other non-dispatchable) systems exceeds load, the excess electricity must be exported to the grid, stored, or dumped. Storage systems permit small-scale renewable energy producers, such as households and industrial facilities, to retain this energy for later sale or use (Parra and Patel 2019). To maximize the value of a given renewable energy and storage application, a consumer must determine the optimal combination of technologies and specifications, based on projected lifetime costs and earnings/savings. If export electricity prices, known as feed-in-tariffs (FITs), are sufficiently high (as seen in Germany), the optimization will likely result in a large storage and PV system. However, utilities tend to reduce FITs (and increase electricity rates) over time, adding complexity to such long-term investments.

2.2. Off-grid storage applications

Off-grid applications can be divided into microgrid and single-household segments. While the literature currently provides no standard definition of a microgrid, the U.S. Department of Energy characterizes it as a group of interconnected loads and distributed energy resources within clearly identified electrical boundaries that acts as a single controllable entity with respect to the main grid (Sumper 2019). A microgrid can be connected to the main grid or stand alone in 'island-mode.' The latter is the focus here: island microgrids offer a viable solution for the electrification of remote locations for which a connection to a larger grid is prohibitively expensive (Krishan and Suhag 2019). The other subcategory, single households, includes all dwellings, generally in remote areas, with no connection to a larger grid.

2.2.1. Microgrid storage applications

Energy and/or arbitrage: The basic concepts described above apply to microgrids. However, for small islands or other isolated areas, little or no possibility for arbitrage may exist if consumers (households in a small village, for example) share similar demand profiles. In such cases, storage would be useful primarily for providing energy and stabilizing the grid. It could also reduce the consumption of liquid fuels (diesel mainly), especially given the increasing adoption of hybrid microgrids that combine solar PV, diesel, and storage. For environmental reasons, minimizing the use of diesel is desirable. However, as the share of renewables increases, the cost of eliminating diesel rises exponentially; this has led to discussion of more innovative methods to achieve 100% renewable microgrids (Baldinelli et al. 2020).

Reserves: As discussed above, storage can provide reserve services to improve grid stability in a cost-effective manner. For microgrids, this is especially useful in tandem with variable output renewable energy sources.

Enhance diesel generator efficiency: Diesel generators are ubiquitous in microgrids. Running a diesel generator at much lower than its rated power reduces its efficiency and results in the 'wet-stacking' problem, in which the diesel fuel is not burnt but rather passes through to the exhaust system. For this reason, storage devices can enhance the efficiency of diesel generators by charging at times of low demand to serve as load (Diab et al. 2019).

Eliminate/reduce renewable energy curtailment: As in other applications, storage deployed in microgrids can retain the excess electricity generated by renewables for subsequent use, reducing the need to dump energy.

2.2.2. Single household storage applications

Energy: A system completely off the grid offers no opportunity for arbitrage. The role of storage would be strictly to provide energy.

Enhance diesel generator efficiency: Same as above.

Eliminate/reduce renewable energy curtailment: If households deploy solar PV for generation, storage can play a complementary role, as explained above.

3. How the Value of Storage Is Calculated

The previous section reviewed the numerous applications of electricity storage at utility and distributes scales, on and off the grid, ranging from the basic provision of energy, to improving grid stability and increasing the efficiency of renewable energy generation. Given such versatility, it is no surprise to see that researchers have adopted numerous methods to quantify the value of storage in varying contexts, and continue to modify existing approaches and develop new ones.

The unique technical characteristics of storage make valuation more difficult than for conventional generation. For instance, the capital costs of conventional fossil-fuel plants are evaluated in terms of cost per unit of power (e.g., $/MW). This approach is insufficient for storage because the energy capacity of the battery (e.g., MWh) determines how much electricity it can discharge (Belderbos et al. 2017). Battery performance, and therefore value, also heavily depends on temperature, which is difficult to model. Other characteristics that affect the valuation of storage include minimum allowed state of charge, self-discharge rate, and battery cycle lifetime. These and several other technical parameters related to storage are summarized in Appendix A.

We conducted an extensive review of the literature on the valuation of storage and found that three types of methodologies are commonly employed for valuing storage in monetary terms: LCOS, production cost models, and market-based approaches. Several other methods also appear, but less frequently. As such, the discussion that follows will be restricted to the methods that were found to be most widely adopted in the literature.

3.1. Levelized cost of storage (LCOS)

Levelized cost of storage (LCOS) repurposes the levelized cost of energy (LCOE) formula to the context of storage. LCOE is the most widely employed metric for comparing the generation costs of different technologies (Fan et al. 2019; Pettinau et al. 2017). LCOE has important advantages: it captures the main cost components associated with a technology, is easy to comprehend, and requires little computational power. However, the approach also has significant limitations. For example, LCOE does not capture certain technology-specific features, such as quick ramping capability and dispatchability. For detailed discussions of the pros and cons of LCOE, see Elshurafa (2017) and Nissen and Harfst (2019).

LCOS and LCOE share the algebraic identity shown in Equation 1 below. The 'levelized cost' equals the average electricity price required over the lifetime of the storage device (generator) to break even with the total costs of its purchase and operation, discounted for the cost of capital. Alternatively, this can be viewed as the electricity price that makes the NPV of lifetime cash flows equal to zero. In the simplest form, the LCOS expression can be written as:

$$LCOS = \frac{CAPEX + \sum_1^n \frac{Costs_n}{(1+DR)^n}}{\sum_1^n \frac{E_n}{(1+DR)^n}} \qquad (1)$$

Where $CAPEX$ is the overnight capital cost, n is the lifetime of the project in years, $Costs_n$ is the cost of operating and charging the storage device at year n, DR is the discount rate, and E_n is the cumulative energy output at year n.

Thus, LCOS gives the ratio of cost to energy and is usually measured in $/kWh. For conventional generators, the costs term in the expression includes fixed operation and maintenance (O&M) costs and variable (generally fuel) costs. For storage devices, it includes O&M costs and the costs of charging.

Studies by Jülch et al. (2015), Jülch (2016), and Smallbone et al. (2017) used the LCOS expression above, and related energy output to energy input through the roundtrip (a charging and discharging cycle) efficiency of the battery. Belderbos et al. (2017) included taxes and decommissioning costs in their LCOS analysis, and introduced other metrics to address operational and profitability issues. Obi et al. (2017) incorporated depreciation, interest, property taxes, income taxes, and residual value into their LCOS calculation. Conversely, Comello and Reichelstein (2019) divided LCOS into separate levelized cost of energy and levelized cost of power components. The authors also accounted for seasonal variations and conducted a detailed analysis of federal support mechanisms in the U.S. Schmidt et al. (2019) incorporated another useful variation by using calendar life and full equivalent cycles to determine when batteries should be replaced. Note that these papers all treat storage as a standalone energy supply technology in their LCOS calculations.

Other research assesses the total value of hybrid systems that combine storage with solar PV or other technologies (Lai and McCulloch 2017; Pawel 2014; Mundada, Shah, and Pearce 2016). These analyses do not provide an explicit cost for the storage component alone. In hybrid applications, the PV system charges the storage system, and this charging can be assumed to occur at a cost (Lai and McCulloch 2017) or not (Pawel 2014; Mundada, Shah, and Pearce 2016), which will affect the valuation.

Generally, LCOS finds the most applicability in off-grid scenarios. The approach becomes less helpful for on-grid storage (or hybrid) systems because it ignores numerous factors that impact cost effectiveness and competitiveness. These include battery size (and for hybrid systems, generation capacity), when and how frequently the system is charged and discharged, prevailing grid electricity prices, and other parameters. Hence, more sophisticated methods that can account for such variables can produce more insightful results.

3.2. Production cost models

As storage systems and their applications become more complex, especially by interacting with the grid, incorporating conditional decisions (for example, to charge the batteries from the grid when prices fall below a certain threshold), or dictating constraints (for example, to charge the batteries from PV only), mathematical models become more critical for conducting quantitative analysis. These can be broadly categorized as optimization and simulation models.

Optimization aims to maximize or minimize an objective function (usually NPV) under specified constraints. It can employ custom-built models or commercially available software. The literature includes many examples of the former, which require significant labor to construct but can be tailored to fit a particular scenario more precisely than commercial solutions. Dietrich and Weber (2018) developed a mixed-integer optimization model for the dispatch of an on-grid solar-storage hybrid system in Germany with five-minute demand and PV production resolution. The model also considers feed-in tariffs for energy exported to the grid. Gitizadeh and Fakharzadegan (2014) study another mixed-integer optimization model, created for residential dwellings in the U.S., which considers both TOU and peak-demand charging to maximize annual net profit.

Researchers have also employed custom optimization models to minimize the impact of solar-storage systems on the grid by reducing peak demand and voltage deviations that result from reverse energy flow (Ratnam and Weller 2018; Ratnam, Weller, and Kellett 2015). Another study used optimization modeling to evaluate the benefit of installing standalone storage systems at small and medium-sized enterprises in Germany, and assessed the possibility of using storage to earn multiple revenue streams from different services (Braeuer et al. 2019). In the context of Germany's day-ahead market, the paper found that these services do not produce financially attractive returns on an individual basis. However, the combined revenue from multiple-service value stacking can result in profitability for some enterprises.

Other papers employ commercially available software to optimize the sizing of solar-storage systems. Elshurafa and Aldubyan (2019) used the software package HOMER to optimize the sizing of a standalone solar-storage system in rural Saudi Arabia, while O'Shaughnessy et al. (2018) utilized REopt to optimize the sizing and dispatch of an on-grid solar-storage hybrid system in a U.S. residential context, factoring in the possibility of load-shifting. Both software packages rely on NPV to assess cost-effectiveness.

Simulation models offer an alternative to optimization models, which may be difficult to construct and require relatively long computation times to solve. Instead, simulation models use brute computational force to find the solution for a scenario with specific inputs. For example, a researcher could specify the potential values/range of electricity prices, PV system capacities, and battery bank sizes, and use a simulation model to calculate NPV for all possible combinations.

Numerous studies have utilized simulation models to assess solar-storage hybrid systems at the distributed scale. Tervo et al. (2018) developed custom code in MATLAB to assess the economics of residential solar-storage systems in all 50 U.S. states and compare their LCOE to the cost of obtaining electricity from the grid. The capacity of the PV systems varied from 1 kW to 10 kW, and the storage systems from 0 kWh to 14 kWh. Similarly, Merei et al. (2016) presented the 'technoeconomics' of installing a solar-storage system for a supermarket in Germany. Here, PV system size varied as a function of peak-load, and storage system capacity ranged from 0 kWh to 50 kWh. The authors also conducted a sensitivity analysis by varying capital costs and other parameters. Another study developed a simulation model to study profitability of on-grid storage in Spain (Dufo-López and Bernal-Agustín 2015), and found that, based on prevailing battery storage costs and electricity prices at the time of the study, storage would have negative NPV in this application.

Other research has employed utility-scale simulation models to calculate the minimum possible cost required (including fuel, O&M, reserves, etc.) to reliably meet demand. This methodology can effectively value storage (at either distributed or utility scale) by taking the difference between the minimum cost of a scenario without storage and an alternative scenario that includes storage but is otherwise identical. For instance, if in a specific year storage results in a $10 million saving over a scenario without storage, for a system with capacity of 200 MW, then the annualized benefit, or value, of storage would be $50 per kilowatt-year ($/kW-year). Note that the literature, when services related to capacity (such as reserves), employs $/kW-year (or $/kW-h, note the added hyphen); the latter denotes a unit of capacity held for one hour.

Using this approach, Denholm et al. (2013) calculated the value of storage deployment in the western U.S., and concluded that storage is much more valuable when providing reserves rather than energy. In another study, Ellison, Bhatnagar, and Karlson (2012) estimated the value of storage for Hawaii, and found that the addition of storage decreased the overall cost of generation. The savings resulted from more efficient operation of conventional generation: storage decreased the amount of spinning reserves inefficiently provided by single- and combined-cycle units. An analysis conducted by the Electric Power Research Institute (EPRI) identified the challenges associated with deploying storage in the midwestern U.S. (Rastler 2011). Notably, the three previous studies used PLEXOS, a commercially available software package for modeling the power and transmission sectors. Kintner-Meyer et al. (2012) utilized a different software package, PROMOD, to assess cost implications of deploying storage in western U.S., and, like other studies above, found that storage deployed for arbitrage only will not be profitable. Finally, a model developed to assess the impact of battery storage on the costs of generation in Australia found that deploying storage can reduce LCOE by 13-22%, and reduce spilled energy by up to 76% (Keck et al. 2019).

Given the flexibility of optimization and simulation models, and their application in different contexts on- and off-grid, at distributed and utility scales, and across different geographies, it is unsurprising that the many studies above find different values for storage. Furthermore, myriad factors impact the financial attractiveness of storage deployment beyond the cost and capabilities of the technology itself. These include electricity prices, the cost of solar modules, the cost and availability of fuels, cost of peaking generation, and the share of renewables in the energy mix.

3.3. Market-based valuation

As the name suggests, market-based valuation uses prevailing market prices to determine the value of a specific service that storage (or any other technology) would provide (Tómasson, Hesamzadeh, and Wolak 2020). At a basic level, this approach applies to any good or service for which there is a functional market. In the context of services relevant to storage, an electricity system operator receives bids from market players seeking to provide electricity or related services, and optimizes dispatch to minimize costs based on these bids.[1] When the operator accepts a bid, the player receives the marginal price of the relevant service (Pérez-Arriaga 2014). Therefore, historical market prices offer a good indication of what a bidder would receive. In a market setting, prices may change rapidly and vary across services, time periods, and jurisdictions. Hence, historical prices should be approached with caution.

A major advantage of market-based valuation is that the value of the service can be attained without any calculation. However, for historical prices to offer a meaningful basis for valuation, one must assume that the introduction of storage (or any technology) will not affect the market. In other words, the impact must be too small to change prices and storage must be a ‘price-taker’ in this context (Rahimiyan and Baringo 2015). As will be shown, this assumption does not always hold as the market for reserve services is small. Thus, if a given storage system is large enough, it could

[1] The system operator also depends on models to describe the market and assess performance. Given the similarities in naming conventions in the literature, these models should not be confused with the simulation/optimization models presented in the previous section.

become a price-maker for certain services (Arteaga and Zareipour 2019, Deboever and Grijalva 2016). For this reason, if a new technology will impact the generation cost, a market simulation model can be built to quantify the implications. Optimization/simulation models can be used in any setting: a vertically integrated utility or open markets for unbundled services. However, market-based valuation models require a market to exist. Nonetheless, simulation and market-based models have many similarities.

Byrne and Silva-Monroy (2012) performed a valuation study for a storage device based on its expected future revenues. They employed historical data from the California Independent System Operator, and investigated the maximum potential revenue for an arbitrage scenario and an arbitrage-plus-regulation scenario through linear optimization. The study found positive value in both scenarios. However, the value gained from regulation far exceeds that of arbitrage. Similarly, Drury, Denholm, and Sioshansi (2011) attempted to determine the value of compressed air storage technology in a number of U.S. states, using historical energy and reserve price data with the aid of a dispatch model. They concluded that arbitrage alone would be unlikely to justify deployment of compressed air storage in most markets. However, the business case becomes more attractive with the addition of reserve revenues—another case in which storage is more valuable when utilized for reserves than arbitrage.

4. Quantitative Review

The previous two sections reviewed the services storage can provide and the methods employed in the literature to value them. Table 2 below compiles the quantitative valuation results and key characteristics from each relevant paper examined in this study. We note that these monetary figures result from a large number of assumptions and calculations, and it is impossible to include them all here. For each distinct deployment — thus, some papers appear in the table more than once — the table reports the scale (i.e., utility or distributed), geography/location, the technology of the storage device (e.g., lithium ion, lead acid, hydro, etc.), the service provided, and a brief description of how the service was valued (LCOS, production cost models, or market models as described in the previous section).

To correctly interpret the numerical figures compiled in Table 2, it is important to note how the cited papers calculated them. LCOS values represent the break-even cost for the storage technology alone, under a set of given assumptions; thus, lower values are more favorable. As described in the previous section, LCOS cannot be immediately translated to profitability or cost competitiveness at either utility or distributed scale because it excludes numerous relevant factors. Similarly, for market-based valuation, results represent the compensation that storage (or any technology) would receive for providing the given service, and assume that its introduction does not impact market prices. By coupling this market value with the capital and operational costs of deploying storage technology, investors would be able to determine whether storage is financially viable or not. In simulation (production-cost) models, the output represents the annualized reduction in costs achieved due to storage deployment versus a scenario without storage; here, higher values are more attractive.[2]

[2] Note that storage may increase, rather than decrease, generation costs. In such cases its value becomes negative.

Table 2. Literature review of valuation methods and resulting monetary figures.

Reference	Scale	Service assessed	Geography	Technology	Valuation method	Monetary figures
Günter and Marinopoulos 2016	Distributed	Peak limiting	U.S. (California)	Li-ion	**Model:** Adopted cost-benefit analysis based on NPV	No explicit monetary figure provided for storage alone
Dufo-López and Bernal-Agustín 2015		Peak limiting	Spain	Various	**Model:** Adopted simulation model and compared NPV of various scenarios	No explicit monetary figure provided for storage alone
O'Shaughnessy et al. 2018		Peak limiting and energy/ arbitrage	U.S.	Nonspecific	**Model:** Authors used a commercial optimization software and augmented it further to minimize NPV of a hybrid solar-storage system	No explicit monetary figure provided for storage alone
Gitizadeh and Fakharzadegan 2014		Peak limiting and energy/ arbitrage	U.S. (North Carolina)	Nonspecific	**Model:** Authors built an optimization model, for a hybrid solar-storage system, to maximize annual net profit	No explicit monetary figure provided for storage alone
Tervo et al. 2018		Energy/ arbitrage	U.S. (50 states)	Li-ion	**LCOE:** Adopted Matlab to calculate an overall cost for a hybrid solar-storage system	No explicit monetary figure provided for storage alone
Merei et al. 2016		Energy/ arbitrage	Germany (Aachen)	Li-ion	**Model:** Adopted a simulation model to calculate annuity costs of several solar-storage scenarios	No explicit monetary figure provided for storage alone
Günter and Marinopoulos 2016		Energy/ arbitrage	U.S. (California)	Li-ion	**Model:** Adopted cost-benefit analysis based on NPV	No explicit monetary figure provided for storage alone
Mahani et al. 2020		Energy and ancillary services	U.S. (New Jersey)	Nonspecific	**Model:** Built a mixed-integer optimization model and calculated NPV	0.1 – 1.5 $/kW (cost savings)
Comello and Reichelstein 2019		Energy	U.S.	Li-ion	**LCOS:** Adopted a variant of the basic LCOS expression differentiating between power and energy components	0.10 – 0.17 $/ kWh
Pawel 2014		Energy	Nonspecific	Li-ion	**LCOS**	1.678 €/kWh
Jülch et al. 2015		Energy	Germany	LA	**LCOS:** Cost includes insurance and inverter	0.74 – 0.98 €/kWh

Reference	Scale	Service assessed	Geography	Technology	Valuation method	Monetary figures
Elshurafa and Aldubyan 2019		Energy	Saudi Arabia	LA	**Model:** Used commercial software to minimize lifetime cost of a hybrid solar-storage system based on NPV	No explicit monetary figure provided for storage alone
Pawel 2014		Energy	Nonspecific	LA	**LCOS**	3.072 €/kWh
Jülch et al. 2015		Energy	Germany	LFP	**LCOS:** Cost includes insurance and inverter	0.75 – 0.83 €/ kWh
Pawel 2014		Energy	Nonspecific	Redox-flow	**LCOS**	0.338 €/kWh
Mundada, Shah, and Pearce 2016		Energy	U.S. (Michigan)	Nonspecific	**LCOE:** Calculates the cost for a hybrid system comprising PV, storage, and cogeneration	No explicit monetary figure provided for storage alone
Dietrich and Weber 2018		Energy	Germany	Nonspecific	**Model:** Adopted an optimization model to minimize NPV of hybrid solar-storage system	No explicit monetary figure provided for storage alone
Günter and Marinopoulos 2016	Utility	Reserve (regulation)	U.S. (PJM)	Li-ion	**Market:** Values obtained from the publicly available clearing prices of reserve regulation	35 $/kW-year (average)
Zakeri and Syri 2015		Reserve (regulation)	Nonspecific	Li-ion	**LCOS**	433 €/kW-year
Zakeri and Syri 2015		Reserve (regulation)	Nonspecific	LA	**LCOS**	256 €/kW-year
Walawalkar, Apt, and Mancini 2007		Reserve (regulation)	U.S. (New York)	NaS and flywheel	**Market:** Value calculated through model-based revenues governed by the market clearing price of the regulation service	$163 – 203/ kW-year
Kirby 2012		Reserve (regulation)	U.S. (California)	Hydro	**Market:** Reported market data for regulation reserve from 2002 to 2011	$105 – 305/ kW-year
Sigrist, Lobato, and Rouco 2013		Reserve (regulation)	Spain	Nonspecific	**Model:** Optimization model	165 €/ kW-year
Denholm et al. 2013		Reserve (regulation)	U.S. (Western)	Nonspecific	**Model:** Optimum dispatch model using a commercial software	$110 – 223/ kW-year
Das, Krishnan, and McCalley 2015		Reserves (spinning)	Nonspecific	Compressed air	**Model:** Optimum dispatch model developed for an IEEE 24-bus system	$~1/kW-year
Kirby 2012		Reserves (spinning)	U.S. (California)	Hydro	**Market:** Reported market data for regulation reserve from 2002 to 2011	$35 – 88/ kW-year

Reference	Scale	Service assessed	Geography	Technology	Valuation method	Monetary figures
Denholm and Letendre 2007		Reserves (spinning)	U.S. (Various)	Nonspecific	**Market:** Prices as available from system operators	$65 – 149/ kW-year
Denholm et al. 2013		Reserves (spinning)	U.S. (Western)	Nonspecific	**Model:** Optimum dispatch model using a commercial software	$65 – 165/ kW-year
Kirby 2012		Reserves (non-spinning)	U.S. (California)	Hydro	**Market:** Reported market data for regulation reserve from 2002 to 2011	$6 – 41/kW-year
Zakeri and Syri 2015		T&D benefits	Nonspecific	Li-ion	**LCOS**	493 €/kW-year
Zakeri and Syri 2015		T&D benefits	Nonspecific	LA	**LCOS**	232 €/kW-year
Zakeri and Syri 2015		T&D benefits	Nonspecific	Compressed air	**LCOS**	161 €/kW-year
Sigrist, Lobato, and Rouco 2013		Peak limiting	Spain	Nonspecific	**Model:** Optimization Model	98 €/kW-year
Jülch 2016		Energy	Nonspecific	Li-ion	**LCOS**	0.23 – 0.37 €/ kWh
Lai and McCulloch 2017		Energy	Africa	Li-ion	**LCOS:** Used a variant of LCOS and named it Levelized cost of delivery (LCOD)	$0.54/kWh
Jülch 2016		Energy	Nonspecific	LA	**LCOS**	0.15 – 0.19 €/ kWh
Obi et al. 2017		Energy	U.S.	LA	**LCOS**	$0.064/kWh
Zakeri and Syri 2015		Energy	Nonspecific	LA	**LCOS**	646 €/ kW-year
Drury, Denholm, and Sioshansi 2011		Energy	U.S. (New York)	Compressed air	**Model:** Annual revenues calculated via an optimization model in a market environment	$62/kW-year
Drury, Denholm, and Sioshansi 2011		Energy	U.S. (PJM)	Compressed air	**Model:** Annual revenues calculated via an optimization model in a market environment	$55/kW-year
Drury, Denholm, and Sioshansi 2011		Energy	U.S. (MISO)	Compressed air	**Model:** Annual revenues calculated via an optimization model in a market environment	$50/kW-year
Drury, Denholm, and Sioshansi 2011		Energy	U.S. (California)	Compressed air	**Model:** Annual revenues calculated via an optimization model in a market environment	$25/kW-year

Reference	Scale	Service assessed	Geography	Technology	Valuation method	Monetary figures
Sioshansi, Denholm, and Jenkin 2011		Energy	U.S. (PJM)	Compressed air	**Model:** Annual revenues calculated via an optimization model in a market environment	$53 – 80/ kW-year
Obi et al. 2017		Energy	Nonspecific	Compressed air	**LCOS**	$0.055/kWh
Figueiredo, Flynn, and Cabral 2006		Energy	Canada (Alberta)	Pumped hydro	**Market:** Annual revenues based on market prices	$122/kW-year
Figueiredo, Flynn, and Cabral 2006		Energy	Netherlands	Pumped hydro	**Market:** Annual revenues based on market prices	$95/kW-year
Figueiredo, Flynn, and Cabral 2006		Energy	UK	Pumped hydro	**Market:** Annual revenues based on market prices	$38/kW-year
Figueiredo, Flynn, and Cabral 2006		Energy	U.S. (PJM)	Pumped hydro	**Market:** Annual revenues based on market prices	$38/kW-year
Figueiredo, Flynn, and Cabral 2006		Energy	Spain	Pumped hydro	**Market:** Annual revenues based on market prices	$23/kW-year
Figueiredo, Flynn, and Cabral 2006		Energy	Germany	Pumped hydro	**Market:** Annual revenues based on market prices	$16/kW-year
Figueiredo, Flynn, and Cabral 2006		Energy	Scandinavia	Pumped hydro	**Market:** Annual revenues based on market prices	$~0/kW-year
Sioshansi, Denholm, and Jenkin 2011		Energy	U.S. (PJM)	Pumped hydro	**Market:** Annual revenues calculated via an optimization model in a market environment	$73 – 113/ kW-year
Smallbone et al. 2017		Energy	Nonspecific	Pumped heat	**LCOS**	0.03 – 0.05 €/kWh
Walawalkar, Apt, and Mancini 2007		Energy	U.S. (New York City)	NaS	**Market:** Value calculated through model-based revenues governed by the market clearing price for four hours of storage	$76 – 211/ kW-year
Lai and McCulloch 2017		Energy	Africa	VRB	**LCOS:** Used a variant of LCOS it names levelized cost of delivery (LCOD)	$0.50/kWh
Jülch 2016		Energy	Nonspecific	VRB	**LCOS**	$0.32– 0.36/ kWh

Reference	Scale	Service assessed	Geography	Technology	Valuation method	Monetary figures
Kirby 2012		Energy	U.S. (California)	Hydro	**Model:** Developed an optimization model governed by market prices	$46/kW-year
Sioshansi et al. 2009		Energy	U.S. (PJM)	Nonspecific	**Market:** Developed an optimization model governed by market prices for 2002-2007	$50 – 100/ kW-year
Denholm et al. 2013		Energy	U.S. (Western)	Nonspecific	**Model:** Optimum dispatch model using commercial software	$35 – 80/ kW-year
Eyer, Corey, and Iannucci Jr 2004		Energy	U.S. (California)	Nonspecific	**Model:** Optimization model with market-governed inputs and prices for 2003	$10 – 50/ kW-year
Byrne and Silva-Monroy 2012		Energy	U.S. (California)	Nonspecific	**Model:** Optimization model	$25 – 40/ kW-year
Eyer, Corey, and Iannucci Jr 2004		Energy	U.S. (PJM)	Nonspecific	**Model:** Optimization model with market-governed inputs and prices for 2001	$20 – 60/ kW-year
Braff, Mueller, and Trancik 2016		Energy	U.S. (Various)	Nonspecific	**Model:** Introduced a dimensionless metric to assess value of storage	No explicit monetary figure provided for storage alone
Lazard 2019		Energy	Nonspecific	Nonspecific	**LCOS**	$0.165 – 0.325/ kWh
Baek et al. 2020		Value stacking (energy and transmission benefits)	U.S. (Illinois)	Lithium-ion	**Model:** Used commercially available software to calculate NPV	$1.4/W (ratio of NPV to battery storage installed capacity)
Sioshansi, Denholm, and Jenkin 2011		Value stacking (energy and capacity payments)	U.S. (PJM)	Pumped hydro	**Model:** Annual revenues calculated via an optimization model in a market environment	$103 – 153/ kW-year
Drury, Denholm, and Sioshansi 2011		Value stacking (energy and contingency reserves)	U.S. (New York)	Compressed air	**Model:** Annual revenues calculated via an optimization model in a market environment	$86/kW-year
Drury, Denholm, and Sioshansi 2011		Value stacking (energy and contingency reserves)	U.S. (PJM)	Compressed air	**Model:** Annual revenues calculated via an optimization model in a market environment	$80/kW-year

Reference	Scale	Service assessed	Geography	Technology	Valuation method	Monetary figures
Drury, Denholm, and Sioshansi 2011		Value stacking (energy and contingency reserves)	U.S. (MISO)	Compressed air	**Model:** Annual revenues calculated via an optimization model in a market environment	$65/kW-year
Drury, Denholm, and Sioshansi 2011		Value stacking (energy and contingency reserves)	U.S. (California)	Compressed air	**Model:** Annual revenues calculated via an optimization model in a market environment	$47/kW-year
Sioshansi, Denholm, and Jenkin 2011		Value stacking (energy and capacity payments)	U.S. (PJM)	Compressed air	**Model:** Annual revenues calculated via an optimization model in a market environment	$93 – 120/ kW-year
Sigrist, Lobato, and Rouco 2013		Value stacking (peak limiting and regulation reserve)	Spain	Nonspecific	**Model:** Optimization model	$230/kW-year
Byrne and Silva-Monroy 2012		Value stacking (energy and regulation reserve)	U.S. (California)	Nonspecific	**Model:** Optimization model	$117 – 160/ kW-year
Kirby 2012		Value stacking (energy, regulation reserves, and spinning reserves)	U.S. (California)	Nonspecific	**Model:** Developed an optimization model governed by market prices	$62 – 75/ kW-year

Note: LA = Lead acid; LFP = Lithium-ferrophosphate; Li-ion = Lithium ion; MISO – Midcontinent Independent System Operator; NaS = Sodium-sulfur; PJM = Pennsylvania-New Jersey- Maryland Interconnection; VRB = Vandium redox flow battery.

5. Discussion

Keeping in mind the distinction between cost and value, Table 2 offers several useful insights. The discussion below will contextualize the observations according to service and valuation method, focusing on the relevance for economics and policy rather than technical or engineering aspects.

5.1. Numerical figures not always provided

The first important observation is that many papers, despite attempting to determine the value of storage in various applications, do not actually quantify this separately. This is mainly true for distributed-scale applications, which typically deploy storage alongside PV. Most relevant studies compare (using NPV or LCOE) the cost of electricity from the grid alone versus from a hybrid solar-storage-grid system. Yet their results often do not explicitly quantify the cost/value of storage in such contexts, which differs from its standalone value and would require a separate *ex post* valuation to determine. The literature review indicates that many authors who examine distributed-scale systems decide not to carry out this extra step, which would not impact the system-level analysis.

On the other hand, virtually all studies in the literature on utility-scale systems provide explicit values for storage, whether as a standalone technology or part of the energy mix. The difference between typical distributed-scale and utility-scale players may help explain why the respective studies adopt different approaches. At the distributed scale, buyers are mainly homeowners and smaller businesses focused on whether a power system will be financially beneficial, making the conceptual value of a given component technology irrelevant. However, many utility-scale investors, utilities, and system operators (whether operating in a vertically integrated setting or a market setting), may want to know the individual contribution of each technology in order to conduct more granular analysis and modeling.

5.2. Reserves provision vs. energy provision

Table 2 indicates that the highest value applications for storage technologies are regulation reserves, followed by spinning reserves and energy/arbitrage (Zafirakis et al. 2016). As Table 1 highlighted, reserve services require smaller storage systems than do energy services, and therefore less capital. Thus, investments in storage for reserve applications tend to be more attractive and have shorter payback periods. However, reserves account for only a small share of the total cost of providing energy in a power system (in the range of a few percent). In other words, the potential market for reserves is much smaller than for bulk energy, and is further limited by competition from other technologies (Denholm and Mai 2019).

Furthermore, when renewables account for a low share of the energy mix, even utility-scale storage currently has relatively modest potential for energy applications, given its lower value and the larger capacity required for it to be competitive. For example, Denholm and Margolis (2018) assessed the potential of replacing conventional peaking capacity in California with storage. At a PV penetration level of 10%, they found that storage could deliver around 2.5 GW, while the peak capacity was 54 GW. In another study (Denholm et al. 2019), the potential of storage in providing peaking capacity was examined for the entire US. Under historical conditions, storage potential was around 28 GW. This capacity is considered small compared with the US generation capacity of around 1,200 GW.

Similarly, Rohit and Rangnekar (2017) estimated that India will have 35 GW storage market potential for utility applications in 2022, versus more than 360 GW total capacity. Blechinger et al. (2014) determined that on over 2,000 small islands worldwide, around 1 GW of storage could be deployed economically. These numerical findings, to reiterate, are a function of the current and future expected costs of storage and all other technologies in the energy mix. However, as shown, most studies indicate that the market potential for storage remains low without a high penetration of renewables. Of course, further cost reductions in the renewables and storage industries will change this. In such discussions, it is important to distinguish between technical limits and market potential. For example, while a grid may be technically ready to accommodate a sizeable storage system, it may only be financially viable to deploy one with half the capacity (Rastler 2010).

5.3. Sensitivity of results to assumptions

As with any modeling exercise, the quality of results depends on the underlying assumptions. The three valuation methodologies discussed in Section 3 involve a large number of assumptions. For optimization/simulation problems, striking a balance between accuracy and tractability is a well-known practice.

LCOS valuation has been employed as the basis for analysis in dozens of published papers in the literature seeking to quantify storage costs. Nonetheless, authors tend to differ in three important ways: (1) the level of detail included for costs and benefits (for example, taxes and salvage/residual value at the end of the storage device lifetime), (2) the key financial assumptions/parameters (such as the upfront costs and discount rate), and (3) the resolution of the time component. The latter is critical if the price of electricity changes throughout the day (in sub-hour intervals) due to market conditions or TOU pricing. Because LCOS is algebraically identical to LCOE, it shares the same shortcomings (Branker, Pathak, and Pearce 2011), and the literature on LCOE is abundant (Aldersey-Williams and Rubert 2019). However, we will briefly exemplify the extent to which results are affected by input assumptions.

LCOS for compressed air storage systems is highly sensitive to roundtrip efficiency and capacity factors. Obi et al. (2017) found that a 5% decrease in roundtrip efficiency results in a 15% increase in LCOS. Note that because these parameters appear in the denominator of the LCOS expression, they result in nonlinear dependence. For lead-acid batteries, on the other hand, the CAPEX has significant influence on LCOS due to the short lifetime of the battery (Jülch 2016). Because the energy delivered appears in the denominator of LCOS, the higher the energy provided by the battery the lower the LCOS. Ironically, with higher discharge, battery lifetime decreases, necessitating more frequent replacements. In other words, nearly all batteries are highly sensitive to the capacity factor (i.e., full-load hours of the battery storage, which is dependent on the available storage hours), and the percent increase in LCOS due to a certain percent decrease in the capacity factor is higher than the percent decrease in LCOS due to the same capacity factor percent increase.

Because of the simplistic nature of LCOS, it finds the most usage and applicability at the distributed scale. At the utility scale, however, most valuations employ simulation or market models, partially in order to capture the value of all interactions between technologies present in the energy mix, which LCOS cannot incorporate. As expected, constructing models at the utility scale requires significantly more data, and accounting for intricate phenomena not a significant concern at the distributed scale, such as forced outages, ramping capabilities, reserves, varying heat rates of plants, and start-up times of power plants. Many of these phenomena are complex and nonlinear in nature, making a model more difficult to solve.

For storage modeling at the utility scale, the look-ahead horizon factor can also impact results significantly. Because the marginal cost of generation for storage is small, in a pure merit-order dispatch environment without look-ahead, storage is given the same dispatch priority as renewables because the value of storing energy is ignored. However, if the model considers that energy prices may subsequently be higher, then it may decide to delay storage dispatch until then. Depending on the foresight duration embedded in the model (hours, days, or weeks), dispatch can change significantly (Khatami, Oikonomou, and Parvania 2019; Wang, Negash, and Kirschen 2017). To maximize arbitrage, the model seeks the largest differential between charging cost and selling price, and this objective will differ depending how far the model looks ahead, the rate of self-discharge of the battery, and the accuracy of the price forecasts.

As with LCOS, in simulation models the time resolution can skew results. In the case of utility-scale simulation, the impact is much more pronounced and can reach billions of dollars. Typically, models are run on an hourly-resolution basis for dispatch purposes (Denholm and Mai 2019). In jurisdictions where the price of electricity changes sub-hourly, the value of the storage arbitrage would be impacted. In the past, the typical one hour resolution has been generally accepted as a reasonable balance between model complexity and accuracy of results in dispatch models, the introduction of storage to the energy mix may render this approach inadequate.

In long-term capacity expansion models with even lower time resolutions, model outputs can vary by more than an order of magnitude. For example, a study that assessed the value of storage in Chile’s electricity system (Diaz, Inzunza, and Moreno 2019) found that a detailed model with a fine time resolution chooses to build 7.8 GW of storage capacity, representing 42% of peak load, while a simplified model with a coarse time resolution chooses to build only 240 MW of storage. These results indicate the value of more precise time resolutions. Further, capacity expansion models generally do not incorporate all ancillary services, which impacts decisions related to both conventional generation and storage (Carrión, Dvorkin, and Pandžić 2017).

5.4. Impact of energy mix on storage value

Table 2 shows that most utility-scale studies on reserves were U.S. centric. The size and maturity of the power sector in the U.S., coupled with the research capability available to perform and publish studies, makes this unsurprising. The U.S. competitive power markets in particular provide a wealth of information and lessons, given that the U.S. is home to seven regional electricity markets that serve nearly 30 states. While the results can be extrapolated within reason to other countries with appropriate modifications, we note that the value of storage is highly dependent on energy mix, commercial environment, and regulatory regime, which vary by jurisdiction. Two critical factors that impact the value of storage within the energy mix are the shares of renewables and natural gas.

As the share of renewables increases within the energy mix, their inherent intermittency limitations create increased value for storage, and more generally for changes to grid operation and/or deployment of complementary technologies. In the above-mentioned study by Denholm and Margolis (2018) that discusses replacing current peaking capacity in California with storage, recall that the potential of storage to provide peaking was around 2.5 GW at a 10% penetration level of PV. However, if the PV penetration reaches 30%, the potential for storage nearly quadruples to about 10 GW. Denholm et al. (2019) conducted a similar study that assessed the potential of storage to provide peaking for the entire U.S., and found that this nearly doubles if the penetration of solar PV increases beyond 10%. With high penetration of renewables, storage can also play a role in reducing the amount of energy curtailed, depending on the renewable technologies deployed and their shares of the energy mix. A case study for the state of Texas (Denholm and Mai 2019) determined that at a renewable share of 55%, increasing storage capacity or increasing hours of storage duration can reduce energy curtailment by up to 8%.

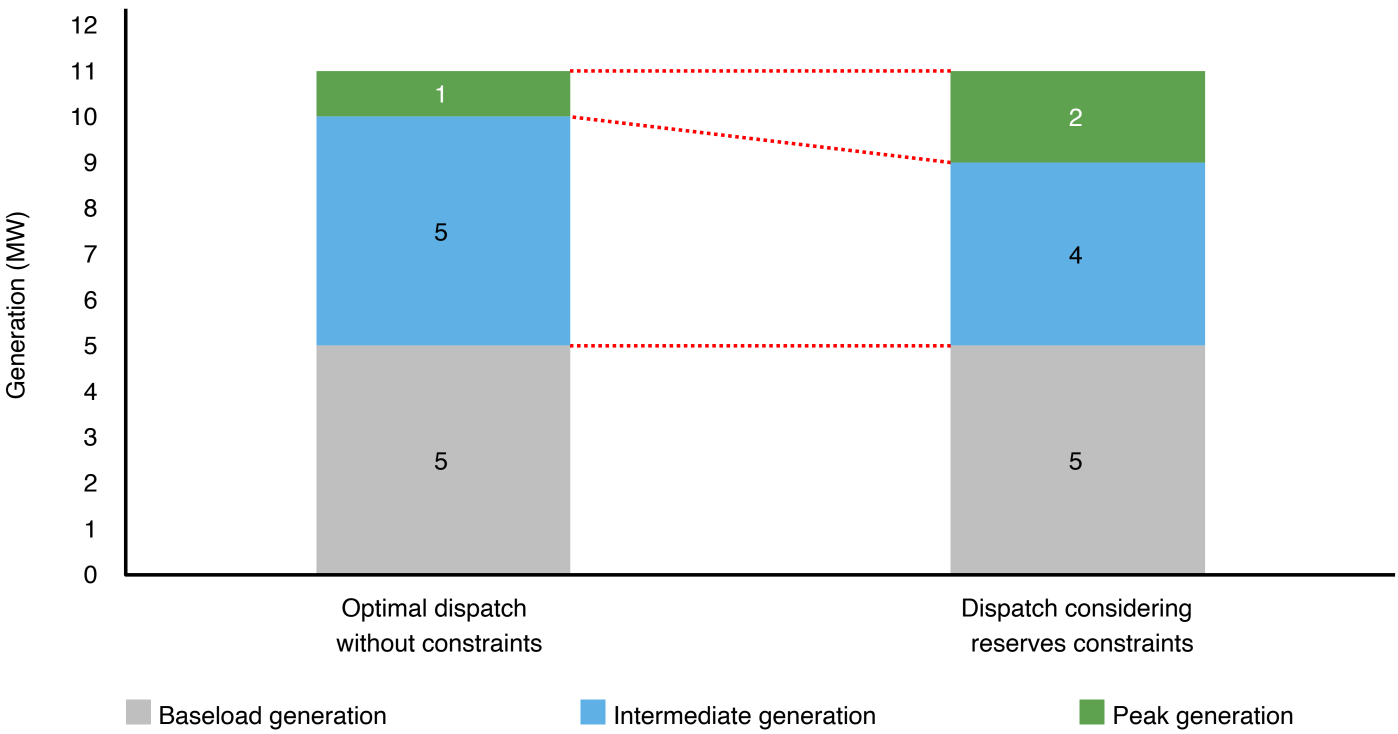
A detailed analysis by Cebulla et al. (2018) reviewed a total of 17 capacity-expansion studies in the context of the U.S., Europe, and Germany. It revealed a noteworthy observation: with increased variable renewables in the mix, the need for storage power capacity increases linearly, but the requirement for storage energy capacity increases exponentially. The studies included renewable shares reaching 100% of the energy mix. The paper also concluded that where solar dominates the renewable share, additional storage is needed, whereas a wind-dominated mix calls for additional transmission capacity.

Natural gas can also enable wider renewable deployment, and in this sense be viewed as competing with storage (Denholm et al. 2013). Gas generators are flexible, pollute less than power plants using liquid fuel, and can provide a number of grid services competitively. As such, depending on the share of gas in the mix, and clearly its price, the potential of storage (equivalently, the value of the service that storage or any other technology would provide) can be significantly affected. In fact, and as shown in Table 2, it is possible that a service can be valued at $0/kW-hr at certain times depending on the demand and technologies satisfying this demand.

To further elaborate on the disproportion in reserves values, two conceptual dispatch scenarios are provided in Figures 1 and 2 for one hour. These hypothetical cases assume that there are three generators meeting demand: (1) a baseload generator with a 5 MW capacity and a generation cost of $5/MWh, an intermediate generator with a 5 MW capacity and a generation cost of $8/MWh, and a peak generator with a 3 MW capacity and a generation cost of $15/MWh. In Figure 1, a situation is shown where the value of the reserves is non-zero, whereas Figure 2 shows a situation where the value of providing reserves is zero. In Figure 1, two dispatch scenarios are provided to meet a load of 11MW for one hour. The one on the left depicts the optimal dispatch with no reserves constraints enforced. For minimum generation cost, the baseload and intermediate generator would be running at their full capacities, and the peak generator would be satisfying the last MW. For such a scenario, the generation cost to satisfy this load is simply the sum of generation costs, i.e., (5 MW x $5/MWh) + (5 MW x $8/MWh) + (1 MW x $15/MWh) = $80/MWh. Realistically, reserve requirements are to be considered in dispatch. In this case, the output of the intermediate generator would be reduced, since it is the flexible unit, and the peak generator would be satisfying 2 MW as opposed to 1 MW in the ideal case. The dispatch considering constraints is shown on the right of Figure 1. The generation cost for this hour under the reserve constraints becomes (5 MW x $5/MWh) + (4 MW x $8/MWh) + (2 MW x $15/MWh) = $87/MWh. In other words, the value of holding reserves, which is the difference in cost between the scenarios, is $7/MW-h. This result is expected as it is the difference in cost between the peak generator and intermediate generator. Note that intermediate generators and peak generators quite often run on gas, and gas prices would have a considerable impact on storage value. For example, and in a study conducted for the western U.S., the value of storage in providing energy services increased from $35/kW-year to $56/kW-year when the price of natural doubled, while the value of storage in providing reserves increased from $65/kW-year to $148/kW-year when the price of natural gas doubled (Denholm et al. 2013).

Figure 1. Dispatch with and without reserves considered (high demand).

A conceptual dispatch scenario for a power system for one hour. On the left, the optimal dispatch is shown without reserves constraints considered. Both the baseload and intermediate generators are running at their full capacities of 5 MW. The peak generator is satisfying the final 1 MW. On the right, reserves are considered, and here the intermediate generator reduces its output from 5 MW to 4 MW to provide reserves, while the peak generator increased its output from 1 MW to 2 MW. The difference in generation cost between the two cases represents the value of reserves provision during this hour.

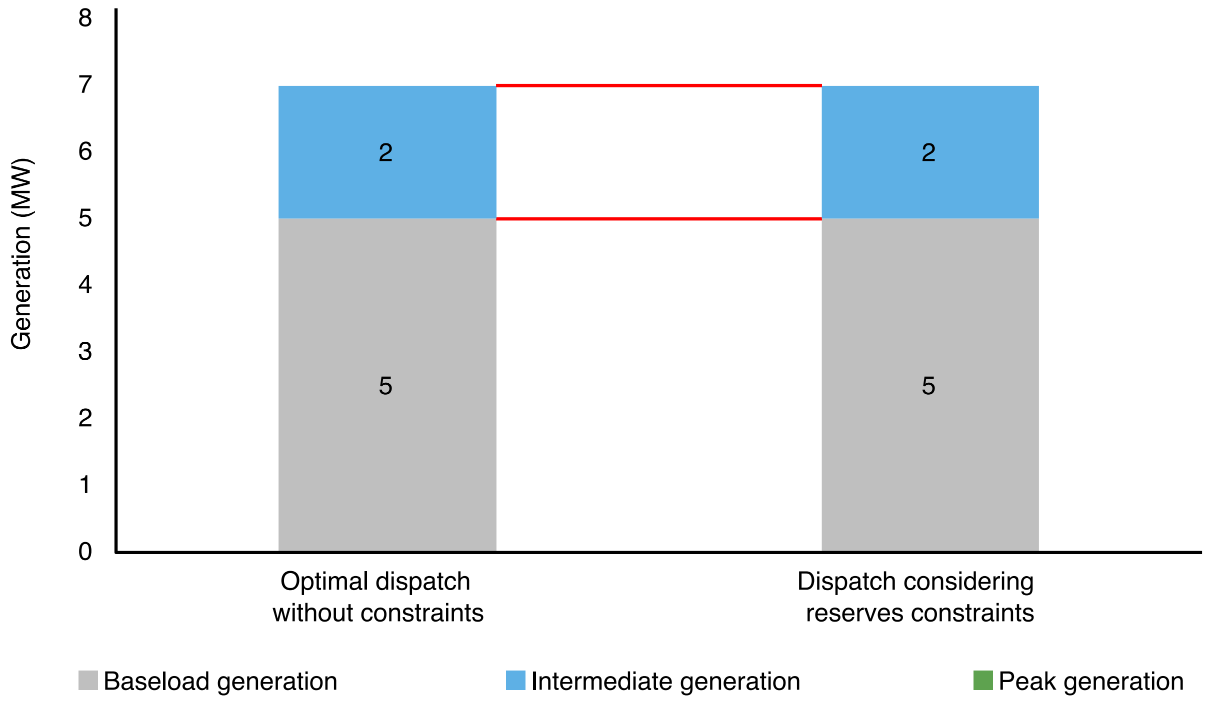


Source: Author's analysis.

In Figure 2, a scenario is shown where the power system is meeting 7 MW of demand (as opposed to 11 MW in Figure 1). Once again, on the left is the optimal dispatch: the baseload generator is running at full load, while the intermediate generator is satisfying the remaining 2 MW. Note also that the peak generator is not contributing to meeting any demand during this hour. The constrained dispatch is shown on the right. Note that both dispatch cases are identical. The intermediate generator is already running and capable of, simultaneously, meeting demand and providing reserves. This translates to having identical generation costs for the optimal and constrained dispatch scenarios, i.e., the cost for holding reserves for this hour is $0/MW-h. These examples show that the value of storage is highly dependent on the energy mix and can vary remarkably throughout the day/season.

Figure 2. Dispatch with and without reserves considered (low demand).

The dispatch of the same system in Figure 1 but at a lower demand level for one hour. Note that the dispatch is not affected by holding reserves. The capacity of the intermediate generator is 5 MW, and there is ample capacity to meet demand and reserves. This means that the cost of holding reserves for this hour is zero.



Source: Author's analysis.

5.5. Value and eliminating deployment impediments

As the worldwide share of renewables grew during the past 20 years, utilities were forced to adjust their operations. Regulators, on the other hand, have sought innovation in electricity market design and governance. Propelled by the downward cost trajectory of storage, another wave of changes is coming (Jones et al. 2017; Miller and Carriveau

2018). Nonetheless, significant challenges impede the adoption of storage, including market, regulatory, and technological obstacles.

5.5.1. Market

Storage can provide numerous services, but without established markets there would be no clear financial incentives to do so. Among these services are black starts, inertial response, avoidance of thermal generation unit starts, increasing system efficiency (which translates to lower fuel consumption), and potential reduction in emissions.

Historically, utilities and regulators have overseen the operation of conventional thermal generation. Thus, the design of compensation evolved around the capabilities and norms of these types of generators (Bhatnagar et al. 2013). As mentioned, the energy market is what creates the overwhelming majority of revenues for generators, with only a small share of revenues coming from ancillary services. Ancillary services are priced based on the costs that are incurred due to withholding capacity from their energy market to be provided to the ancillary market, as was shown in Figure 1. Further, the provision of ancillary services can generally be provided easily by a generator, since the generator is already on and supplying energy. For storage however, the situation is very different. The storage device may be deployed for the sole purpose of providing ancillary services (and no contribution to the energy market). Hence, if the storage device is large enough to supply the entire ancillary service needed then the price of providing ancillary services can drop to (near) zero, and storage will receive no revenue to recover its capital costs. Pricing services based on the marginal cost is suitable for incumbent generation, which possess substantial fixed and variable operation and maintenance costs. However, for storage, where the capital costs are high but operational costs are low, this classical market compensation scheme is problematic. The latter is also true for renewables, and significant research is currently being conducted to design markets that possess a significant share of renewables (Gerres et al. 2019; Peng and Poudineh 2019).

This observation of how storage can skew market prices is of extreme importance when discussing the value of storage. In Table 2, there are a number of entries where the value of storage is equated with the market value of the service that is currently being provided *before* storage enters into the market. In other words, it assumes that no change in competition dynamics will occur. However, and as discussed in this section, it is possible that storage can collapse a certain ancillary market if the storage device is large enough (bearing in mind the ancillary service market is small). As such, the assumption that the storage technology will be remunerated at market prices (i.e., be a price-taker) must be made with caution.

5.5.2. Regulatory

At the regulatory level, storage is considered a difficult technology to regulate as it can provide services across the complete value chain of electricity. Storage can contribute to energy markets, capacity markets, and ancillary markets. Further, storage can contribute at the generation, transmission, and distribution levels simultaneously. At the generation level, storage can be particularly valuable when co-located with renewable power plants to reduce curtailment or reduce transmission capacity needed to integrate this renewable plant. Similarly, storage can be built within the transmission network and provide congestion relief or defer capital investments.

At the distribution level (and on-grid microgrids as well), storage can aid in power quality issues, increase the lifespan of the distribution system, and avoid building substations. Given this versatility, storage can technically provide a number of services at different segments of the electricity value chain, but it will not necessarily receive compensation for all these services due to regulation restrictions (Sioshansi, Denholm, and Jenkin 2012). Even when regulators intend to modify existing regulations to allow storage to participate in one or more markets, approvals and implementation are generally slow. In addition to participation constraints, electricity markets/regulators often do not associate a value for being more flexible in providing a service. For example, storage devices can provide some ancillary services faster than typical fossil-fuel resources, but this additional advantage is not necessarily valued. New regulation in the U.S. have realized this shortcoming and have actually associated a value with the quality of service provided in their mandates.

Given these challenges at the market and regulatory levels, it could be argued that storage can be more valuable in a vertically integrated utility setting rather than a market setting. In the vertically integrated case, wherever storage is deployed and irrespective of what the main driver of its deployment was, all the benefits that storage brings about would be realized by the utility. Ultimately, the value-staking benefits would be realized and translated into cost reductions. This is also in line with the values that are compiled in Table 2 showing that a single service provided by storage is not necessarily high enough to justify investments, i.e., value staking becomes the only viable route and is easier to realize in a vertically integrated utility setting. The same does not apply in a market setting, as the investor in storage will not be compensated for all the services/benefits that storage can provide, which negatively impacts the financial viability of storage projects and, consequently, deters investment in storage in market environments.

5.5.3. Modeling and analysis

Utilities have been functioning effectively and reliably for decades, accumulating a wealth of experience that they have translated into sophisticated modeling capabilities. However, this mainly revolves around traditional forms of generation. Although previous utilities incorporate hydro storage, newer storage technologies have evolved with added functionalities. As a result, previous techniques and norms are no longer adequate for market analysis and valuation, especially given the rise of renewables. Recall that storage has unique characteristics that warrant a departure from previous approaches, such as being unable to provide energy indefinitely, the need for look-ahead, and the resulting impact on scheduling/dispatch (Kazemi and Zareipour 2017), and the sensitivity of the value of storage to time resolution.

While storage remains immature compared to legacy utilities, the literature shows that it is attracting increased research attention (Bera et al. 2019, Dubarry et al. 2019). Many software packages have been enhanced and updated to encircle built-in storage modules that facilitate the duties of modelers for dispatch and long-term planning purposes. In addition, many utilities are taking laudable steps toward better understanding storage by deploying pilot projects. Once again, these developments resemble the trajectory of renewables over the past two decades.

5.5.4. Technology

Technology-related barriers associated with storage technologies also impede deployment. The foremost is cost: while battery prices have been declining and are expected to keep falling (Cole and Frazier 2019), storage cannot be considered cost competitive for all services and for all countries. Despite significant advancements, storage faces an uphill battle because conventional generation also continues to become more efficient as industry players invest heavily in research and development activities. Storage also confronts a dearth of materials, particularly for lithium-ion battery technology (Gil-Alana and Monge 2019). The growing electric vehicle sector, which also utilizes lithium-ion batteries, exacerbates this challenge.

5.6. Summarizing valuation methods

This section provides a summary of the three main valuation methods adopted in the literature, and offers a brief qualitative review of the pros and cons of each.

LCOS is the easiest method to employ and is not computationally intense. However, it provides the least insight, especially when storage is part of a complex power system. LCOS is better suited for comparing generation technologies individually than assessing storage within a mix. Nonetheless, the approach offers an initial screening metric: the larger the LCOS for a particular service, the higher market prices must be to break even.

The production-cost and market models share important attributes. Most notably, both approaches were designed to minimize the cost of delivering energy. Furthermore, both models would generally be run for a single year and exclude the capital costs of new technologies. However, the market model uses the bids of market participants as inputs (Goebel et al. 2016). Because of the uniqueness of storage, they deserve special consideration when devising their offering and bidding strategies (Tian et al. 2020). With the aid of the LCOS, additional calculation post-simulations can be used to estimate returns or payback periods. For a vertically integrated utility, a simulation model can derive the marginal cost of a service. However, in a market setting, the historical values for a specific service may not necessarily reflect the marginal cost only. Rather, other market-specific factors may have played a role in increasing (or decreasing) the price, such as scarcity price effects or carbon penalties. As such, if the market model does not consider these additional factors, it will not arrive at prices comparable to those historically observed. Note that building a model is not required for the market approach if it is expected that introducing a new technology will not impact the market significantly. However, the addition of storage impacts the operation and dispatch of electricity systems. As a result, relevant studies tend to include market models, as reflected in the results summarized in Table 2.

In addition to the disparities mentioned above, the three methods of valuation represent different quantities: (1) LCOS produces break-even cost, (2) production cost models estimate cost-savings, and (3) market-based models represent potential compensation. As a result, the concept of competitiveness must be contextualized to be meaningful. Below, Table 3 summarizes the characteristics of the three approaches.

Table 3. Summary and assessment of valuation methods.

Valuation method	Basic description	What the numerical value represents	How to interpret the valuation	Strengths	Drawbacks
Levelized cost of storage (LCOS)	Relates lifetime costs to deploy and manage a storage device to the total energy it delivers.	LCOS represents a **cost** (in $/kWh) that reflects the average sale price of energy required to break even with total spending on storage.	The **lower the LCOS**, the **more attractive** the storage technology.	- Relatively easy to calculate - Requires limited input data - Enables practical comparisons of various technologies - Effective at the small/distributed scale	- Ignores certain operational details - Cannot describe interactions between different technologies - Sensitive to assumptions - Provides little insight at the utility scale
Production-cost modeling (i.e., simulation)	A model is built to assess generation costs with and without storage in the energy mix. The difference between these scenarios represents the value of storage.	The value represents **cost savings**: the difference between generation costs with and without storage. (If the latter has a higher cost, storage possesses a 'negative' value.)	The **higher the value** (i.e., the cost savings), the **more attractive** the storage technology.	- Values storage as part of the energy mix - Values different services provided by storage - Can evaluate multiple scenarios and the impacts of changes in the energy mix on the value of storage - Applicable in vertically integrated and market environments	- Data intensive - May require considerable computational time and resources, depending on model size - Requires strong technical and modeling expertise - Sensitive to assumptions
Market-based modeling and/or valuation	The value of a service that storage provides is derived from current market prices for the same service. Historical data provide a useful guideline. In its basic form, this method assumes the entry of storage into a market does not initially change the price of the relevant service.	The value represents the **monetary remuneration** for a particular service provided by storage. This can be directly based on market prices, or on a model built to estimate how the market value changes when storage enters the energy mix.	The **higher the value** (i.e., monetary remuneration), the **more attractive** the storage technology.	- Can value storage (or any technology) without any calculation if a market exists - Captures value of different services provided by storage - If a model is built, can evaluate multiple scenarios and the impacts of changes in the energy mix on the value of storage	- Only applicable if a market exists for the service in question - Assumes storage does not affect dispatch and its operation - If a model is used, also shares the drawbacks of production-cost modeling above

6. Concluding Remarks and Insights

This paper has thoroughly reviewed the literature on how to determine the monetary value of electricity storage at both utility and distributed scales. It identifies three primary valuation methodologies — LCOS, production-cost, and market-based models — each with advantages and disadvantages. LCOS is easy to employ but cannot capture the value of storage when deployed in a power system. The production-cost and market models provide greater accuracy at the expense of considerably more demanding data compilation and mathematical formulation.

The three valuation methods represent different monetary quantities. LCOS determines an average break-even cost, measured in $/kWh. The production cost model estimates the cost savings achieved by deploying storage, in $/kW-year. The market model represents the compensation for a given service provided by storage in the relevant power market segment. It is important to note that all three approaches can be applied to other generation technologies as well. However, storage deserves dedicated research as a key emerging technology with unique features and capabilities that differ greatly from those of conventional thermal and renewable generation.

The literature survey indicates that reserve services are currently the most valuable application for storage. However, even in this case the returns may be too low to attract investments. Furthermore, while storage can produce additional value by providing other services in the electricity value chain, regulations often prevent this. Thus, we argue that in the near-term, storage offers more value to vertically integrated utilities, which can fully realize the benefits of storage to achieve lower system-wide generation costs, than to investors in market environments. Until the cost of storage falls sufficiently low and/or regulations become significantly more flexible, widespread deployment of storage will likely remain slow. Nonetheless, some markets have taken material steps to enable storage to compete with existing services.

Over the last two decades, the rise of renewable technologies has required utilities to adjust their business practices and introduce new modes of operation. Regulators have also needed to become more innovative in how they govern the electricity value chain and how to fairly compensate participants. In many ways, current trends in the deployment of storage resemble the initial stages of the proliferation of renewables. It is beneficial for policymakers and industry players to review the lessons offered by the emergence of earlier disruptive technologies in the electricity sector.

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Appendix A

The following summarizes technical parameters and characteristics related to storage. They are ordered alphabetically.

Annual degradation: The yearly decrease in the amount of energy that a battery can store.

C-rate: The rate at which a battery will discharge its maximum capacity. The base 1C rating reflects full discharge in one hour. For example, a 100 ampere hour (Ah) battery, at a 1C rate, will discharge 100 amperes in one hour. At a 2C rate, it will discharge 200 amperes in 30 minutes, and so on.

Cycle lifetime: The number of times a battery charges and discharges (i.e., cycles) before it fails or can no longer meet specified benchmarks.

Depth of discharge: The percentage of a battery's rated capacity that has been discharged. For example, a 100 kilowatt-hour (kWh) capacity battery that has been discharged to 30 kWh would have reached a 70% depth of discharge.

Energy capacity: The amount of energy stored in a battery, generally measured in Ah or watt-hours (Wh).

Minimum allowed state of charge: Batteries can be damaged if they reach a sufficiently low state of charge (typically below 20%). Hence, manufacturers generally recommend that batteries never be discharged below a specified threshold known as the minimum allowed state of charge (MSOC). Adhering to MSOC recommendations prolongs the lifetime of the battery.

Power capacity: The maximum possible discharge rate that can be drawn from the battery, and is measured in Wh.

Roundtrip efficiency: Due to charging losses, a battery will not preserve all electricity delivered to it. For example, a unit with 90% charging efficiency will retain 90 kWh out of 100 kWh. Similarly, a battery will deliver less power than it has stored. If the same battery has 90% discharging efficiency, it will deliver 81 kWh out of the 90 kWh. The product of the charge and discharge efficiencies (here, 81%) is known as 'roundtrip efficiency.'

Self-discharge: The loss of energy stored in a battery due to the intrinsic nature of the technology. This occurs without the battery being connected to a load.

State of charge: The current level of a battery's charge. If a 200 kWh unit is discharged to 150 kWh, its state of charge is 75%. (Note: this is the inverse of depth of discharge, which would be 25%).

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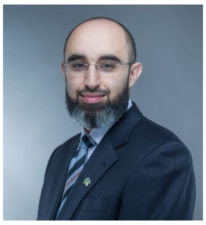
About the Author



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Dr. Amro Elshurafa is a Research Fellow at King Abdullah Petroleum Studies and Research Center (KAPSARC), Riyadh, Saudi Arabia, and possesses 15+ years of experience in the fields of energy and technology on three continents. His research interests lie in renewable energy policy, power systems modeling, and hybrid microgrid design and optimization. He has led and executed several national energy modeling initiatives both on the distributed- and utility-scale. Dr. Elshurafa is the author of 40+ papers and the inventor of several patented technologies. He holds a PhD in electrical engineering complemented thereafter with an MBA in finance.

About the Project

Because proper evaluation of any technology is crucial to its proper regulation (which subsequently ensures its profitability), this paper provides a thorough review on how the value of storage has been calculated in the literature. Being able to associate a monetary value to storage technologies aids utilities and system operators to better plan for their energy mix future and aids investors in more accurately calculating returns on their investments. In light of this, this paper aims to answer two questions: (1) How does the literature associate a monetary value to the various services that storage provide?; (2) What are the strengths and weaknesses of these methods?

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