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CHAPTER 8

Grid-scale energy storage

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Abstract

Grid-scale storage technologies have emerged as critical components of a decarbonized power system. Recent developments in emerging technologies, ranging from mechanical energy storage to electrochemical batteries and thermal storage, play an important role for the deployment of low-carbon electricity options, such as solar photovoltaic and wind electricity. This chapter details the types of technological learning models to evaluate the experience rates (ERs) for key grid-scale storage technologies, including lithium-ion and lead-acid batteries, pumped hydro storage, and electrolysis and fuel cells. It updates the state of the literature to determine learning rates of these and other grid-scale storage technologies. We discuss methodological issues in determining ERs for grid-scale storage systems, which often provide multiple applications and services on the grid. In addition, the chapter highlights future outlooks and new areas for research, including topics related to learning-by-doing, learning-by-searching, and manufacturing localization to derive further insights. Rapid cost reductions in lithium-ion batteries have the potential to disrupt electricity and transportation sectors, creating further complementarities and innovation cycles. More rigorous data collection for grid-scale storage systems on cost indicators that incorporate multiple services and applications provided by storage, life cycle greenhouse gas emissions from storage options, and materials availability of emerging battery chemistries could inform better policies to enable low-carbon power systems.

Chapter Outline

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8.1 Introduction

Grid-scale energy storage has the potential to transform the electric grid to a flexible adaptive system that can easily accommodate intermittent and variable renewable energy, and bank and redistribute energy from both stationary power plants and from electric vehicles (EVs). Grid-scale energy storage technologies provide the means to turn the power system into a dynamic market of distributed producers and consumers, indeed, "prosumers" of energy.

Electricity can be stored through the conversion of different types of energy—for example, mechanical energy in the form of pumped hydropower or flywheels, electrochemical energy for batteries, electrical energy storage in capacitors, chemical energy in the form of hydrogen, and thermal energy such as pumped heat or ice cooling devices. Flywheels that use mechanical storage take electric currents and use them to spin a disk, which can store electricity in the rotational inertia of the disk.

On the main grid, pumped hydro storage has provided electricity storage for decades; however, new options are emerging. Storage systems operate at different scales—including those that enable load balancing for mini-grid systems, which includes those that are isolated and those that can interact with the large-scale utility grid.

Technological learning that leads to cost reduction and performance improvements for these storage technologies could enable reliable electricity supply with intermittent renewable sources that are directly competitive with fossil fuel-based electricity. Technological learning curves may reduce the uncertainty level of future capital costs and technology applications.

The market for a diverse variety of grid-scale storage solutions is rapidly growing with increasing technology options. For electrochemical applications, lithium-ion batteries have dominated the battery conversation for the past 5 years; however, there is increased attention to nonlithium battery storage applications including flow batteries, fuel cells, compressed air energy storage, supercapacitors, and flywheels. Globally, lithium-ion batteries have attracted the most attention due to their multiple applications at the grid-scale and rapid cost declines for consumer products and EVs. Pumped hydro storage maintains the largest existing market share of grid-connected energy storage. While certain lithium-ion batteries have the most attention to date in terms of market deployment for both vehicles and grid-scale applications, numerous opportunities remain for newcomer grid-scale mechanical, thermal, or electrochemical storage solutions.

The economic value of storage technologies also varies across application, technology, and, ultimately, through battery chemistry or physical performance. Grid-economics and alternative remuneration schemes for energy storage on the grid provide multiple revenue streams for grid-scale storage owners; opportunities where previous electricity generation technologies may not be able to compete (Stephan et al., 2016; Davies et al., 2019).

Pumped hydro storage historically has the most installed capacity of any energy storage capacity on the grid with nearly 184 GW of installed nameplate capacity (US DOE Global Energy Storage Database, 2019). The basic concept utilizes gravity and potential energy to pump stored water in a reservoir up from a low elevation to a higher elevation. Pumped hydro storage has opportunities for expansion, especially as an option to retrofit existing large-scale hydropower plants and turn them into storage, which has been one option under consideration in places with a large hydropower dependency such as Laos and Switzerland (Schmitt et al., 2019).

Lithium-ion batteries are available today and are a promising electrochemical storage technology for their dual applications on the grid and for EVs offering a wide range of energy densities, operating temperature ranges, and scales for deployment. Key components of lithium-ion batteries include positive and negative electrodes and an electrolyte. Graphite-based electrodes are the most popular; however, new materials and battery chemistries have experimented with different positive electrodes such as lithium-phosphate or manganese-based cells. Typically, lithium-ion cells are distinct from the actual battery and are formed in cylindrical, flat, or pin shapes. The cells are contained in packs. Current research and development includes the increase of cycle life, power density, and safety concerns to reduce flammability risks.

In 2010 the total volume of lithium-ion batteries was 20 GWh largely owing to portable electronics. Since then, production has been growing annually by 26% reaching a total market size of 120 GWh in 2017 (Avicenne Energy, 2018). While the electronics market gradually slowed down, production of lithium-ion batteries continued to increase, primarily due to the growing demand from EVs. Overall, the market share of lithium-ion batteries for EVs and stationary storage increased from about 5% early this decade to more than 60% in 2017, surpassing the sales for electronics (Fig. 8.1). Still, volumetric energy densities of 600−650 Wh/L in cylindrical cells have been reported (Choi and Aurbach, 2016).

As of 2017, global capacity of electrochemical system storage reached about 1.6 GW, and lithium-ion batteries are the main type used, accounting for about 1.3 GW or 81%, in terms of power capacity in 2017 (Fig. 8.1). Deployment of residential lithium-ion batteries behind-the-meter was estimated at around 600−650 MWh (or about 200 MW) in 2016 (Schmidt et al., 2017; Sekine and Goldie-Scot, 2017), which is substantial, considering that it represents almost 20% of the total lithium-ion battery capacity installed for system

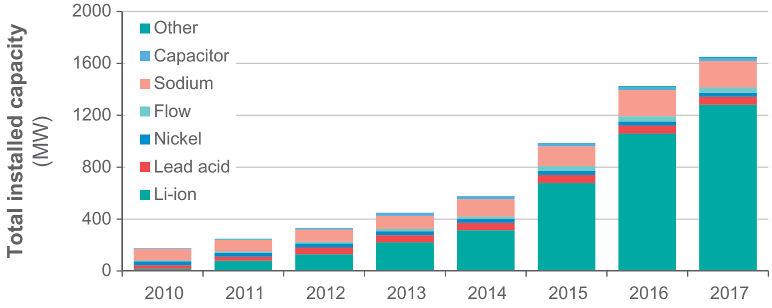

Figure 8.1
Global cumulative installed capacity of electrochemical grid-scale storage (Tsiropoulos et al., 2018).

storage. Bloomberg New Energy Finance reports additional behind-the-meter storage capacity of 650 MWh in commercial and industrial sectors (Sekine and Goldie-Scot, 2017). Dramatic increases are expected in the coming years, with a number of state and federal mandates, and large utility-scale projects expected to result in the deployment of multiples of the 2017 capacity.

Flow batteries offer potential advantages to lithium-ion technologies at the grid scale. Flow batteries are formed of two electrochemical cells that can be separated by a membrane where ion exchange occurs. Often times, the separation of the liquids in an electrolyte mean that one could build a larger battery that scales with the volume of the liquid and area of the membrane. This allows for distinct advantages at the grid scale compared to lithium-ion batteries that are optimized for transportation applications. For instance, the typical flow battery design allows for a decoupling of the power density and energy capacity, which means that batteries can increase their duration. Compared to lithium-ion batteries, flow batteries maintain separate electrolytes and electrodes, which decouples their energy—power ratio and offers a variety of new material chemistries for next-generation batteries and grid-scale storage. Unlike most chemical batteries whose performance degrades after a few thousand cycles, flow batteries can maintain their charge-discharge characteristics for over 100,000 cycles over 20-year lifespans. In addition, flow batteries contain much fewer risks for explosion or fire than their lithium-based counterparts. Conventionally, aqueous redox-flow batteries have dominated the research discussion; however, now alternative materials have emerged ranging from organic metal-free flow batteries based on quinones to vanadium- and zinc-based options. Emerging chemical flow batteries also range across aqueous and nonaqueous solutions (Dunn et al., 2011; Larcher and Tarascon, 2015).

Fuel cells have struggled to achieve commercial success due to the lack of materials science advances in catalyst or membrane technologies, combined with a lack of suitable infrastructure to deploy in a hydrogen-based economy. Nevertheless, with excess and abundant intermittent renewable electricity stemming from utility-scale solar and wind farms, fuel cells are becoming an increasingly viable option to reelectrify hydrogen for power or transport applications.

Compressed air energy storage offers new seasonal and long-duration opportunities for high power and utility-scale energy storage. However, the affordability and availability of compressed air storage varies geographically, thus significantly limiting its potential. Compressed-air-energy storage often uses natural gas as a fuel to combust in the pressurized air and expand with the compressed air to generate electricity. Natural gas expands the capacity and efficiency of operating a compressed-air-storage facility (Succar and Williams, 2011). There are also options to use compressed-air-energy storage without natural gas inputs; however, these projects remain at the demonstration phase. There are two existing commercial compressed air energy storage plants totaling only 400 MW installed capacity—located in underground caverns mined from salt in Germany (290 MW) and the United States (110 MW). Recent studies demonstrate achievable storage in the range of \$0.42–\$4.71/kWh in saline aquifers (Mouli-Castillo et al., 2019).

Flywheels, mechanical energy storage devices using the rotational energy in a spinning disk, also have the potential for rapid performance improvements as technologies gain access to commercial markets. Flywheels are a type of mechanical storage that store rotational energy proportional to the square of their rotational speed. Major applications include frequency regulation and voltage control of power output as a source of torque. Flywheels can be used as spinning reserves. Larger flywheels are also increasing in the duration of their storage, making them another promising grid-scale storage option. The majority of profitable revenue streams for flywheels rely on providing frequency control tasks; however, new economically viable applications are emerging (Diaz-Gonzalez et al., 2015). Mini-grid studies highlight the ability for flywheels to integrate hybrid photovoltaic (PV) mini-grids at a low-cost and reduce the overall system costs by providing stability and storage services. As distributed energy resource architectures change, grid-scale flywheels operating in larger power system networks could gain tractability. Lower cost material advances for flywheel technologies also enable potentially greater learning similar to wind turbines due to the largely mechanical nature of the energy storage compared to electrochemical options.

Supercapacitors can provide short bursts of power on the grid. Physically, they exploit the difference in electrical potential across an electric field and can provide fast-responding bursts of power. Supercapacitors can also be used in vehicle applications and are notably interesting for micro-grid or distribution system level applications that may require higher levels of voltage control than other types of battery storage.

The different technologies noted here have different properties and can provide electricity over seconds, hours, or even weeks. All of these applications fulfill different roles in a power grid with high penetrations of intermittent renewable electricity. For instance, supercapacitors and flywheels that may provide short duration bursts of power into the grid may work in conjunction with longer duration flow batteries that may provide hours of storage. Pumped hydropower storage or hydrogen gas in a power-to-gas facility could provide seasonal storage over long durations in case there are supply−demand mismatches in renewable dependent power systems. It is likely that the different roles of the technology will coevolve as policies and applications create new niches. Grid-scale storage could provide complementary or enabling capabilities to generation sources such as solar and wind. Combined flow-battery and solar-PV systems could generate “baseload” electricity. In addition, the types of storage needed at different timescales may vary, and just because one distribution feeder has a flow battery installation would not preclude the growing technical and economic viability of supercapacitors or flywheels in the same system.

Taken together, the variety of emerging energy storage technologies for grid-scale applications has created a newly competitive ecosystem for clean energy systems to reduce costs, gain experience in manufacturing and deployment, and increase innovations to improve their CO_2 emissions, use fewer rare earth materials, and become safer for human health and the environment.

8.2 Methodological issues and data availability for technological learning

Technological learning and experience curves offer improved analytics and more generalized theories of technological change. Various types of quantitative models have been proposed to quantify and investigate the rates of technology adoption, investment in R&D, innovative cluster effects and technological spillovers, and policies that encourage emergent technological progress. All of these technological change agents have remained active for battery storage technologies. A variety of tools exist to examine technological learning for grid-scale storage technologies in further detail and are summarized here.

Traditional experience curves are based on the idea of “learning-by-doing” and relate the deployment and cumulative production of a storage technology with cost reductions. The one-factor experience curve model is appealing because the idea that firms learn from experience in the past seems intuitive, and by reducing the complex process of innovation into a single parameter, the model is simplified (Gross et al., 2013). They also have been described as the most objective method to project future cost of technologies (Farmer and Lafond, 2015). The underlying reasons for cost reduction as a result of learning-by-doing in manufacturing are identified as spreading overhead cost over larger volumes, reducing inventory cost, cutting labor cost with process improvements, achieving greater division of labor, and improving efficiency through greater familiarity with the process (Abernathy and Kenneth, 1974).

One-factor experience curves focus on relating the unit cost of a technology to its cumulative installed capacity. In the case of storage, this would relate to the amount of electricity stored. The typical learning rate is a useful metric because one can understand that for each doubling of installed cumulative capacity, the associated percentage cost should be reduced. The one-factor experience curve provides a theoretical framework to evaluate cost reductions systematically using a log-linear relationship, dating back to “Wright’s law” in the manufacturing sector (Wright, 1936; Rubin et al., 2015). Conceptually simple, a one-factor approach allows for broad technological comparison. This can be achieved in the electricity storage sector as well and encompasses many of the factors related to the cost trajectory of an emerging technology.

However, one-factor curves lack causation and accountancy to the various cost reducing factors. They show how cost may reduce over time but provide no explanation for the underlying reasons beyond its relationship to cumulative output (Junginger et al., 2008). Additional cost-reducing factors are R&D expenditures (learning-by-searching; Cohen and Levinthal, 1989); improvement of product characteristics via user feedback (learning-by-using; Kahouli-Brahmi, 2008); and network relationships between research laboratories, industry, end-users and political decision-makers that can lead to spillover effects (learning-by-interacting) (Kahouli-Brahmi, 2008). Some authors suggest that experience curves largely reflect economies of scale (Hall and Howell, 1985) and may underestimate rapid innovations and materials science advances that change design or standardization of the technology or related changes in inputs for materials or labor. This weakness in the one-factor model has been explored in the development of solar and wind studies and also applied to lithium-ion batteries (Qiu and Anadon, 2012; Nemet, 2006; Zheng and Kammen, 2014; Kittner et al., 2017). These alternative models view cost reductions “beyond the learning curve” and attribute industry structure, technical barriers, and investment in R&D as better or additional indicators driving the cost reduction of critical low-carbon technologies. Efforts to incorporate further two-factor and multifactor experience curve models for a diverse set of energy storage technologies are underway.

Two-factor experience curves typically incorporate a proxy for innovation or R&D investment into the experience curve models. For lithium-ion energy storage, two-factor models have more closely aligned with current projections of battery storage development compared to one-factor experience curves (Kittner et al., 2017). Data availability and model complexity remains one of the foremost challenges to implement two-factor learning rates into a large-scale energy system optimization model that may help assist capacity-expansion efforts.

Therefore many of the major techno-economic energy system optimization models treat technological learning and experience rates (ERs) as exogenous to the model. However, when experience curves become endogenous to the model, there are better synergies and

Table 8.1: General data collection issues for electricity storage technologies.

Issue	Resolution	Applicability
Data is not for cost but for price	Use price data as indicator for costs	☑
Data not available for desired cost unit	Convert data to desired unit if possible Use available data as a proxy	☑
Data is valid for limited geographical scope	Price data assumed to reflect global marketplace Capacity data scaled to global market if applicable	☑
Cumulative production figures not available		
Data is in incorrect currency or currency year	Convert currency and correct for inflation and PPP	☑
Early cumulative production figures are not clear or available		
Supply/Demand affecting costs significantly	Use data as is but recommend tracking and updating	☑
Lack of empirical (commercial scale) data		

PPP, Power purchase parity.

opportunities to understand how R&D investment and/or future deployment policies could help lower overall system costs for electric grid operations in the long term. This could also significantly aid deep decarbonization efforts across the power sector and related industries (Rubin et al., 2015).

An overview of general data collection issues applicable to grid-scale storage technologies is summarized in Table 8.1. One main issue using current experience curve datasets for the electricity storage technologies presented here remains that the number of data-points, as well as the number of doublings of cumulative capacities, is very limited. This is due to the nascence of emerging battery chemistries and alternative technologies. The number of data-points for lithium-based systems is especially low. However, current data stay close to the fitted experience curve, resulting in a low error in the established learning rate. For flow battery systems, however, the data-points represent only about three doublings of cumulative capacity, and the technology is still very much on the cusp of commercialization (Schmidt et al., 2017). Variations in reported prices from the fitted experience curve result in a high error for the established learning rate. The data for utility-scale lithium battery systems reflects the exceptionally fast price decline of lithium batteries, which was observed in 2017. However, one of the main challenges to modeling data based on prices is the inability to fully capture knowledge spillover effects across similar technologies or storage applications. Spillover effects between different storage types are not considered here in detail. It is likely that there are spillover effects for lithium-ion batteries, in terms of cells, pack components, and power electronics across applications such as consumer electronics, EVs, and stationary systems.

Particularly important for battery storage technologies remains the functional unit considered for an experience curve analysis. Given that batteries and other energy storage technologies serve multiple applications, there may be strengths and weaknesses when characterizing costs. For instance, a capital cost expressed in terms of $/kW would certainly weigh the power density application of the storage device more heavily than the duration of storage, which could be a factor better represented by studying the cost in terms of $/kWh or levelized cost of stored electricity (Schmidt et al., 2019a). At the same time, grid-scale storage engineering may continue to measure advances in power or energy density in a volumetric way that considers the $/kg or $/L for critical components such as the electrolyte or the electrode. New metrics exploring the levelized cost of energy storage capture the unit cost of storing energy, subject to the system not charging, or discharging power beyond its rated capacity at any point in time (Comello and Reichelstein, 2019). Yet these metrics require site- and technology-specific data that may not be easy to implement when considering experience curves, since different dimensions of battery performance and economically viable applications can change with new innovations. Most often, experience curve datasets report the declining cost of lithium-ion storage in terms of $/kWh. This remains a useful metric, but as an increasing number of grid-scale applications related to frequency response, voltage control, storage capacity, and ancillary services become economically viable, the challenge in measuring progress related to cost reductions becomes less straightforward than technologies that generate electricity only.

As is common when analyzing experience curves, we use price data as a proxy to reflect all cost input factors (R&D, sales expense, advertising, overhead, etc.), which makes the analysis vulnerable toward pricing policies (Abernathy and Kenneth, 1974). As discussed in Chapter 2, there are several stages in the market deployment of technologies with specific dynamics between the cost and price of a technology. High data variance can lead to significant variations of ERs across studies and data sets. Depending on the spread of the data, it is possible to calculate different learning rates by changing the start and end point of the analysis and the inclusion or exclusion of outliers (Junginger et al., 2010). In particular, when price data is used, a period of at least 10 years' worth of historical data or two orders of magnitude of cumulative output should be available for price trends to be reliably reflective of cost trends (Gross et al., 2013; Junginger et al., 2010), which is rarely the case for many novel electricity-storage technologies.

Geographies and temporal scope of the data matter too. A majority of studies in the United States and Europe highlight dramatic cost reductions for lithium-ion batteries. Tropical regions may utilize alternative battery technologies or storage mechanisms based on technology and materials availability due to the potential for overheating existing technologies. Sodium–sulfur batteries require an operating temperature at nearly 300°C, and lithium-ion battery performance may decline in hot and humid environments. That may cause added stress and cost for these batteries. In addition, more geographically constrained storage options—ranging from compressed air energy storage to pumped hydro storage—require suitable site selection to enable cost-effective deployment. For instance, a recent study identifies the range of storage costs when siting compressed air storage in saline aquifers for the United Kingdom (Mouli-Castillo et al., 2019). This raises a fundamental question whether geographically specific technologies such as compressed air storage can be assessed using learning curves due to their low levels of standardization and site-specific siting requirements that heavily influence the cost of deployment. In mountainous mini-grid or island regions where diesel is often used, there could be synergistic advantages of using energy storage technologies to reduce the overall cost of a mini-grid or improve the mini-grid's energetic performance which also could impact the learning curve (Kittner et al., 2016). Further studies to explore cost reductions across a variety of countries, scales, and geographies would better indicate global progress as often experience curves omit soft-costs or other project development costs that would potentially change based on region.

Experience curves are incapable of predicting step-change innovations or accounting for product changes that might improve performance for the same costs (Abernathy and Kenneth, 1974; Nemet, 2006). It has been argued that radical product changes constitute new products that exhibit new experience rates (Junginger et al., 2010). Moreover, in situations with significant product changes, other indicators than the specific investment costs may be more appropriate to reflect learning outputs, such as product functionality or the levelized cost of electricity for a power-generation technology (Watanabe et al., 2009; Wiesenthal et al., 2012). For example, lithium-ion batteries may experience significant performance improvements with different material compositions in anode or cathode or the development of solid electrolytes.

The idea of experience improvement at a constant rate is also critiqued. Some argue that costs reduction is stronger during the R&D phase due to radical discontinuity (Staffell and Green, 2013; Ferioli et al., 2009). Others argue that learning might be stronger in the commercial phase due to competition (Söderholm and Sundqvist, 2007). ERs can inform near-term forecasts and longer term strategies, better than alternative methods, and provide a standard basis for comparison across technologies. Following the logic that relative cost shares of components with high rates decrease over time, a reduction of the aggregated experience rates for products over time appears feasible (Ferioli et al., 2009). This can be represented in energy systems models with "kinked" (piece-wise linear) curves or ERs that depreciate with time (Kouvaritakis et al., 2000; Seebregts et al., 1998; Epple et al., 1991). Table 8.2 highlights components of electric energy storage technologies and their contribution to further cost reductions. As electrodes currently comprise a large portion of the overall cell cost, new materials innovations for electrodes could achieve further cost reductions. Wiring and interconnections could also provide cost reductions, but perhaps not at the same potential scale as these costs have already moved into mature phases of the learning curve related to other

Table 8.2: Components of electricity storage technologies and indicative cost contributions (Schmidt et al., 2017).

Technology scope	Indicative contribution	Reported technologies
Cell	19%	
Electrodes	46%	–
Electrolyte	14%	*18,650 cell costs for EV packs reported at*
Separators	15%	*145 US$/kWh* (Cobb 2015)
Current Collectors	19%	
Terminals	4%	
Cell container	2%	
Battery (consumer electronics)	*no data*	
Power electronics	*no data*	Lithium-ion (electronics)
Housing	*no data*	
Module	*Included in pack*	
Thermal conductors	9%	Lead-acid (multiple)
Cell group interconnectors	0%	
State-of-charge regulator	85%	
Terminals	1%	
Provision for gas release	2%	
Module enclosure	3%	
Pack	11%	
Wiring, interconnections and connectors	21%	Lithium-ion (EV)
Housing	15%	Nickel–metal hydride (HEV)
Temperature control	7%	Electrolysis (utility)
Power electronics	24%	Fuel cells (residential)
Battery Management System	33%	
Exworks System	35%	
Inverter	*45%*[93]	–
Container	*45%*[93]	
SCADA/controller	*10%*[93]	
System	35%	
Transport	–	Lithium-ion (residential, utility)
Installation	-	Lead-acid (residential)
Commissioning	-	Redox-flow (utility)
		Sodium–sulfur (utility)
		Pumped hydro (utility)
	100%	

EV, Electric vehicle; *HEV*, hybrid electric vehicle.

electrical equipment. Identifying synergistic cost-reduction opportunities between hardware and soft costs could be important for further learning curve research.

Finally, an important distinction between products that require extensive on-site construction and those mass-produced in centralized factories must be made, due to the often highly specific, custom-built nature of the former resulting in lower ERs (Junginger et al., 2008).

8.3 Results

8.3.1 One-factor learning curves

Prices for storage technologies differ by scope, application, and size. Here we review most recent one-factor experience curves for grid-scale storage technologies. The results for electricity storage experience curves are differentiated along two main dimensions, application category, and technology scope. Application category covers portable (electronics), transport (hybrid EV—HEV, and EV) and stationary (residential, utility); technology scope covers cell, battery, module, pack, ex works system, and system level.

Fig. 8.2 shows decreasing product prices as per energy capacity with increasing cumulative installed nominal energy capacities for most electricity storage technologies. Pumped hydro (system), lead acid (module), alkaline electrolysis (pack), and lithium ion for consumer electronics (battery) and EVs (pack) exhibit current prices below 200€/kWh with above 100 GWh cumulative installed capacity. The relatively low ERs below 5% of the first two are contrasted by 17% for electrolysis (pack) and 30% and 22% for lithium-ion batteries and packs, respectively. Technologies between 1 and 100 GWh cumulative installed capacity, such as nickel−metal hydride (pack), utility-scale lithium-ion (system) or sodium−sulfur (system), show current prices between 200 and 600€/kWh and ERs of 11% and 16%. Those below 1GWh, such as residential lithium ion (system), lead acid (system), redox flow (system), and fuel cells (pack), cost more than 800€/kWh with ERs between 13% and 16%.

The price and cumulative capacity data used for electricity storage technologies come from peer-reviewed literature, research and industry reports, news items, energy storage databases, and interviews with manufacturers. In the literature, learning (based on manufacturing cost) and ERs (based on product price) are sometimes used interchangeably. The sources in the referenced literature were therefore double-checked to ensure the use of actual product price data.

The geographic scope of the data is global. Where cumulative deployment data is available on company or country level, the data is scaled to global level. Regarding price data, it is assumed that the global marketplace ensures that these are globally applicable (Wiesenthal et al., 2012) and those technologies where prices are more likely to vary by geography are highlighted. Regardless of geographic applicability, it can be assumed that identified ERs are applicable globally.

Technology scope for electricity storage technologies is differentiated into cell, battery, module, pack, exworks system, and system level. While exworks system refers to the factory-gate price of complete electricity storage systems, system level includes the cost for transportation, installation, and commissioning if applicable. Additional information on the cost components included at each level can be found in Table 8.2.

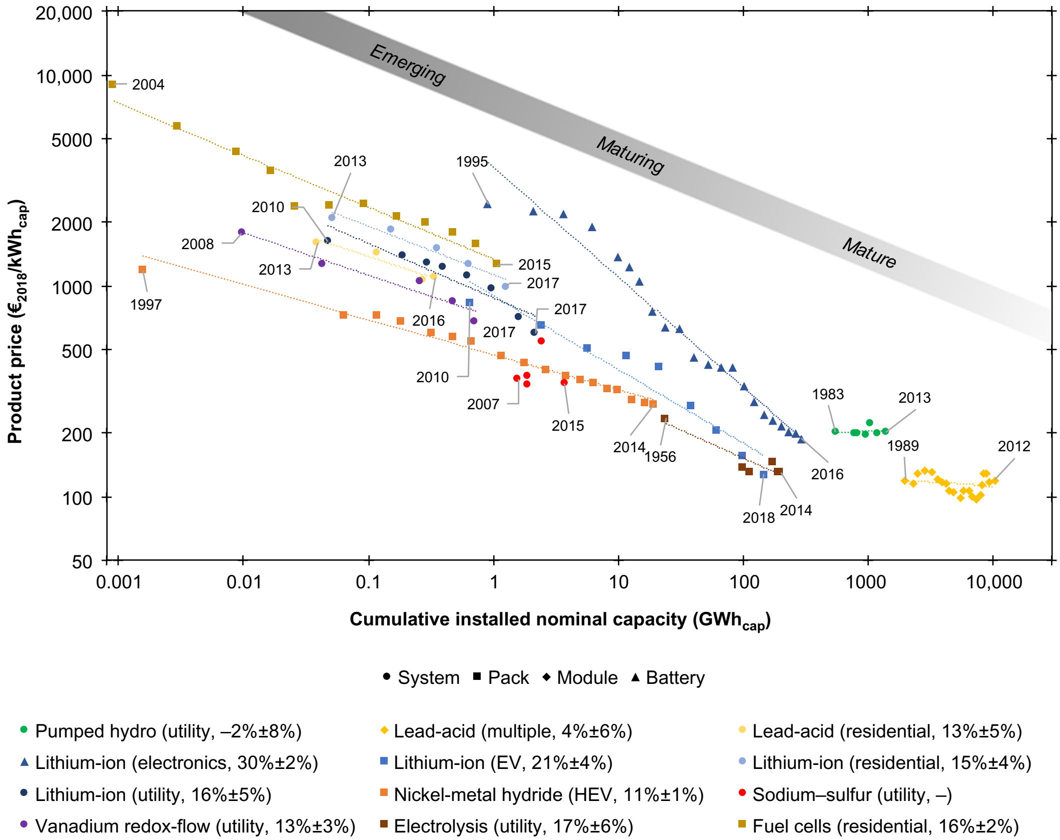

Figure 8.2

Experience curves for electricity storage technologies. Results show product prices per nominal energy capacity. Dotted lines represent the resulting experience curves based on linear regression of the data. Top legend indicates technology scope, and bottom legend denotes technology (including application and experience rate with uncertainty). Experience rate uncertainty is quantified as its 95% standard error confidence interval. Gray bars indicate overarching trend in cost reduction relative to technology maturity. Fuel cell and electrolysis must be considered in combination to form an electricity storage technology. kWh_{cap} is the nominal energy storage capacity. *Source: Updated from Schmidt et al. (2017).*

Experience rate uncertainty is determined using the 95% standard error-based confidence interval (CI). While this is relatively small ($< \pm 5\%$) for most emerging and maturing technologies, most mature technologies (pumped hydro, lead-acid modules, alkaline electrolysis) exhibit high ER uncertainty ($> \pm 5\%$) and are not significantly different from zero ($P > .05$). This is the result of the relatively short data series in terms of doublings of cumulative capacity. Ideally, a dataset for experience curves should cover two magnitudes of cumulative capacity deployment, in order to be significant (Junginger et al., 2010). This is the only the case for fuel cells, nickel–metal hydride batteries, and consumer electronics and EV lithium-ion batteries.

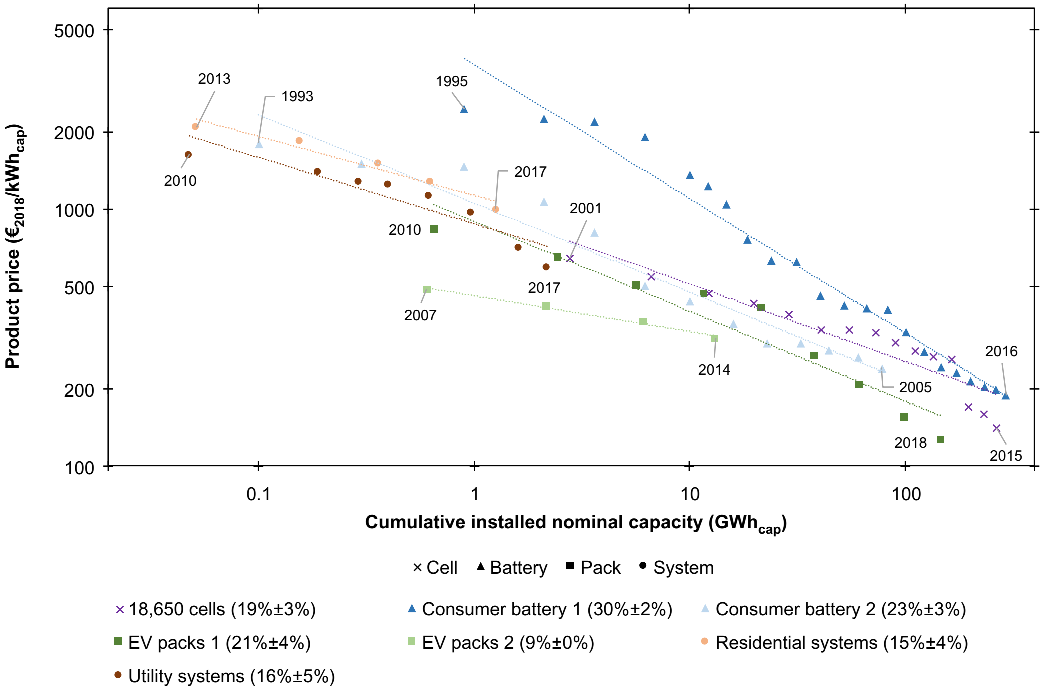

Figure 8.3

Experience curves for lithium-ion technologies (energy terms). Results are shown for product prices per nominal energy capacity. Dotted lines represent the resulting experience curves based on linear regression of the data. Top legend indicates technology scope, and bottom legend denotes technology (including experience rate with uncertainty). Experience rate uncertainty is quantified as its 95% standard error confidence interval. *Source: Updated from Schmidt et al. (2017).*

Electricity storage technologies with insufficient data are excluded, but these may still hold promise in the future. For sodium–sulfur, no feasible ER could be determined from the compiled data (displayed in Fig. 8.2 for reference).

In addition, it can be observed that ERs for lithium-ion technologies decrease with increasing technology scope (Fig. 8.3). Higher ERs for cells and batteries than for packs and systems imply that cost reductions are likely driven by experience in cell manufacturing rather than other components required in packs and systems. Stronger cost reduction for consumer electronics batteries compared to cylindrical cells could reflect the ongoing shift from cylindrical (e.g., 18,650 dimension) to more cost-competitive prismatic and laminate cells used for consumer electronics batteries (Pillot, 2014). Strong cost reduction for cylindrical cells between 2013 and 2015 might be the result of increased demand in EV packs, partly driven by Tesla (Pillot, 2014), which enhanced the experience curve effect and moved the technology down along the experience curve.

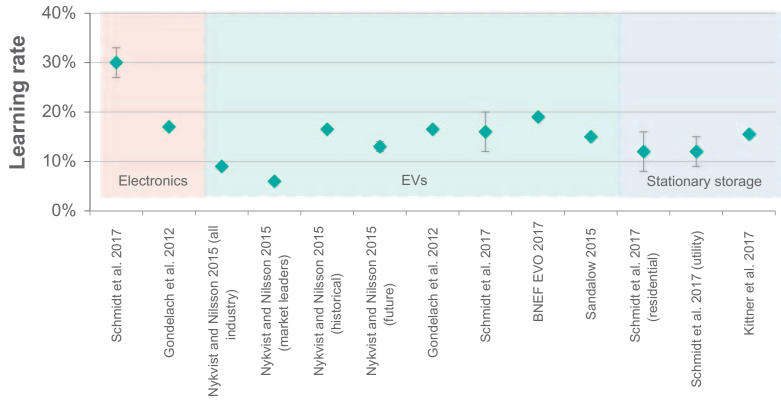

Figure 8.4
Experience and learning rates of lithium-ion batteries across different applications (Tsiropoulos et al., 2018).

Furthermore, these models are not conducted in isolation. Fig. 8.4 shows different learning rates that have reported for lithium-ion batteries based on a variety of methods and data sources including the incorporation of two-factor models (Kittner et al., 2017; industry reports BNEF EVO 2017; and across applications ranging from stationary to vehicle and consumer applications). Though imperfect, this chart begins to also uncover the challenges related to knowledge spillovers and data uncertainty from a lack of cross-industry, cross-sectoral knowledge transfer. The period of analysis, the technology boundaries, and the metrics used (e.g., cost or price, annual or cumulative production) offer possible explanations as to why the values range. For lithium-ion batteries, Schmidt et al. (2017) note that learning rates tend to decrease with increasing technology scope. Learning rates of inverters, a key component of stationary storage systems, are reported at 19% (± 1%) (IRENA, 2016; Fraunhofer ISE, 2015; Schmidt et al., 2017).

8.3.2 Multifactor learning curves

Although conventional one-factor experience curves retain a good level of explanation from 2010 to 2015, recent years of grid-scale storage experience have generally overestimated prices when focused only on economies of scale. In a similar vein to Nemet (2006), multifactor experience curve approaches can integrate the knowledge and innovation acquired from technical improvements, investment in R&D, or alternative industry aspects that could influence cost reductions. For instance, when substituting patent activity for cumulative battery production in a study on ERs for lithium-ion batteries, Kittner et al. (2017) find that the learning rate could nearly double when considering patents only. This is explained by a learning rate of approximately 15% based on cumulative production (over the timescale 1991–2015) and 31% based on patent activity alone (a proxy for R&D efforts). Therefore two-factor models can attribute part of the cost reduction to innovation. While imperfect, these alternative approaches seek to integrate existing technological innovation system theory, innovation policy studies, and extra knowledge spillovers into learning curve models. In these cases, they can often implement, with a high correlation, the critical factors related to cost reductions. From a materials perspective, Kittner et al. (2017) also found that lithium and cobalt prices had weak correlations with the price reduction due to highly diversified materials composition and resilient design features of grid-scale lithium-ion batteries that are not subject to wild price changes due to the lithium and cobalt market.

Multifactor learning curves have the potential to identify key characteristics related to the cost reduction of storage technologies and highlight differences across technologies and applications. For instance, materials chemistry may play a significantly larger role in determining the ER of fuel cells compared to lithium-ion batteries due to the high materials cost of a catalyst for fuel-cell production. Recent assessments do not find cobalt and lithium to significantly limit the cost-reduction potential for existing lithium-ion cells (Kittner et al., 2017; Ciez and Whitacre, 2016). However, for nonlithium storage solutions, there could be raw material bottlenecks as discussed later in the chapter.

The application of multifactor learning curves remains a key component of the innovation literature that is currently evolving. Recent studies are trying to incorporate two-factor and multifactor experience curves endogenously to energy systems optimization modeling tools. This presents a methodological challenge and source of uncertainty given the numerous challenges facing data collection, validation, and verification.

8.4 Future outlook

Using the derived experience curves, future prices for electricity storage based on increased cumulative capacity can be projected (Fig. 8.5), and the feasibility of these projections tested against indicative cost floors is defined by raw material and production costs.

When projecting the experience curves forward to 1 TWh cumulative capacity, the categorization of electricity storage technologies along product prices and cumulative installed capacities can be refined into cost-reduction trajectories for the three-application categories. Prices for stationary systems reduce to a narrow range between 150 and 330€/kWh, and for battery packs reduce to between 80 and 150€/kWh, regardless of technology. This implies that the only technology that manages to bring most capacity to market is likely to be the most cost competitive. Prices for portable batteries reduce to 100€/kWh.

The shaded regions in Fig. 8.5 are visual guides indicating the cost-reduction trajectory for each application category (at a particular technology scope). These narrow to the above-mentioned price ranges. For fuel cells and electrolyzers, prices are only reported on pack

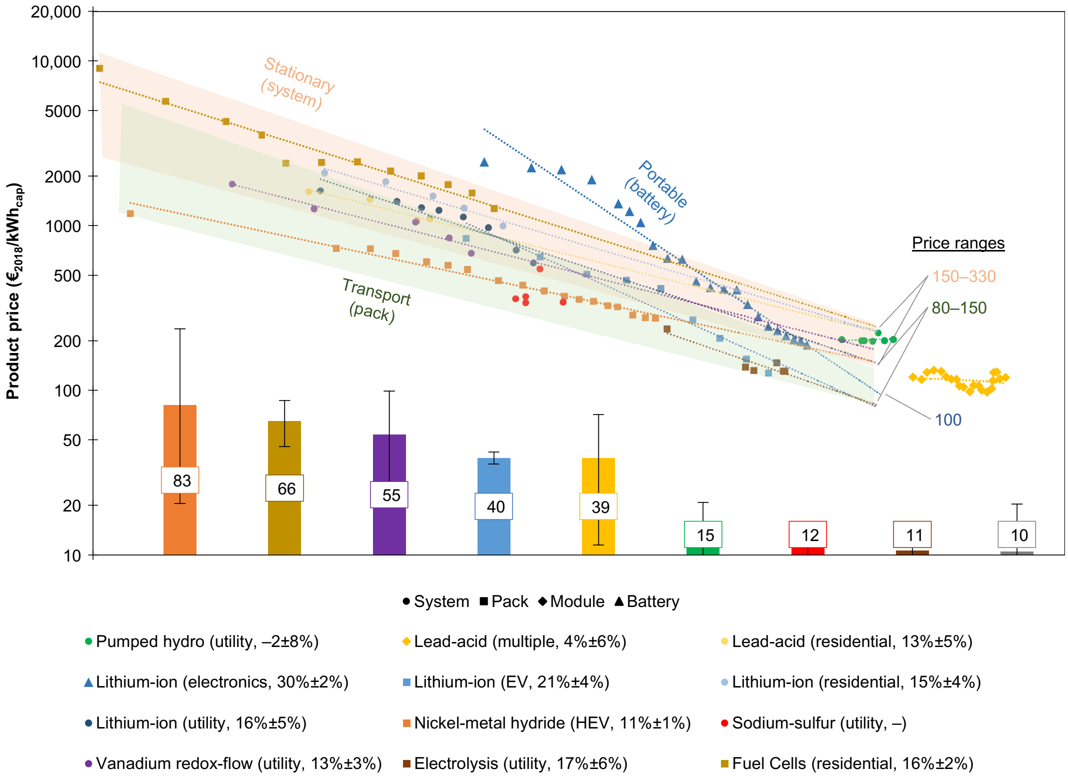

Figure 8.5

Future cost of electricity storage technologies at 1 TWh cumulative capacity. Experience curves (*dotted lines*) are projected forward to analyze product prices at future amounts of cumulative capacity. The bars show the raw material cost of the technologies per system for pumped hydro and per pack for all other technologies. These are calculated by multiplying material inventories from the literature with commodity prices of the past 10 years. Error bars account for variations in each technology's material inventory and commodity prices. Top legend indicates technology scope and bottom legend denotes technology (including application and experience rate with uncertainty). kWh_{cap} is the nominal energy storage capacity. *Source: Updated from Schmidt et al. (2017).*

level. The combination that could be used for stationary storage would cost 330€/kWh at pack-level (electrolysis: 80€/kWh, fuel cell: 250€/kWh), setting the upper bound of the range for stationary system. However, at system level, this combination would cost more, implying a higher upper bound. Pumped hydro systems and lead-acid modules are beyond 1 TWh cumulative installed capacity but cost 200€/kWh (pumped hydro) and 130€/kWh, respectively, which is well within the ranges identified for stationary storage systems and transport packs.

Due to the empirical rather than analytical nature of experience curves, extrapolations are subject to uncertainty of the derived ERs and uncertainty associated with unforeseeable future changes (technology breakthroughs, knowledge spillovers, commodity price shifts) (Junginger et al., 2010; Gross et al., 2013). When accounting for uncertainty of the underlying price and capacity data, the resulting price range at 1 TWh is 90−440€/kWh (systems), 70−160€/kWh (packs), and 95−105€/kWh (batteries).

Experience curve studies should include cost floors in extrapolated forecasts to avoid excessively low cost estimates (Junginger et al., 2010; Gross et al., 2013). Raw material costs for each technology are calculated by multiplying material inventories from the literature with commodity prices of the past 10 years (Fig. 8.5). The average raw material cost across all technologies is significantly below their ER projection. Production and other costs are typically below 20% (Argonne National Laboratory, 2015; James et al., 2014) of final system price for electrochemical, or between 50% and 80% (IRENA, 2016) for mechanical storage technologies, that are technologically mature. This confirms that the identified cost reduction potentials to 80−330€/kWh are feasible without limiting materials availability. Even if this would be the case, material requirements could potentially be further reduced per kW or kWh of energy-storage capacity.

However, it should be acknowledged that despite using price ranges of the past 10 years, there is still high uncertainty on the development of commodity prices. On the one hand, there could be raw material and other input bottlenecks as storage takes off for particular technologies such as fuel cells and increasing commodity prices, while on the other hand, the competition will potentially attract new producers of raw materials and other inputs, depressing commodity prices, and spurring innovation.

To map future cost reductions onto time, the market diffusion process of electricity storage technologies is modeled with the archetypal sigmoid function (*S*-curve) that has been observed for the deployment of several technologies (Rogers 1995; Schilling and Esmundo, 2009).

It is found that 1 TWh cumulative capacity could be installed for most new technology types within 5−20 years (Table 8.3). By 2030 stationary systems may cost between 200 and 440€/kWh, with pumped hydro and an electrolysis−fuel cell combination as minimum and maximum values, respectively. When accounting for ER uncertainty, the price range expands to 150−520€/kWh (min: utility-scale lithium-ion, max: electrolysis−fuel cell). The price range for transport applications in 2030 is 50−190€/kWh (40−200€/kWh with uncertainty). Lithium-ion EV pack prices may fall to 50€/kWh by 2030 due to the high ER of 21% combined with the high demand if 15 million EVs are sold annually by 2030 (MacDonald, 2016). This equals more than 700 GWh annual capacity, compared to 50 GWh for utility storage. Lower demand projections combined with a lower ER for nickel−metal hydride HEV battery packs, means prices could be reduced only to 190€/kWh. Lithium-ion

Table 8.3: Future cost of electricity storage technologies relative to time.

€$_{2018}$/kWh$_{cap}$	2020	2025	2030	2035	2040	2045	2050
Pumped hydro (system, utility)	205 ± 0	205 ± 1	206 ± 4	207 ± 8	208 ± 13	209 ± 18	209 ± 21
Lead-acid (module, multiple)	109 ± 0	109 ± 0	109 ± 0	109 ± 1	109 ± 1	108 ± 1	108 ± 2
Lead-acid (system, residential)	669 ± 147	416 ± 178	292 ± 173	243 ± 166	220 ± 161	206 ± 158	196 ± 155
Lithium-ion (battery, electronics)	149 ± 3	114 ± 5	94 ± 5	81 ± 6	72 ± 6	65 ± 6	60 ± 6
Lithium-ion (pack, EV)	121 ± 7	79 ± 11	51 ± 12	35 ± 11	27 ± 10	23 ± 10	21 ± 9
Lithium-ion (system, residential)	794 ± 62	465 ± 102	308 ± 102	248 ± 97	221 ± 94	204 ± 92	193 ± 90
Lithium-ion (system, utility)	474 ± 63	302 ± 85	214 ± 85	169 ± 81	146 ± 78	133 ± 76	124 ± 74
Nickel–metal hydride (pack, HEV)	250 ± 3	218 ± 4	191 ± 6	172 ± 6	159 ± 7	149 ± 7	143 ± 7
Vanadium redox-flow (system, utility)	451 ± 65	310 ± 78	236 ± 78	197 ± 76	176 ± 73	163 ± 72	154 ± 71
Electrolysis (pack, utility)	125 ± 1	118 ± 3	103 ± 9	88 ± 13	78 ± 15	72 ± 17	67 ± 17
Fuel cell (pack, residential)	900 ± 50	518 ± 72	334 ± 68	266 ± 64	235 ± 61	216 ± 58	203 ± 57

Cost projections based on experience rates and S-curve type market growth assumptions for consumer electronics, HEVs, electric vehicles, residential storage and utility-scale storage. Hundred percent market share assumed for each technology in their application category (e.g., electronics, EV, HEV, residential, utility). Uncertainty based on experience rate and growth rate uncertainties. Fuel cell and electrolysis must be considered in combination to form an electricity storage technology.
EV, Electric vehicle; *HEV*, hybrid electric vehicle.
Source: Updated from Schmidt et al. (2017).

batteries for consumer electronics would be at 95€/kWh by 2030 (90–100€/kWh with uncertainty).

The identified price range of 200–440€/kWh for stationary systems by 2030 lies within other projections (100–450€/kWh). However, individual products such as the lithium-ion based *Tesla Powerwall 2* were at an estimated retail price of 360€/kWh already by 2017 (Tesla Motors, 2016). A possible explanation could be synergistic learning effects for an electricity storage technology across applications due to shared components, cross-over techniques, or knowledge spillovers, leading to cost reductions not considered in this analysis (Kahouli-Brahmi, 2008). This pricing level could also reflect deliberate underpricing as part of a pricing strategy in newly commercialized products. In contrast, the cost projections in this study are based on the assumption of 100% market share for each technology in their respective application, which yields optimistic trajectories, and would support the projections at the upper end of the literature.

The range of 50−190€/kWh for transport packs is at the lower end of similar projections (50−540€/kWh), but supported by recent industry announcements of lithium-ion cells reaching 70€/kWh as early as 2022 (Cobb, 2015). Since higher estimates come from expert interviews versus lower from ER projections, the difference could be based on the latter placing more emphasis on future capacity additions, which would be significant if transportation is electrified. Conversely, increasingly competitive markets have driven strong price reductions since 2014, which could overestimate the underlying production cost reductions and distort the derived ERs (The Boston Consulting Group, 1970).

It should also be noted that the price projection for lithium ion battery packs beyond 2030 approaches the raw material cost floors identified in Fig. 8.5. This means that if these projections were to come true, significant reductions in commodity prices, improvements in energy density, or changes in commodity composition of lithium-ion batteries must be achieved. The latter two developments are within that timeline in current lithium-ion innovation roadmaps (Global EV Outlook 2018, 2018; Thielmann et al., 2015).

The future outlook for a variety of grid-scale storage technologies and applications provide a rapidly emerging field that requires innovative methods and analytical tools to understand. Major innovation theories related to learning-by-doing, learning-by-searching, economies of scale, and manufacturing localization are all required to consider how grid-scale storage technologies can become key features of a deeply decarbonized power system running on intermittent renewable electricity.

8.5 Conclusions and recommendations for science, policy, and business

Academia, policymakers, and industry can all contribute to the development and encouragement of the use of technological learning models to understand cost reduction and performance improvement related to grid-scale storage technologies and their associated innovations. Because of the wide range of grid-scale solutions that incorporate electrochemical batteries all the way to compressed air and pumped hydro-based storage, experience curve models need to consider a variety of indicators related to cost—beyond simply €/kWh or €/kW. However, the largest obstacle to achieving new indicators related to technological learning in grid-scale storage remains quality data availability.

A major theme revolving uncertainty in technological learning for grid-scale storage is the actual lack of experience and data to make quality forecasts. The rapid pace of materials science advances on the battery chemistry front especially introduces new challenges that have not been faced by energy innovations such as hydropower dams or natural gas−combined cycle plants. Therefore vigilance and increased call for transparency and public access of data remains the key to validating new learning curve models. Furthermore, by encouraging public−private partnerships to share data, there are new opportunities for understanding an innovation ecosystem. The key challenges for grid-scale storage remain quantifying and comparing technologies on a fair basis when batteries may perform multiple applications and functions on the grid. They may provide difficult-to-quantify services such as deferred investment in infrastructure when implemented on the grid and also provide electricity that may be "expensive" from a generation standpoint, but from a systems' approach could lower overall costs. Therefore technological learning studies that incorporate alternative indices related to the life cycle greenhouse gas emissions from storage options, materials availability of emerging battery chemistries, and cost indicators that incorporate multiple services and applications provided by storage can begin to inform policy and research investment.

One particular concern remains that a spate of recent studies (Schmidt et al., 2019b; Fares and Webber, 2017; Hittinger and Azevedo, 2015) demonstrates that under current grid conditions, implementing existing lithium-ion and other battery storage options at the grid-scale, could increase the overall carbon emissions on the grid, due to economically efficient electricity market bidding strategies. However, as highlighted by Louwen et al. (2016) for energy return on investment and CO_2 emission impacts of PV modules, there could be experience-based improvements in materials intensity and CO_2 emission impacts of different battery storage technologies. This can also be coupled with research that quantifies the "energy stored on energy invested." Further research that explores further technological learning along nontraditional indices including materials recycling and footprints, cycle life, roundtrip battery efficiency, and net energy ratios have been underdeveloped related to cost metrics.

From an economic perspective, cost remains one of the key indicators. New data for nonlithium-based grid-scale storage options needs to be transparent and available as new chemistries, flywheels, and fuel cells emerge. Learning curves in the case of grid-scale storage can inform public policy and R&D investments. Low-cost and innovative storage technologies are critical to achieve low-cost, deep decarbonization of the electricity system. Experience curves inform policymakers and industry to work together to develop research-based roadmaps and pathways toward building experience through new technologies. One-factor and multifactor learning curves can both inform society on the cost to deploy new technologies and the expected return on investment and inform strategies to balance resources to effectively gain deployment and research-based experience to drive down the cost of new technologies.

Research development, demonstration, and deployment measures have decreased in the United States over the past decade (Margolis and Kammen, 1999; Nemet and Kammen, 2007; Kittner et al., 2017). Globally, this remains concerning, even as deployment and investment in behind-the-meter storage increases in Germany and as spillover effects from consumer battery industries in South Korea and China develop. However, there are key reasons to believe, based on the data presented in this chapter, that energy-storage systems are already cost competitive and will outcompete traditional electricity-generation technologies in the next 5 years. Therefore better policies to understand this evolution and manage the transition to enable "baseload" renewable electricity systems require the methodological development of experience curves. More data and studies are needed across a variety of technologies and geographies to increase model accuracy and validation.

Research is largely concentrated in Europe and the United States, whereas grid-scale storage manufacturers are typically located in China and South Korea. The main markets for deployment of electricity grid-scale storage technologies are expected to occur most significantly in China, South Korea, and South and Southeast Asia. Therefore in rapidly growing regions, where high levels of investment are moving toward new technology deployment, there is a need for further information sharing, collaboration, and studies across markets to improve the understanding of technological learning and experience curves.

Fundamental theoretical and applied research that integrates an interdisciplinary approach to economic change, materials science advances, physical grid engineering, and human behavior is necessary to advance grid-scale storage to the level of technological maturity rivaling solar panels and wind turbines. The future of storage is exciting and therefore should invite strategic efforts to share information resources, invest in critical R&D expenditures necessary to promote innovation, and coevolved deployment activities to gain experience and understanding in low-carbon energy systems.

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