The battery storage in the energy transition: A projection of the Levelized Cost of Energy Storage 2020–2030

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Abstract

Electric storage could accelerate the energy transition; however, its future competitiveness remains highly uncertain. In this research I establish perspectives on the role of the lithium-ion battery in the electric grid during the 2020–2030 period, providing an analysis of the value chain and the main public policies at the global level oriented toward the lithium-ion battery. In addition, I propose a new methodology for the calculation and projection of the Levelized Cost of Energy Storage (LCOS) as a function of hourly discharge capacity. This methodology would estimate economies of scale with greater precision than other proposals. The results show a 49% reduction in the LCOS between 2020 and 2030, reaching a value of $USD64/MWh for a 4-hour capacity. This would imply a more competitive battery for long-duration services in isolated markets and/or markets with a high penetration of renewable energy.

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1 Introduction

At the end of the 2010s, expectations regarding the potential of energy storage in the energy transition were emerging with great force. On December 8, 2019, the Academy awarded the Nobel Prize in Chemistry to the principal developers of the lithium-ion battery, which according to the award declaration had brought multiple benefits to humanity, notably the capacity to...

> *"...store significant amounts of solar and wind energy, making possible a society free of fossil fuels"*
>
> -The Royal Swedish Academy of Sciences, 2019.

The exponential growth of the lithium battery as a stationary energy storage system has driven the creation of a broad set of industry and institutional reports evaluating the competitiveness of the lithium battery in different applications and services of the electricity market (Bloch C., Newcomb J., Shiledar S. & Tyson M., 2019; Fitzgerald G., Mandel J., Morris J. & Touati H., 2015; Energy Information Agency (EIA), 2018).

These studies have been complemented by those that analyze the adoption of the utility-scale lithium battery at different geographic levels, both globally (International Energy Agency (IEA), 2014; International Renewable Energy Agency (IRENA), 2017) and regionally, as in the case of Europe (Tsiropoulos I., Tarvydas D. & Lebedeva N., 2018) or Latin America (Paredes et al., 2019).

This large number of reports, focused both on the competitiveness of the lithium battery in the electric grid and on the energy storage industry, have served well as a descriptive map of its current and future state in the market. However, these studies do not offer specific methodologies and results regarding the factors that would influence the cost of the lithium battery for stationary use and, more importantly, the marginal relationship between storage cost and renewable energy integration.

In order to provide clarity on the real cost of storing electricity, various works in the literature have proposed the metric known as the Levelized Cost of Energy Storage (LCOS), also read as the average cost of storing one unit of electricity. This methodology, which is not yet standardized, has received several methodological proposals, which differ principally in their calculation, depending on the type of technology and the market services to which it is applied, with the aim of achieving greater estimation accuracy.

For example, Schmidt, Hawkes, Gambhir & Staffell (2019) projected the probability of a reduction in the Levelized Cost of Energy Storage (LCOS) of 9 energy storage technologies for different electricity market services from 2018 to 2050. Their results showed that the lithium-ion battery would be the leader in most of these services by 2030, including peak demand control. However, the results of Schmidt et al. (2019) are given for a battery with a fixed discharge capacity. In parallel, Comello & Reichelstein (2019) proposed an LCOS projection for several hourly discharge capacities toward 2030; their results, however, are for a residential-capacity application.

While previous research on this topic has offered an empirical interpretation of the causes and factors that would influence the reduction in the cost of the lithium-ion battery, to the moment of writing this thesis and to the author's knowledge, no study has proposed an LCOS projection of a utility-scale lithium battery under a methodology that captures economies of scale as a function of discharge capacity. A methodological approach in this direction would be of great importance for optimizing utility-scale energy storage capacity given an electricity market price profile.

In this research I propose an LCOS projection of the lithium battery from 2020 to 2030 for its use in peak demand control across several discharge capacities. This result is supported by an analysis of the current perspectives and trends of the lithium battery in the electricity market. Accordingly, the organization of this thesis is divided into five chapters, which in turn are divided into sections and subsections.

Chapter two is therefore an analysis of the state of the art of the lithium battery in the electricity market. This chapter is in turn divided into three sections. The first section is an interpretation of the implications of the lithium-ion battery in the electricity market. The second section is a description of the state of the art and trends in the value chain of the lithium-ion battery. The third section sets out the most relevant public policies aimed at accelerating the adoption of utility-scale energy storage at the global level. In summary, this chapter is a balance of opportunities and threats in the future development of the lithium-ion battery.

Chapter three is a literature review on experience-curve methodologies and LCOS calculation focused on the lithium battery. Chapter four is a projection of the price of the energy component, derived from the experience curves. Then, adjusting the battery price to the corresponding parameters, I forecast the LCOS of the utility-scale lithium-ion battery from 2020 to 2030.

Chapter five contains both the discussion of the results and the conclusions of this research. It ends with an interpretation of the role of utility-scale energy storage in Mexico and the world toward 2030.

It is currently clear that an active role of public policy in the adoption of energy storage, together with the market signals created within the electric grid, would deepen the role of the lithium-ion battery in accelerating the energy transition, opening a broad path of opportunities for further innovations in the energy storage sector to take place in the future, providing greater economic benefits to the players in the electricity industry while at the same time increasing the use of renewable energy.

2 The lithium battery in the electricity market

The decarbonization of the economy is the most urgent issue on the global agenda in the long term; multiple supranational organizations and national governments have recognized the importance of transitioning as quickly as possible to the adoption of clean energy. At a juncture in which the reduction of Greenhouse Gases (GHG)[1] has not advanced with sufficient speed, greater action must be taken in order to avoid the economic consequences of an increase in the global average temperature of more than 1.5°C above pre-industrial levels (Intergovernmental Panel on Climate Change (IPCC), 2018).

In the discussion about which strategies should be implemented, special attention has been paid to the economic sector that generated the most CO2 emissions in 2018 (IEAg, 2020): the electricity sector. Its importance becomes even more relevant going forward, due to the anticipated electrification of mobility (IEA, 2020) — the second sector responsible for the largest CO2 emissions — as well as rising income in various countries. Both are important drivers of the increase in electricity demand at the global level over the next two decades.

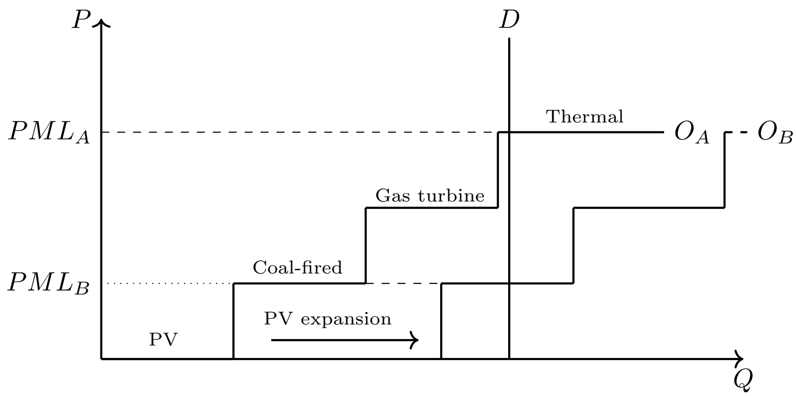
In parallel, technological progress is anticipated to promote the adoption of Variable Renewable Energy (VRE) in the global energy matrix. Various studies and reports estimate that in 2040 wind and solar energy will be the main sources of electricity generation worldwide (IEA, 2019; Bloomberg New Energy Finance (BNEF), 2019; McKinsey&Company, 2019)[2].

However, a high penetration of Variable Renewable Energy (VRE) would imply multiple technical and economic challenges for the electricity system. Before presenting those difficulties, a brief explanation will be given of the price- and quantity-allocation model of the wholesale electricity market; afterwards, the attributes of energy storage in this scenario will be explained.

[1] In addition to carbon dioxide (CO2), these mainly comprise methane (CH4), nitrous oxide (N2O), and chlorofluorocarbons (CFC).

[2] The IEA (2019) figures refer to the Sustainable Development Goals (SDG) scenario.

Figure 2.1: Merit order effect
Source: Author's own elaboration



Technical challenges in the adoption of renewable energy

In the wholesale electricity market, generators[3] place their energy capacity into the system gradually according to their marginal costs. The generator with the lowest marginal cost is the first to inject energy into the electric grid, and this order continues in an ascending step-wise fashion according to each producer's marginal cost, until the last generator to enter the system is the one that meets electricity demand. This dispatch occurs after the grid operator has placed a base generation reserve for security. This allocation model is known as the Merit Order Effect (MOE).

Since intermittent generation plants produce at zero marginal cost, they are given priority in the dispatch order over thermal plants. Without the latter being fully shut down, an increase in installed VRE capacity would substantially affect the total output of the former.

Figure 2.1 illustrates equilibrium in two electricity systems with identical demand but different energy mixes. System "A" satisfies its energy needs with the entry of a thermal plant, while system "B", having a higher penetration of Photovoltaic (PV) energy, reaches equilibrium with a coal-fired plant. It is important to note that this equilibrium is only for a given moment in time.

Equilibrium is continuously adjusted throughout the day, depending on the

[3]In Mexico this includes several market participants: generators, last-resort suppliers, qualified-service suppliers, basic-service suppliers, and non-supplier marketers (Electricity Industry Law, 2014).

conditions of the electric grid. The equilibrium price is calculated according to the nodal Local Marginal Price (LMP), which is defined as:

$$PML = CE + CC + PT \tag{2.1}$$

where CE = Energy component, CC = Congestion component, and PT = Technical losses. An increase in installed VRE capacity would lead to lower LMP values, as shown in Figure 2.1. However, an intensification of this behavior could lead to scenarios that are adverse to future renewable-energy investment.

For example, Acemoglu, Kakhbod & Ozdaglar (2017) found that the excess of renewable energy capacity in the energy portfolios of certain generation firms in Germany had considerably exceeded the needs of the electricity system on certain days of the year, leading to very low electricity prices that even reached negative levels[4]. Paradoxically, this behavior inhibited further investment in renewable energy.

However, in an environment of high VRE penetration, the most important challenge would arise not from the price-allocation model but from the technical difficulties, since these would affect the electricity system regardless of the organizational model. The intrinsic reliability and efficiency problems would intensify due to the natural characteristics of VRE generation.

Denholm & Margolis (2008) observed that in the Electric Reliability Council of Texas (ERCOT) future additions of solar capacity would cause very large variations in the intraday net load curve[5], specifically between midday and the afternoon. In 2013, the California Independent System Operator (CAISO) named this phenomenon the "Duck Curve", because the bottleneck created in the net load curve made it resemble the shape of a duck. The same effect was also observed in Hawaii, a state with even greater solar penetration. There it was named the "Nessie curve", characterized by a bottleneck in the load curve that is even more pronounced than the duck curve. Figure 2.2 shows the CAISO net load curve from 2012 to 2018.

In the case of high solar penetration, and given the maximum naturally available output, the net load curve would reach a production limit similar to a "U"

[4]It makes economic sense to pay for electricity to be dispatched rather than to stop producing it.

[5]Net load is total energy supply minus intermittent energy.

Figure 2.2: The duck curve

Source: IRENA, 2019. Average hourly net-load curve for March in the CAISO.

shape, up to the point allowed by the technical requirements, which will be traced by the system's tolerance to variations in the net load curve itself. Because there are certain firm plants that cannot quickly stop, increase, or reduce their output, whether due to technical constraints or to high economic costs, their generation capacity has a limit. To guarantee the correct functioning of the electricity system, the frequency level of the grid must always remain in full synchronization[6]. A change in electricity demand or supply must be instantaneously compensated by the same magnitude.

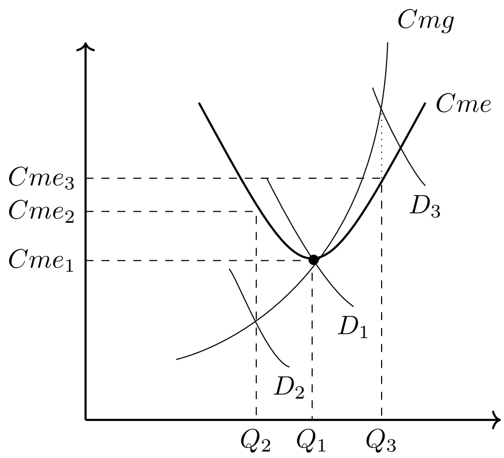
Therefore, the "limit" of penetration achievable with VRE would not be set by climatic behavior but by grid security constraints. This would set the true frontier of attainable variable renewable energy penetration.

This scenario implies not only a reliability problem but also an efficiency one. The increase in production variability under which some thermal plants would have to operate in order to guarantee system security would affect their average production costs. The arrival of solar energy in a system supported mainly by firm sources would create an efficiency loss in the latter's production. Figure 2.3 shows the cost function of a firm generation plant for three moments of the day.

Assuming that, before any solar arrival, the system was at an optimal installed capacity in which the variance of the production function minimized hourly average costs, we begin from a moment of the day where firm production capacity (D_1) is optimal. However, given an expansion of installed solar capacity, the production level would shift firm energy to its minimum point at midday, when solar irradiation is at its maximum, reducing the firm plant's production level to D_2. Finally, a subsequent decline in solar production toward the late afternoon,

[6] In Mexico the frequency must remain at 60 Hz.

Figure 2.3: Cost function of a thermal generation plant
Source: Author's own elaboration



coinciding with the peak in electricity demand, would shift the equilibrium level from D_2 to D_3. The increase in solar energy would entail an increase in the Average Costs (AC) of firm plants.

In other words, the arrival of solar energy would intensify the under-production of thermal plants, resulting in an efficiency problem.

In the long term, a high penetration of renewable energy would lead to a reliability problem, whereas in the short term it would be an efficiency problem. These problems arise from the production characteristics of VRE, which can be listed as follows:

1. Intermittency: Prolonged intraday periods in which energy production is considerably reduced or even drops to zero.
2. Temporality: The production function follows a pattern explained by climatic and natural factors, with hourly periodicity.
3. Seasonality: The total average daily output varies depending on the season of the year.

Long-duration energy storage

Among the proposals to cope with greater VRE adoption without compromising system security are, principally, the reduction of variable-energy dispatch

Figure 2.4: Energy arbitrage with a lithium battery
Source: Hassan, Cipcigan, Jenkins (2016)

[redacted]

("*Curtailment*"), scheduled control of electricity demand ("*Demand response*"), and an increase in installed capacity of gas plants for smoothing the demand peak. These proposals, although effective in ensuring electricity-system security, face various limitations, specifically when it comes to maintaining the highest possible efficiency and the maximum achievable reduction in GHG emissions.

Energy storage, for its part, differs from the previously mentioned solutions in that it does not require a reduction in renewable-energy supply or in electricity demand, but rather better management of the former. Its function is essentially to store energy when there is a relative abundance of it, and to shift it to a time of greater need within the day. In essence, energy storage finds its justification in the intra-temporal difference between the supply and demand of electricity. This use can be simplified in Figure 2.4.

A significant shift of energy through energy storage would have a "flattening" effect on the net load curve. On one hand, by absorbing part of the relative oversupply during afternoon hours, the valleys of the net load curve would be lifted; subsequently this capacity could be dispatched at the peak demand point, reducing the steepness of that crest. This implies greater certainty in electricity prices, a higher level of system reliability, and therefore greater resilience of the electricity system in the face of larger amounts of variable renewable energy.

Studies of the effects of energy storage providing demand-reduction services have been applied in various cases, such as Texas, the Northeastern U.S., California (Denholm, Nunemaker & Wesley (2019)), and other electricity systems across the U.S. (Mallapragada D., Sepulveda S. & Jenkins, 2020; Denholm, Nunemaker & Wesley (2019)). The results show a positive relationship between the level of VRE penetration and the optimal energy storage capacity.

Figure 2.5: Average hourly day-ahead market prices in BCS for the second half of July (2016–2019)
Source: Centro Nacional de Control de Energía, 2020. The hourly average was constructed from the average local marginal prices of all BCS nodes.

However, a substantial "flattening" of the load curve in any electricity system in the world is not currently possible due to the high cost of energy storage. As of 2020, most installed utility-scale lithium battery capacity is allocated to frequency regulation services (IEA, 2020), which aim to maintain system security, whether due to a supply drop caused by a cloud blocking the sun, a reduction in wind speed, or a sudden variation in demand.

A reduction in the cost of electricity storage would be key to opening a path that accelerates VRE adoption. Recognizing the value of energy storage for this purpose, several countries have promoted actions to increase the competitiveness of energy storage, which include regulation, financing of demonstration projects, and fiscal incentives in production and adoption, to name a few.

During this decade, the relationship between renewable-energy penetration and the value of energy storage is expected to deepen in various electricity markets around the world. In Mexico, the electricity system of Baja California Sur (BCS) is in an "energy island" situation, isolated from the National Electricity System (SEN) and from the national gas pipeline network. This system shows a variation between the average minimum and maximum electricity prices of approximately $50 USD/MWh[7] in the Day-Ahead Market (DAM). This is visible in Figure 2.5.

A cost of storing electricity that is lower than the difference between maximum and minimum prices would provide an opportunity for economic gains, in addition to all the previously mentioned benefits in terms of greater renewable-energy adoption and positive externalities.

[7] Exchange rate as of March 1, 2020.

In the following section I briefly describe the development of the lithium battery across different applications throughout history, its current positioning in the electricity sector, its competitiveness with respect to other Energy Storage Systems (ESS), and the future prospects for its application at utility scale.

2.1 Background

Although there is considerable consensus among industry, academia, and governmental institutions regarding the future preponderance of the lithium battery as the main energy storage technology of the 2020s, other options currently exist in the market.

In aggregate, the types of energy storage technologies can be grouped mainly into mechanical, electrochemical, electrical, and thermal categories.

As of the end of 2019, pumped hydro — a mechanical technology — is the type of energy storage with the lowest average cost per installed unit ($/MWh), and is also the one with the largest capacity ratings up to that point[8]. First used at utility scale at the beginning of the 20th century, with 93.4% of total utility-scale capacity as of 2019, it is the most important ESS in the world (CNESA, 2020). The remainder of global installed capacity is distributed mainly among lead-acid, flow, nickel, lithium, and sodium thermal batteries (DOE, 2019).

During the 2010s, other ESS saw their relative capacity increase substantially. Excluding pumped hydro, the ESS that added the most energy storage capacity to the electric grid was the lithium-ion battery. As of 2010, lithium batteries went from less than 100 MW of utility-scale capacity to becoming the second technology with the most capacity deployed at utility scale, with around 3.2 GW installed globally (IEA, 2019; CNESA, 2020).

In contrast to pumped hydro, the lithium battery can provide a form of energy storage with essentially no geographic restrictions, and compared with other electrochemical ESS, it has higher discharge efficiency, longer useful life, and lower cost per installed unit ($/MWh). Thermal and mechanical energy storage technologies have also shown efficiency improvements but, as discussed further on, several studies project that the lithium battery will be the most competitive

[8]Bath County Pumped Storage Station is the world's largest energy storage plant: with a capacity of 3,003 MW / 24,000 MWh it reaches a discharge capacity of 8 hours.

Figure 2.6: Installed utility-scale lithium battery capacity (MWh) in the U.S., 2011–2019

Source: Energy Information Agency, 2020.

ESS by 2030 in various scenarios (Schmidt et al., 2019).

With a reduction of more than 85% in the price of the energy component (or battery pack) from 2010 to 2018 (Bloomberg New Energy Finance (BNEF), 2019), together with the technical characteristics already cited, the lithium-ion battery is the leading reference for utility-scale energy storage technology at the global level toward 2030.

An example of the growth trend of the lithium battery in the electricity market is the one observed in the United States (DOE, 2019)[9] — the country with the largest energy storage capacity in the world. From 2011 to 2018, the lithium battery was the technology that added the most installed capacity to the electric grid in that country, growing 24-fold in 7 years (IEA, 2020)[10]. Figure 2.6 shows the installed utility-scale lithium battery capacity (MWh) in the U.S. from 2011 to 2018.

At the same time, the size of lithium battery projects worldwide has grown year after year. Important projects of this type around the world are located in Ulsan, South Korea (150 MW); Hornsdale, Australia (100 MW / 129 MWh); Miyagi, Japan (40 MW); and Zhangbei, China (14 MW / 63 MWh). As of January 2020, the largest announced project in the world would be located in Monterey, California, with a capacity of 566 MW / 2,200 MWh (Chediak, 2018).

While other technologies, such as flow batteries and lead-acid batteries, have reduced their prices substantially over the past decade, the lithium battery has stood out for its sustained percentage decline in historical price and for its

[9]Reviewed on November 1, 2019.

[10]The only exception is 2014, when flow batteries were the type of ESS that added the most capacity in the U.S.

technical improvements. This has projected it very strongly in the market over any other emerging energy storage technology for the 2020s.

In the following section I expand on the current role of the lithium battery at the grid level and on the development outlook to 2030.

The future of the lithium battery

The global installed utility-scale energy storage capacity at the end of 2019 was 183 GW. The lithium-ion battery represented close to two-thirds of the total non-hydro capacity (DOE, 2019)[11].

Installed utility-scale lithium battery capacity worldwide is estimated to reach 81 GW in 2024 (Curry et al., 2017), 181 GW in 2030 (IRENA, 2017)[12], and at least 1,000 GW in 2040 in terms of total battery supply (World Bank, 2019). The lithium battery will therefore go from representing 1.6% of global installed energy storage capacity in 2018 to 40% of the total in 2030 (IRENA, 2017).

According to the International Energy Agency, 200 GW of energy storage capacity will be needed in 2030 to meet the Sustainable Development Goals (SDG) (IEA, 2019c). This scenario implies that close to one-fifth of total world electricity will come solely from solar and wind sources.

Will the deployment of energy storage be fast enough to meet that target?

The competitiveness of energy storage systems depends on multiple factors, so it is complicated to capture it in a single metric. The penetration of renewable energy and transmission networks, the availability of hydrocarbons, and local regulation, among other factors, all play an important role in positioning energy storage as a competitive complement to VRE.

On the other hand, a holistic analysis of its competitiveness at the regional scale is enabled when these characteristics manifest themselves in the behavior of a specific market. In such cases, the cost of storing energy is key to the study of its competitiveness at a particular level.

The dynamism of the lithium battery industry experienced during the 2010s

[11] Data from the Energy Storage Database of the U.S. Department of Energy are added progressively, so they are only an approximation of the actual installed capacity.

[12] Figures refer to the doubling case.

enabled an important reduction in the price of the components used in utility-scale installations, facilitating the materialization of several utility-scale projects worldwide. Future opportunities in the value chain, the increase in EV production, the adoption of a new regulatory framework for energy storage technologies around the world, increased R&D investment, and greater renewable-energy penetration would all contribute to the persistence of this dynamism.

However, short-term threats such as raw-material shortages in the supply chain, environmental risks, or the emergence of a new disruptive technology in the electricity sector (which would be highly beneficial) could cause a slowdown in this dynamism.

In the rest of this chapter I develop a qualitative analysis of the opportunities and risks in the lithium battery industry. The results of this analysis are subsequently complemented by the model proposed in Chapter 4. Specifically, this chapter analyzes the value chain, the public policies aimed at utility-scale adoption, and the market outlook for the lithium battery in its utility-scale application.

2.2 Value chain

This section describes the current state of the value chain and the expected outlook for the lithium battery, with special emphasis on a time horizon of 2020 to 2030.

The four main activities of the value chain can be summarized as those shown in Figure 2.7.

Figure 2.7: Value chain of the utility-scale lithium battery

Extraction → Assembly → Commercialization → Recycling

The main challenges in these activities can be considered as emerging in the 2010s, in the wake of the nascent EV industry and stationary storage systems. Below, I extend an interpretation of the main characteristics of each of these activities.

Figure 2.8: Cobalt futures purchase price, 2010–2019
Source: Investing, 2020.

Extraction

Extraction is usually mentioned as the greatest threat to the lithium-ion battery value chain in the short term. Growing concerns about the availability of the various minerals used in battery construction are a source of considerable uncertainty in the industry.

These minerals are especially lithium and cobalt. In 2019, production and proven reserves of both minerals were highly concentrated in a few countries. For example, more than 50% of cobalt production came from the Democratic Republic of the Congo alone, while about 85% of proven lithium reserves were located in Argentina, Australia, and Chile (USGS, 2020).

This uncertainty has translated into volatility in the prices of these minerals. For example, between 2017 and 2018, the combination of expectations of an increase in lithium battery demand and speculation on cobalt availability caused the futures purchase prices of that mineral (Figure 2.8) to nearly triple in the London Exchange Market (LEM).

After reaching a peak price of around $USD 100,000/ton, the futures price returned to the average values observed in 2016. This return in price can be explained mainly by two reasons: (1) the expansion of cobalt supply caused by the opening of artisanal deposits in the Democratic Republic of the Congo, which would lead to a relative abundance of the mineral; and (2) the anchoring of speculation regarding the future price of this mineral would result in lower volatility-driven demand, which would subsequently create pressures for a price reduction (Slav, 2019).

For a meaningful analysis, the importance of variations in mineral prices must be contrasted with their impact on the cost or price of battery components. BNEF (2019) estimated that a 100% increase in the price of cobalt would raise the total battery pack cost by 3%. In the case of nickel, lithium, manganese, and aluminum, a doubling of their prices would increase the cost of the battery pack by less than 5%.

The evidence cited at the beginning of this chapter shows that when the costs of lithium and cobalt rose by around 100% between 2017 and 2018, the price of the battery pack fell by 17.7%. The data offered by BNEF (2019) are reinforced by the study of Ciez & Whitacre (2016), which notes that for the lithium cell, a 300% increase in the price of cobalt would raise its price by 10%.

However, this does not mean that the cost of minerals cannot take on greater importance in the future. Yang, Lisa, Pan, Chiang, and Green (2019) warn that an accumulation of mineral price increases could lead to dangerous volatility, which could translate into a significant share of these minerals in the cost of the battery, particularly once manufacturing costs have been reduced. This discussion is expanded somewhat further in Chapter 3. What is clear is that volatility caused, for example, by social unrest in the Democratic Republic of the Congo could result in a sharp cut in cobalt supply, creating a shortage that, if prolonged, could lead to cobalt-price increases that could represent serious difficulties for the commercialization of batteries.

As the industry adopts less cobalt-intensive cathodes and replaces them with cathodes that are more intensive in other minerals (e.g., nickel), concerns of this type are expected to diminish. Such cathode adoption is motivated essentially by an increase in the battery's energy density and not specifically by political-social volatility; however, challenges in safety and cost still remain. In the next two subsections I expand in greater detail on these processes.

Manufacturing

The assembly of a utility-scale lithium-ion battery requires, but is not limited to, the battery pack, inverter, container, management software, and cooling system. The battery pack is in turn built from a lithium cell, module, and interconnectors. The cell is composed of a cathode, anode, separator, and elec-

Table 2.1: Selected components of the utility-scale lithium battery
Source: Data from Olivetti et al. (2017), Frankel et al. (2018), Blomgren (2016).

Cathode	Cell	Battery pack	Utility-scale installation
NMC 811	Anode	Cell	Battery pack
NMC 622	Cathode	Connectors	Management system
NCA	Separator	Module	Inverters
LFP	Electrolyte		Container

trolyte. The cathode is subdivided mainly into NMC-type[13] (811, 622, 111, etc.), NCA (LiNiCoAlO2), and LFP (LiFePO4). Finally, as mentioned previously, the construction of the cathode depends mainly on lithium, cobalt, nickel, manganese, iron, and other metals.

The first row of Table 2.1 shows the main components used in the utility-scale lithium battery, ordered from left to right by assembly complexity and broken down in turn into their principal subcomponents.

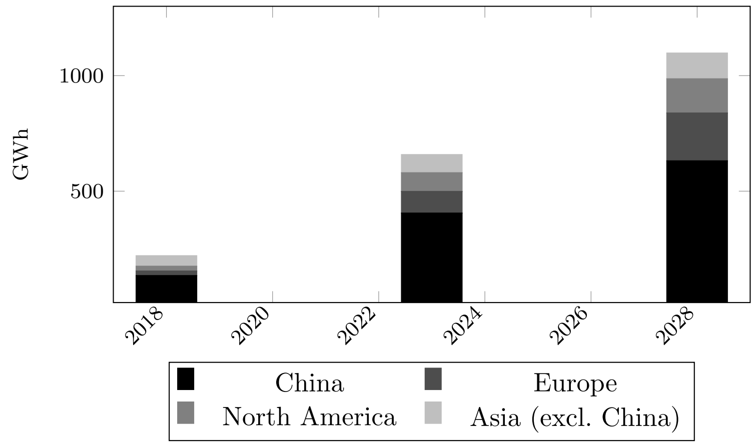
Much of the literature on battery improvements — whether toward longer useful life, higher density, greater specific energy, better safety, or faster charging speed — has focused mainly on the components of the lithium cell, specifically the anode, cathode, and separator. This interest has centered on the cathode, the component that is expected to change gradually in its assembly in the short term.

Assemblers are expected to gradually adopt cathodes that are less intensive in cobalt, with NMC 811 being one of the most frequently cited as the short-term leader (Xu, Lin, Doeff, & Tong, 2017). This is because NMC 811, compared with the other NMC-type cathodes, offers higher energy density — around 200 Wh/kg — lower energy-retention degradation over cycles, and lower cobalt use per unit of energy (Olivetti, Ceder, Gaustad, & Fu, 2017). As of 2020, the NMC 811 cathode is used in some of the products of leading market firms such as Contemporary Amperex Technology (CATL), Build Your Dreams (BYD), and Tesla Inc./Panasonic (Deing, 2019).

Despite this, NMC 811 has not been fully adopted, owing to the following circumstances: (1) NMC 811 has a higher probability of catching fire compared with its less cobalt-intensive counterparts, given the greater release of oxygen

[13] The acronym stands for Nickel-Manganese-Cobalt, while the numbering is the mole ratio used per element; for example, NMC 811 refers to a cathode with a ratio of 8 moles of nickel, 1 of manganese, and 1 of cobalt.

Figure 2.9: Annual global lithium-battery production capacity by region (GWh)
Source: Benchmark Mineral Intelligence (2018)



(Bak et al., 2014); and (2) a higher cost per unit of energy, arising from the nickel synthesizing process (Manthiram, 2017; Sun et al., 2017).

Nevertheless, the substitution, removal, and addition of materials in the cathode is expected to be one of the first modifications to achieve improvements in lithium batteries. Following these advances, the replacement of graphite with silicon in the anode is anticipated, as is even the replacement of the electrolyte in the case of lithium-air batteries (Frankel, Kane, & Tryggestad, 2018; Xuan W., Otsuka A., & Chagnes A., 2019). However, the speed at which these modifications are adopted will depend largely on the relationships and the expertise that industry participants build in the coming years (Goldie-Scot, 2019).

These are, in part, the trends on adoptions and changes in manufacturing; in parallel, both production and the geographic location of production are expected to undergo a major change in the 2020s. Various consulting firms estimate that lithium battery production will grow substantially over the 2020s. Benchmark Mineral Intelligence (2018) projects that global lithium battery production will increase from 135 GW in 2018 to 1,100 GW in 2028; Brattle Group (2018) projects 1,200 GW by 2028; while Roskill (2019) estimates that installed production capacity in 2029 will rise to 2,000 GW.

Figure 2.9 shows the installed production capacity across different regions of the world.

Sales of lithium batteries solely to meet EV demand are projected to grow tenfold in ten years (IEA, 2020) (see Table C.1). This large quantity of batteries will consequently demand a large capacity to process them for their best use, whether through refurbishing or recycling.

Commercialization

The commercialization of the lithium battery encompasses different products such as electronic devices, mobility, and residential, industrial, and utility-scale units. The production of the lithium cell itself is a component included in all five segments.

As for the battery pack, its application is included in all the segments mentioned above except electronic devices. There are currently dozens of OEMs[14] in charge of the design and final manufacture of battery packs; a select group of these firms includes Samsung SDI, LG Chem, CATL, Panasonic, BYD, Tesla Inc., SK Innovation, Duracell, and others.

Many of the companies in charge of battery pack assembly are also the final commercializers of the utility-scale installation. In the case of firms with different cross-cutting components across final products, they can obtain economies-of-scale advantages in the market. A notable example would be BYD, which commercializes EVs, residential units, and utility-scale units. By increasing demand for one of these products, the firm can leverage its experience and economies of scale to lower the average assembly costs of its other business lines. Various automotive firms can only take advantage of their knowledge and experience in battery-pack manufacturing, since they produce only a single product that uses it.

Beyond the lithium cell and battery pack, there are other types of components used in the utility-scale battery that benefit from product overlap among commercializers. In this regard, Tesla Inc., by producing both batteries and PV panels, gains an advantage in producing the inverters used in both.

As the adoption of utility-scale energy storage units increases, improvements in their design are expected to follow (Frankel et al., 2018). The practical case of Tesla Inc.'s products can serve as an example of this trend. In 2017, the lithium battery plant at Hornsdale, Australia, used a stationary-system design

[14]Original Equipment Manufacturer.

from the commercial product known as “Power Pack”, which stored 0.232 MWh per container. In 2020, at Moss Landing, California, the design used for that plant would employ a product released that same year, known as “Megapack”, with a capacity of 1.5 MWh per container. The design improvements of the second product over the first include reductions in design costs, smaller land-use footprint, and lower engineering and on-site construction costs.

Recycling

The circular economy in the lithium battery industry is perhaps the topic of greatest long-term interest in energy storage. It is estimated that in 2030 the market for refurbished second-life EV batteries will reach an annual processing capacity of around 200 GWh and exceed $30 billion USD in value (Engel H., Hertzke H., & Siccardo G., 2019). The growing number of batteries that will reach the end of their useful life after 2030 has spurred the creation of public-policy strategies along several axes, around securing sufficient, sustainable, and competitive capacity to recycle and refurbish the required quantities of lithium batteries.

At the global level, the early actions promoted by the European Commission stand out. As background, in 2006 the EU had a battery-recycling regulation in Directive 2006/66/EC (Official Journal of the European Union). Anticipating the future growth in lithium battery demand, the EU enacted a series of new rules on management and recycling (Directive (EU) 2018/851).

The Circular Economy Action Plan emphasizes that the recycling of battery-derived minerals must be a priority for the EU, and establishes the goal of increasing the competitiveness of battery recycling in the EU (Lebedeva, Di Persio, & Boon-Brett, 2017).

In the U.S., the Department of Energy (DOE) has promoted the creation of programs to incentivize innovation in recycling processes through awards, including the Energy Storage Grand Challenge. Likewise, in 2019 the DOE announced the creation of an R&D center on recycling, called the ReCell Center. In addition, the DOE has driven innovation in recycling solutions through a program called the “Battery Recycling Prize”, which sought to reward firms with innovative proposals for battery-recycling development. This prize amounted to $USD 5.5 million across all funding rounds (DOE, 2019).

China's Ministry of Industry and Information Technology has established internal rules that require EV manufacturers to maintain sufficient capacity to collect and recycle lithium-ion batteries (Stanway, 2018).

As of the beginning of 2020, there are a wide number of firms with different processes for recycling minerals derived from lithium batteries, including The Furukawa Battery Co., Electrovaya, Active Power, Fluence, Saft, EnSync, Maxwell Technologies, Inc., and AltairNano, among others.

The most widely used battery recycling processes at present are: (1) hydrometallurgical, (2) mechanical, (3) pyrometallurgical, and (4) a combination of hydrometallurgical and pyrometallurgical methods.

Below I explain the importance of recycling for the sustainability of large-scale energy storage projects.

Safety

The increase in lithium-battery demand poses long-term challenges to the security of mineral supply. A relatively high degradation rate of the lithium battery in any application and a short useful life, together with high recycling costs, are factors that could lead to a serious shortage of raw materials in the long term.

In 2019 there were 145 million tons of possible cobalt reserves identified as by-products and in offshore deposits; however, only 6.9 million tons were proven reserves (USGS, 2020). To put the long-term needs in proportion with proven reserves, the latter can be contrasted with the storage capacity that could be built from them. Assuming the use of the NMC 811 cathode, building 1 MWh of storage would require 94 kg of cobalt (Olivetti et al., 2017). Therefore, global proven cobalt reserves would allow the construction of 73 TWh of energy storage, sufficient to meet the world's average daily electricity demand in 2017 (IEAg, 2020)[15]. Table 2.2 shows the corresponding relationship in greater detail for lithium and cobalt.

The purpose of Table 2.2 is to contrast current storage capacities with what is achievable given current technological capabilities. In the long term, the cost of recovering minerals from batteries, as well as the efficiency of the lithium batteries themselves, will be key to explaining a long-term storage system based

[15]The average daily electricity demand in 2017 was 65 TWh.

Table 2.2: Cobalt reserves and lithium-battery production limits
Source: Mineral-reserves data from USGS (2020) and mineral requirements from Olivetti et al. (2017).

Mineral	2019 reserves (tons)	kg/kWh (NMC 811)	Limit (TWh)
Cobalt	6,900,000	0.094	73
Lithium	14,000,000	0.111	126

on this technology.

Since recycling capacity must exceed battery degradation in the year in question, the fact that recycling techniques can yield minerals at competitive prices becomes key to validating the competitiveness of lithium batteries as a solution in the energy transition.

The problems derived from this scarcity can be mitigated by improving the recycling techniques of lithium, cobalt, manganese, aluminum, and other essential inputs used in lithium batteries, in order to ensure greater use of resources, as well as by improving the collection of lithium batteries used in EVs, ESS, and electronic devices.

2.3 Public policy

The opportunities that energy storage can provide in the energy transition have been recognized by multiple governments and supranational entities. In this regard, public intervention — through fiscal incentives, regulation, standardization, public-private partnerships, and other state strategies aimed at explicitly promoting non-hydro grid-scale energy storage — has been widely promoted in no less than a half-decade.

This section provides a complementary view of the industry's outlook on the lithium battery, focusing in particular on the opportunities implied by state intervention along different channels for its development.

Fiscal incentives

The main fiscal policies that have facilitated the integration of energy storage have largely been granted to demonstration projects. These projects have

Table 2.3: Installed utility-scale energy-storage capacity targets in the U.S. as of 2020
Source: California, New York State, and Massachusetts data from EIA (2018); New Jersey data from Allen, R. (2020).

State	MW	Year
California	1,875	2020
New York State	1,500	2025
	3000	2030
New Jersey	2,000	2030
Massachusetts	200	2020

been backed by different levels of government around the world. In 2013, the California Public Utilities Commission (CPUC) signed a series of energy-storage capacity contracts with various electricity generation companies, with the initial goal of meeting an energy-storage capacity target of 1,325 MW by 2020, which would subsequently be raised to 1,875 MW (EIA, 2018). With this action, California became the first government at any level to establish an energy-storage target (RAEL, 2017).

Subsequently, several U.S. state governments have set utility-scale energy-storage targets, with some explicitly requiring that this storage come from "advanced" forms. Table 2.3 lists selected legislations that have set capacity targets in the U.S. as of March 2020.

Subsequently, at the federal level, investment in demonstration projects was supported by the American Recovery and Reinvestment Act (ARRA), an economic stimulus program after 2009, with up to $185 million in support for 538 MW of energy storage capacity. This program benefited 16 projects across multiple technologies in total (Bender, Byrne, & Borneo, 2015).

Among the most notable channels that have gained popularity is the promotion of tax exemptions for investments in energy-storage units. A salient example of this type of policy is the Investment Tax Credit (ITC) of the U.S. federal government, which applies a 30% reduction in income tax on the value of an energy-storage installation. However, this incentive is directed exclusively at applications in private buildings and at installations smaller than 30 MW (NREL, 2018), and is therefore not aimed at utility-scale storage.

Within the policy mix aimed at accelerating energy-storage adoption, California's "Self-Generation Incentive Program" (SGIP) grants residential and commercial users a differentiated tariff on the energy dispatched from energy storage.

Table 2.4: Selected public policies for the adoption of utility-scale energy storage
Source: Data from DOE (2016, 2020), Sandia National Lab, World Bank (2019), Massachusetts State (2019).

Agency	Program	Objective(s)
Department of Energy (USA)	The Energy Storage Technology Advancement Partnership (ESTAP)	A program of the DOE's ESI; it seeks to create public-private alliances. The mission is to create a network among ESS asset owners and U.S. state entities (a public-policy program to increase ESS deployment).
Department of Energy (USA)	Clean Energy States Alliance (CESA)	Funded by Sandia National Lab and the DOE to extend state-level participation in the creation of energy value.
World Bank	Battery Storage Program and Energy Storage Program (ESP)	\$1 billion in WB funds and \$4 billion in private funds to install more than 17.5 GWh of advanced energy storage in developing and middle-income countries.
European Commission	The Strategic Battery Action Plan	To create joint strategies with private firms for building more energy storage.

This tariff is adjusted according to several conditions, depending on the share of energy coming from renewable sources and the size of the installation; when the system exceeds 6 MW of installed capacity the incentive falls to zero.

An important share of global financing for the deployment of energy-storage capacity has come from the World Bank's (WB) investment rounds in "advanced" energy-storage projects. The WB project financing aims to inject \$USD 1 billion into ESS projects in developing countries and to leverage another \$3 billion from public-private sources.

Another instrument promoting energy storage has been public-private partnerships, which seek to create connections, knowledge exchange, and even the joint launch of projects between private actors and government entities. Table 2.4 shows selected programs focused on the global promotion of energy storage.

Regulation

Regulation governing the adoption of energy-storage systems for providing services to the electricity grid has become one of the main public-policy lines around the world to accelerate the adoption of energy storage without creating market distortions.

Among the first notable tariff-regulation actions that benefited energy-storage technologies were the changes made in Orders 755 (2011) and 784 (2013) of the Federal Energy Regulatory Commission (FERC). Both orders introduced modifications in the tariffs for primary frequency regulation[16], according to the response capability of the various generation technologies in the market. This made it possible for supply coming from a high-speed response source to receive better remuneration.

Given the speed of power delivery of the lithium battery compared with thermal plants, the lithium battery gained advantages for frequency-regulation services and benefited from these modifications.

Subsequently, in 2018, the FERC, through Order 841, mandated a new modification that explicitly sought to facilitate greater adoption of energy-storage systems. The order instructed grid operators to establish differentiated tariffs that recognize the capabilities of energy-storage systems in providing ancillary services.

Research, development, and demonstration

The understanding emerging from various empirically based studies indicates that public policy in promoting and financing R&D is an essential part of technological innovation. Paul Romer (1990) proposed to understand the relationship between innovation and economic growth by quantifying the changes resulting from increases in R&D investment and in output per worker, as well as the factors that incentivize economic agents to invest in R&D. He thought of technological change as "the heart of economic growth".

As an example in the energy sector, Margolis & Kammen (1999) found a strong correlation between the number of registered patents and public R&D investment in the energy sector in the United States. Their study yielded similar results in other sectors of the economy, such as telecommunications and transportation.

[16] A short-term electricity-market service that enables the leveling of frequency in response to system imbalances.

Figure 2.10: Public R&D investment in energy storage and grid technologies, IEA (1974–2018)

Source: International Energy Agency (2019).

According to Hart, Bonvillian, & Austin (2018), public R&D is key to the current development of competitive grid-scale energy-storage sources. Their interpretations also warn that increasing R&D is more than necessary, given a possible *lock-in* effect in lithium batteries. In other words, the rapid development of lithium batteries could overshadow the maturation of other types of technologies with high market potential. By becoming the only technology, other types of solutions would face large economic barriers to compete and subsequently mature.

In 2018, public R&D investment in energy storage and grid-improvement technologies among IEA members reached a five-year historical peak. Figure 2.10 shows the historical series for the period 1974–2018 (IEAd, 2019).

The main promoters of R&D investment in energy storage are the United States, China, the European Union, South Korea, and Japan. Although as of 2018 China is the leading global investor in energy-storage R&D (IEAe, 2019), the U.S. has historically been the main promoter in this area, which has materialized in the creation of multiple programs and agencies over time, with many of these programs created during the past decade.

Between 2009 and 2012, the U.S. federal government made an R&D investment of $1,316 million USD in energy-storage technologies, distributed across different departments and agencies (U.S. Accountability Office, 2012). For 2020, the U.S. federal government had budgeted an R&D investment of $158 million USD in the Advanced Energy Storage Initiative (AESI) program. In this regard, Hart D. (2019) noted that the U.S. federal R&D budget in 2020 had in fact been reduced relative to previous years because it was now disaggregated across several programs; for example, in 2015 the budget had been accounted at around

Table 2.5: Selected R&D programs in energy storage worldwide

Program	Objective(s)	Source
Advanced Energy Storage Initiative (AESI)	Incentivize projects on advanced forms of electricity storage in the United States.	DOEc (2020)
Energy Storage Program	Financing of energy-storage technologies and projects.	DOEd
Battery 2030+	European Union R&D financing program in energy storage.	ec.europa.eu
Joint Center for Energy Storage Research (JCESR)	DOE materials-innovation center for ESS, founded in 2012.	JCER (2020)

$300 million USD.

As of 2020, there are multiple centers in the U.S. whose objective is to finance research, development, and demonstration (RD&D) projects in energy-storage technologies. Some examples are the Advanced Research Projects Agency—Energy (ARPA-E), created in 2007, and the Joint Center for Energy Storage Research (JCESR). For instance, ARPA-E has driven financing for ESS demonstration- and development-stage projects through multiple partnerships with U.S. universities and firms. One notable program is Duration Addition to electricitY Storage (DAYS), which has funded ESS projects able to reach a discharge duration between 10 and 100 hours.

Table 2.5 lists selected public programs related to R&D investment in energy-storage technologies in the United States and elsewhere.

The inclusion of greater investments and R&D strategies has become evident across multiple nations. These actions would result in a medium- and long-term push for the development of energy storage.

Private R&D investment

"Venture capital" investment has also made it possible to unlock innovation processes both at the testing stage and in market expansion, with the latter being especially larger.

IEAf (2019) estimates that private R&D investment in batteries in 2018 amounted to $USD 900 million, much of it from automotive companies. Mercom Capital Group, in turn, estimated venture-capital investment in energy-storage companies at approximately $USD 1,800 million for 2019 (Mercom Capital, 2020).

In disaggregated terms, private R&D investment is difficult to estimate due to the scarcity of public data; however, financing amounts can be obtained from notable players in the sector. For example, Breakthrough Energy, an energy-sector venture-capital fund, and the European Commission invested 50 million to finance research in energy-storage companies through a financial instrument called InnovFin (European Commission, 2018). Mission Innovation is a notable example of public-private investment. This grouping seeks to increase R&D investment in promising technologies for the energy transition from different private and governmental sources, including energy-storage technologies as a category.

The role of R&D investment is key in accelerating technological development. Differentiating among sources of R&D investment becomes necessary in order to identify the impacts where each can be effective at different stages of a good's maturation. Thus, public investment plays an indispensable role in promoting those projects that lack the capacity to deliver competitive economic returns in the short term but nonetheless hold great potential for the future, while private investment is best suited to drive the development of commercially proven technologies.

The combination of R&D financing sources can represent an opportunity for greater industry learning across technologies at different stages of maturity, which could ensure the advancement of prominent technologies while promoting the use and full maturation of those that are already commercially proven.

3 Literature review

3.1 Experience curve

Given the importance of technological change in the economy, a strand of the literature has been devoted to explaining the processes and motives that drive innovation. Arrow K. (1962) proposed that technological change resulted from learning and that learning, in turn, was a process resulting from experience. His model, focused on the economic implications of "learning by doing", estimated the experience of an industry as a function of the increase in cumulative capital investment. In other words, technological change would be driven by the increase in cumulative production of capital goods.

Wright T. (1936), in contrast to Arrow K. (1962), proposed a very simple model, but one of great subsequent relevance in industry. His log-log Ordinary Least Squares (OLS) model explained the cost trend of goods in the aeronautical industry, using the increase in cumulative industry output as the explanatory variable. This regression can be expressed in equation 3.1:

$$LogY = \alpha + \beta_1 LogX_1 + \varepsilon_i \tag{3.1}$$

where Y is the cost of the good, X_1 is cumulative production, β_1 is the estimator of X_1, α is the intercept term, and ε_i is the error term.

In order to observe the change in cost in whole numbers in a single equation and make it easier to read, the value of β_1 is substituted into equation 3.2. This equation is known as the "learning curve".

$$C_f = C_i A_i^{\beta_1} \tag{3.2}$$

where C_f is the cost in the final year, C_i the cost in the initial year, A_i the cumulative-production variation index, and β_1 is the logarithmic regression coefficient.

For comparison purposes, the percentage cost reduction each time cumulative production doubles is generally used. This relationship is known as the "Learning Rate" (LR) and is defined in equation 3.3.

$$LR = 1 - 2^{\beta} \tag{3.3}$$

Later, Bruce B. Henderson (BCG, 1970) proposed replacing the cost explanatory variable with prices, with this modification justified by the fact that prices capture important elements that lie outside the production process, such as R&D investment and marketing. He called this new equation the Experience Curve (EC). Today, this equation and the corresponding Experience Rate (ER), analogous to the learning rate, are widely used in industry and academia as metrics for projecting the maturation and prices of various goods, from data units to components of photovoltaic panels and wind energy.

The experience curve in energy storage

In this regard, some research and market reports have used the ER to predict the price of certain components of the utility-scale lithium battery, whether the lithium cell (Kittner et al., 2017) or the battery pack (Curry et al., 2017; Berckmans et al., 2017).

For example, Schmidt O., Hawkes A., Gambhir A. & Staffell I. (2017) produced a relevant study of the price trend of an important range of energy-storage technologies. They calculated the experience curves of battery packs, lithium battery cells, and residential and utility-scale installations. Their results yielded an ER of 30%, 16%, and 12% for battery cells, battery packs, and utility-scale installations, respectively.

In addition to these calculations, Schmidt et al. (2017) built experience curves for 6 other energy-storage technologies, showing that in 4 of the 6 referenced cases there was a good fit ($R^2 > 0.9$). Given the breadth of observations across different technologies, their results provide empirical evidence on the effectiveness of ECs in interpreting the price trend of energy-storage technologies.

However, the interpretation of the EC computed on the total price of the utility-scale lithium battery could lead to an unclear interpretation if the cost is separated into the prices of the different components that make it up.

In the case of the utility-scale lithium battery, given the differences in the price-reduction rates of its components — such as the battery pack, inverters, and others — disaggregating the calculation into the main components would improve the quality of the price forecast. For example, the battery pack, which is the highest-cost component of the utility-scale lithium-ion battery[1] and of Electric Vehicles (EVs)[2], is projected to see its global production increase by 800% over ten years, which would generate substantial industry learning.

In this research I propose separating the calculations of these concepts rather than computing or adopting an aggregate ER for the utility-scale installation as a whole.

Practical limits of the experience rate

In addition to the use of the ER to forecast the price of a good given certain maturity conditions and a particular time horizon, there is a debate about how effective it is in practice for certain goods.

General criticisms of the ER center especially on its ability to make estimates for mature products or when innovations arise in near-perfect substitute products. The innovation of a good capable of substituting another would imply the displacement of the product in question, which would make the experience curve an inefficient methodology (Abernathy W. & Wayne K., 1974). Even Arrow K. (1962) himself stated that the relationships proposed in the experience curve should not be taken as a public-policy tool.

The lithium battery is no exception to such criticisms. For example, Ziegler, Sam, Yang, & Green (2019) argue that the results proposed in the work of Schmidt et al. (2017), Kittner et al. (2017), and BNEF (2018) are overly optimistic relative to market realities and that the methodology used was unrealistic. This criticism is directed primarily at the fact that battery-pack price reductions cannot continue indefinitely as a function of cumulative production, so in fact there is a price floor, set by the cost of the minerals used. Base labor costs and the profit rate could also be included.

However, there are some elements that give us reasons to consider the ER an

[1] This depends on the hourly discharge capacity: the larger it is, the greater the relative weight of the battery pack in cost. For a one-hour discharge capacity, the cost of the energy component represented even more than the largest cost as of 2025 (Frankel, Kane, & Tryggestad, 2018).

[2] This term includes battery-electric and plug-in hybrid vehicles of the following types: passenger vehicles, light commercial vehicles, buses, and trucks.

effective tool for forecasting the prices of the components used in the utility-scale battery. First, as explained in Chapter 2, minerals represent about 5% of the battery-pack price, so there is ample room for the final battery-pack price to fall without requiring a change in mineral prices. Second, the evidence of good fit in the lead-acid battery, commercialized for decades (Schmidt et al., 2017), provides a comparative maturity benchmark for the lithium battery, which can currently be considered in a maturation phase. This is reinforced by the IEA's (2014) characterization of the lithium battery as a "maturing" technology, so a reduction in its price could still be achievable.

To better illustrate this situation, reference can be made to Moore's Law. This states that every two years the number of transistors in a microchip would double, since *"the cost of a chip is roughly inverse to the number of components on it"* (Moore G., 1975). Evidence has shown that since it was stated more than 45 years ago, the prediction of this "law" has held with high precision. However, several industry actors, including the author himself, have predicted the obsolescence of this law because, due to physical limits, it is expected to cease holding very soon. There is currently a debate around this (Rotman D., 2020).

In this regard, the reduction in the price of the utility-scale battery is largely explained by industry learning driven by the expansion of EV production. Given the close to 800% increase in annual battery-pack production from 2018 to 2030, a substantial reduction in the price of this good is expected during that period.

3.2 Levelized cost of energy storage

The Levelized Cost of Energy Storage (LCOS) is the metric used to calculate the average unit cost of storing electricity for a storage technology over its useful life. Its basic structure is the ratio between the total cost of the asset and the total energy it will be able to store. Adjusted to different parameters depending on the type of technology, it is typically calculated for a fixed discharge capacity (D_h). Its generic equation is usually presented as:

$$LCOS = \frac{(C_s + \sum O\&M + CI)(1+\alpha)^{-N}}{E(1+\alpha)^{-N}} \tag{3.4}$$

where $LCOS$ = Levelized cost of energy storage, C_s = system investment cost, $O\&M$ = fixed operation and maintenance costs, α = capital discount rate, CI = installation costs, E = energy the system will be able to store over its useful life, and N = years of useful life of the asset.

Among the studies that have proposed an LCOS metric for the utility-scale lithium battery are Pawel (2014), Schmidt O. et al. (2019), Lazard (2019), Lai C. & McCulloch M. (2016), and Jülch V. (2016). The methodologies of these publications differ in their use of adjustment parameters, whether by adding the cost of discharge efficiency, salvage value, or others.

These studies generally compute LCOS according to the discharge-duration capacity (D_h), which is typically 4 hours or less. In studies that include the evaluation of different discharge capacities ($D_h = k_e/k_p$), it has been found that as the energy-component capacity (k_e) is increased relative to the power-component capacity (k_p), the LCOS decreases.

One proposal that has shown considerable progress in its use for energy-sales optimization is that of Comello & Reichelstein (2019). This metric measures the marginal sensitivity of the LCOS of a residential lithium battery as a function of discharge time (D_{hr}). By separating the adjustment factors that affect the costs of k_e and k_p, a non-uniform variation in them is observed as D_{hr} increases.

For example, as discharge intensity increased, degradation would rise, and this cost was passed solely to the battery pack (k_e), rather than the same rate being applied globally to the entire installation. Furthermore, separating the LCOS into components makes it possible to measure useful life and degradation separately, increasing its precision.

This feature makes the LCOS more effective when attempting to optimize capacity. By knowing the revenues from wholesale electricity sales, one can adjust either k_e or k_p to obtain the highest profits.

The aim of this analysis is to use forecasts of energy and power prices to compute the LCOS of a utility-scale lithium battery for use in peak-demand control from 2020 to 2030, with the feature that the metric captures the marginal changes across discharge capacity D_h.

4 Methodology

4.1 Data

Forecast of the energy component price

The forecast of the energy-component price required the prior calculation of the Experience Rate (ER) and the projected global sales of battery packs (2020–2030). The ER estimate, in turn, required two datasets: (1) the battery-pack price (2010–2019) and (2) historical battery-pack production (2010–2019).

As for global battery-pack production data, both historical and forecast, these were obtained indirectly, since no public source providing them could be found. The calculation of annual production was obtained by multiplying EV sales (passenger vehicles, light commercial vehicles, buses, etc.) by the energy requirement of the relevant vehicle segment[1] (kWh). Historical (2010–2019) and forecast (2020–2030) EV production data by segment were obtained from IEAa (2020) and IEAb (2019), respectively. The energy requirement per segment type was assigned according to the market-leading vehicle or, when no annual sales data by vehicle type were available, by consulting a notable model within the industry on the basis of brand prestige and time. Cumulative production and the energy-capacity requirements per EV are detailed in the annex tables A.8 and A.4, respectively.

It is important to clarify that the forecast EV sales (IEAb, 2019) come from the Sustainable Development Goals (SDG) scenario, which estimates that in 2030, 30% of new vehicle sales will be of some type of EV (plug-in hybrid or battery electric). Except for the 2020 and 2030 observations, this dataset does not account for the drop in EV demand caused by the 2020 global economic recession; however, cumulative demand to 2030 is expected to deviate by less than 5% relative to the forecasts in the Global EV Outlook 2019 of IEAb (2019).

For the historical battery-pack prices (2010–2019), these are a weighted average of the purchase-sale contracts agreed globally by various market participants (BNEF, 2019). The reason for choosing this sample is that it is the historical price database with the largest number of available observations. Since these prices are an average, most of the sample is represented by EV applications,

[1]See Table A.4 to view the vehicles by segment for the relevant designation.

so there is a bias relative to the prices of battery packs for stationary use. To the author's knowledge, there are no public, disaggregated data exclusively for stationary use.

In addition, the lack of public data for annual battery-pack production in any period, disaggregated by product type (EVs, utility-scale, residential), makes the battery-pack production calculation presented here partial. This may result in an actual experience rate that differs from the one estimated, as well as in an underestimation of the future reduction in the battery-pack price.

However, data based on the public figures from the Bloomberg L.P. (2019) platform show that historically (2010–2018) EVs represent more than 90% of total battery-pack sales, and that by 2030 this figure remains close to 90%. Furthermore, the results of this research, as will be seen below, are close to those of other studies on the topic. The battery-pack price (2020–2030) from selected literature can be consulted in Table A.9 of the annex.

Levelized cost of energy storage

For the forecast price of the power components — that is, those components of the utility-scale installation that are not the battery pack (inverters, cooling system, software, etc.) — the "high" scenario data from Cole & Frazier (2019) for 2020–2030 were used. This scenario is an average of various industry and academic sources. This scenario was chosen because the battery-pack price under the same ("high") scenario was the one that best aligned with the results of this research.

Finally, the LCOS technical coefficients were obtained as follows. The discharge efficiency and the 5% capital cost were obtained from Lazard (2019), while the degradation rate and O&M expenses came from Schmidt et al. (2019). Details of all the LCOS technical parameters can be found in Table A.5 of the annex.

4.2 Forecast of the energy component

This subsection presents a forecast of the energy-component price based on the experience curve. The differences between the data in this model and those of Schmidt et al. (2017) are: (1) the method for computing the energy requirement (kWh) from vehicle demand; and (2) the price and cumulative-production sample is broader compared with Schmidt et al. (2010–2016), being extended with observations through 2019.

The experience-curve regression is expressed in equation 4.1.

$$logP = \alpha + \beta_1 LogA_i + \varepsilon \tag{4.1}$$

where P is the battery-pack price, A_i is cumulative production, α is the intercept, β_1 is the estimator of A_i, and ε is the error term. Table 4.1 shows the regression results from equation 4.1.

Table 4.1: Log-log OLS: Cumulative production and price

	Dependent variable:
	Price
Cumulative production	-0.292^{***}
	(0.032)
Constant	6.962^{***}
	(0.124)
Observations	10
R^2	0.911
Adjusted R^2	0.900
Residual Std. Error	0.222 (df = 8)
F statistic	82.107^{***} (df = 1; 8)
Note:	*p<0.1; **p<0.05; ***p<0.01

Solving the Experience Rate equation $(1 - 2^{\beta_1})$ yields a battery-pack price reduction of 18.4% each time cumulative production doubles. This result can be contrasted with the findings of Schmidt et al. (2017) and BNEF (2018), which were 16% and 18%, respectively.

With the ER defined, we proceed to compute the forecast battery-pack price. First, the cumulative-production variation index (GWh) of battery packs from 2020 to 2030 is computed. Using the data on annual EV sales and the energy capacity per segment, the annual battery-pack production is determined. It can be expressed as:

$$A = \sum_{j=1}^{7} x_{ij} y_j, \quad i = 1, 2...10; j = 1, 2...7 \tag{4.2}$$

Figure 4.1: Battery-pack price, 2020–2030

where x is total sales, y is the energy requirement per segment, i is the production year, and j is the vehicle segment. Solving the experience curve for each year with equation 4.3 yields the forecast battery-pack price for each year, where n is the number of years ahead being forecast.

$$P_{i+n} = P_i(\frac{A_{i+n}}{A_i})^{\beta_1}, \quad i = 1, 2...10 \tag{4.3}$$

Figure 4.1 shows the 2020–2030 forecast from this research and from selected publications in Table A.9 of the annex.

It is worth noting that the results of this research start as the most optimistic in 2020; however, by 2030 all of the studies' forecasts tend to converge, and for that year the results of this research are \$68/kWh, the second-highest price in the sample.

The reason for the optimism in this model relative to the early observations is that the battery-pack production forecast is based on an estimate of the IEA's 30@30 scenario (IEA, 2019), which implies electric-mobility adoption consistent with the Sustainable Development Goals (SDG), as mentioned at the beginning of this chapter.

Finally, the results of this forecast are supported by the analysis in Chapter 2 of this research, which reveals the progress made in the value chain and state intervention in production, consumption, and R&D investment. In addition, the programs in different countries that incentivize the adoption of zero-emission transport (IEA, 2020) would be one of the key drivers underlying this forecast.

Given the elements observed in the value chain, public policy, and the results of this experience curve, it can be concluded with high probability that a battery-pack price below \$100/kWh would be reached by 2030.

4.3 LCOS forecast

The LCOS equation for a lithium battery is usually presented as the ratio between the real cost of the asset and the net energy it can dispatch over its useful life, yielding the unit cost of energy storage. This calculation simplifies the estimate for a fixed discharge capacity; however, for the lithium battery, as the hourly discharge capacity (D_h) increases, the levelized cost of each component rises non-proportionally. Estimating these variations is important for profit maximization. In addition, current LCOS methods for a lithium battery generally apply a single depreciation rate and the same useful life across all components, bundling them into capital cost. A discrimination of the degradation rate between the power and energy costs is needed. Therefore, if we separate the LCOS by the different cost concepts that make up the battery, we obtain the following equation:

$$LCOS(\$/MWh) = LCOEC + (LCOPC + O\&M + CI)\frac{1}{D_h} - VD \tag{4.4}$$

where $LCOS$ = Levelized cost of energy storage, $LCOEC$ = Levelized cost of the energy component, $LCOPC$ = Levelized cost of the power component, $O\&M$ = Levelized fixed operation and maintenance cost, CI = Levelized installation cost, and VD = Levelized salvage value.

Each of these terms represents the weight of each concept on the average unit cost of storing electricity (MWh). Unlike traditional LCOS proposals, each concept is "leveled" by a unique denominator that matches the characteristics of the numerator, rather than by a global denominator. It is worth remembering that the LCOS is always read as the average unit cost of storing one unit of energy (MWh), and not of power (MW).

The LCOEC (Levelized Cost of the Energy Component) is the ratio of the unit cost of one unit of energy-component capacity (1 MWh) (υ_e) to the net energy it will be able to store over its useful life, where n is the number of 100%-completed discharge cycles in a year, N the useful life of the energy component (in years),

η_e the charge/discharge efficiency, π the battery's degradation factor, and γ the capital discount factor, where α is the discount rate ($\frac{1}{\sum_{i=1}^{N}(1+\alpha)^i}$). Therefore, the LCOEC is defined as in equation 4.5.

$$LCOEC = \frac{\upsilon_e}{(N * n * \eta_e * \pi_e * \gamma)} \tag{4.5}$$

The energy-component degradation factor (π_e), that is, the average annual retention level, is the adjustment of the annual degradation rate (Θ_e) to the battery's discharge capacity over its useful life, and is calculated as:

$$\pi_e = \frac{1 + \sum_{i=1}^{N-1}(1 - \Theta_e)^i}{N} \tag{4.6}$$

Since π_e is the battery's average degradation factor, its multiplication with the gross discharge capacity of the battery pack yields the system's net energy capacity. Subsequently multiplying this result by η gives the net energy dispatched by the system, and multiplying it by γ then discounts the opportunity cost of the capital invested in the battery. We regroup these terms in equation 4.7, which is the adjustment denominator for the energy component and will be useful later.

$$\rho_e = (N * n * \eta * \pi * \gamma) \tag{4.7}$$

The Levelized Cost of the Power Component (LCOPC) — that is, the cost per unit of energy (MWh) of those components used in the construction of the battery that do not include the battery pack (υ_p), also known as Balance of System (BOS) components — includes containers, inverters, management software, and so on. Its equation can be defined in the same way as the LCOEC equation, replacing the technical values of useful life and depreciation accordingly, yielding:

$$LCOPC = \frac{\upsilon_p}{\rho_p} \tag{4.8}$$

where ρ_p is the same expression as ρ_e, except that here the system's own power-degradation factor is used ($\tau = \frac{1+\sum_{i=1}^{N-1}(1-\Theta_p)^i}{N}$), which, as in the previous case, is estimated in the same way, with Θ_p being the annual degradation rate of the power component.

The costs outside the installation comprise the Installation Cost (CI) — including construction, land, design and engineering, labor, etc., also known as Engineering, Procurement, and Construction (EPC) — and the fixed operation costs (O&M), that is, those mainly related to maintenance and cooling of the system. These terms can be regrouped as follows:

$$\theta = \frac{CI}{\frac{\rho_e + \rho_p}{2}} + \frac{O\&M}{\rho_e} \tag{4.9}$$

For installation costs, these are divided by the average of ρ_e and ρ_p, a differentiation required by the differences in useful life between each component as well as the degradation index of each, justified primarily by the fact that the battery pack can be replaced while keeping the same power components. With these concepts defined, we now turn to the salvage value (VD), which is the recycling value that the energy component reaches at the end of its useful life. It is estimated by multiplying the recovery rate (ω) by the energy component and by the battery's discharge capacity.

$$VD = \frac{\upsilon_e * \omega}{\rho_e} \tag{4.10}$$

Finally, the costs not falling under any of the previous categories, known as "Other Costs" (soft costs) — which are mostly represented by permits, insurance, and taxes — vary considerably across countries and are therefore not considered in this research.

The LCOS equation can be regrouped as follows:

$$LCOS = \frac{\upsilon_e}{\rho_e} + (\frac{\upsilon_p}{\rho_p} + \theta)\frac{k_p}{k_e} - VD \tag{4.11}$$

Substituting the forecast price values of υ_e and υ_p into the equation, we obtain the LCOS forecast for 2030 across different discharge capacities, shown in Figure 4.2.

The result shows that the LCOS for a D_h of 4 hours falls by 48% from 2020 to

Figure 4.2: LCOS by discharge capacity (2020–2030)

[redacted]

Figure 4.3: LCOS disaggregated by concept, 2030

[redacted]

2030, reaching \$63/MWh. In addition, as D_h increases, the LCOS decreases, explained by the non-linear increase in the levelized cost of certain concepts as discharge capacity grows.

It is important to mention the assumption of a fixed cost on (υ_p) up to a 4-hour discharge capacity. This assumption is a simplification on the LCOS sensitivity: υ_p increases slightly when D rises, but not at the same rate as υ_e (Fu et al., 2018). This assumption can be modified by introducing a coefficient in the equation as more market information becomes available, allowing for a continuous formulation. The reduction in LCOS for an increase in D_h can be estimated by the equation $\frac{\partial LCOS}{\partial D_h}$, which can be solved as:

$$\frac{\partial(\frac{\upsilon_e}{\rho_e} + (\frac{\upsilon_p}{\rho_p} + \theta)\frac{1}{D_h})}{\partial D_h} = -D_h^{-2}(\frac{\upsilon_p}{\rho_p} + \theta) \tag{4.12}$$

The inverse quadratic relationship of υ_p and θ with D_h shows the LCOS reduction trend for an example of discrete discharge capacities. Finally, as D_h becomes larger, the value of LCOS tends to take the value of υ_e. Figure 4.3 shows the weight of each concept in the LCOS for 2030 according to discharge capacity.

Profit optimization

With LCOS variations as a function of D_h established, we now fix an optimal system capacity according to the differential between the maximum and minimum electricity prices (pp). For this case, this price differential is restricted to the maximum prices at the peak-load point. If the electricity-price function is a periodic function, with a peak at the maximum price and a valley at the minimum, it can be represented by the function $\cos(x)$, and the revenue obtained from the wholesale electricity-price differences (pp) for peak-demand control can be defined by the following equation.

$$\int_5^8 Cos(x)_{Max}dx - \int_1^4 Cos(x)_{min}dx = pp \tag{4.13}$$

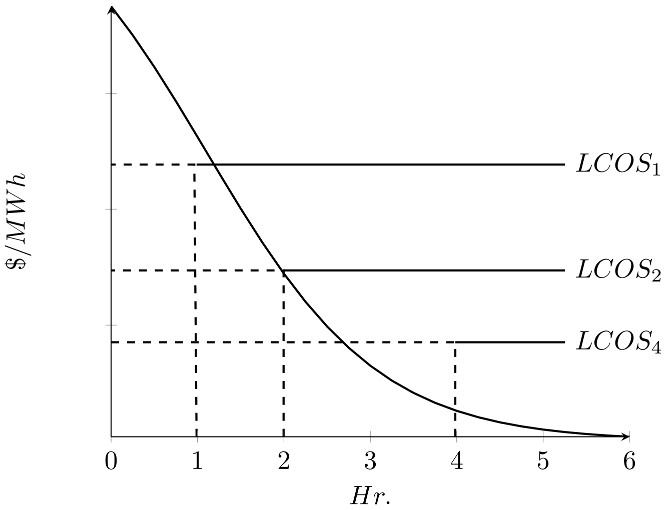
Profit maximization is reached when the average unit cost of storing electricity equals the marginal revenue from energy arbitrage, which can be expressed by equation 4.14:

$$\begin{aligned} LCOS &= pp \\ \frac{\upsilon_e}{\rho_e} + (\frac{\upsilon_p}{\rho_p} + \theta)D_h^{-1} &= pp \end{aligned} \tag{4.14}$$

The reduction in the marginal revenue from energy arbitrage grows as the amplitude of the intraday purchase quantities expands. Given the load curve of an electricity system, the drop in marginal revenue is likely to be very steep just after passing the peak-load point and relatively invariant over a prolonged period after that point. The amplitude of the intraday electricity-price difference would depend largely on the penetration of variable renewable energy in the system, which could grow dramatically with an increase of the latter. Assuming an energy-arbitrage revenue curve with the shape $\frac{1}{1+e^x}$, profit maximization can be visualized in Figure 4.4.

In this scenario, a one-hour discharge capacity ($LCOS_1$) is economically viable; however, since the LCOS is below the marginal revenue from energy arbitrage (pp), there is still room to expand the installed capacity. A four-hour discharge capacity ($LCOS_4$), on the other hand, despite showing a lower average cost per unit of energy storage, has an LCOS that is still higher than the decline in energy-arbitrage revenue at that point; this configuration would entail

Figure 4.4: Profit maximization over installed capacity
Source: Author's own elaboration



overcapacity. The two-hour discharge capacity ($LCOS_2$) takes advantage of the largest discharge capacity possible without incurring any loss; since at this point it equals the marginal revenue, there is neither over- nor undercapacity installed. The rectangular area formed by the dotted lines below $LCOS_2$ represents the battery's total profits.

Assuming a continuous discharge-capacity configuration, rather than a discrete one as in this case, equation 4.3 can be expressed as a curve as a function of hourly capacity — that is, an infinite set of connected points, not just three points as in Figure 4.4. Finally, this scenario assumes that the battery is a price taker; in other words, its size cannot influence wholesale electricity prices.

5 Discussion and conclusion

The need for energy storage arises from the power gap between the load curve and the supply of variable renewable energy. If there were a perfect synchronization between the two curves, energy storage would have neither economic nor technical justification.

In this research I project the Levelized Cost of Energy Storage (LCOS) of the utility-scale lithium battery from 2020 to 2030 using a methodology that differs from the current literature, mainly because it captures economies of scale as a function of hourly discharge capacity.

Additionally, in order to forecast the reduction in the price of the utility-scale lithium battery with greater precision, the capital cost is disaggregated into two components, the energy component and the power component. This disaggregation makes it possible to capture the price trends of both concepts, which are explained by different factors.

Then, by adjusting the battery's capital costs to technical parameters along with operation and maintenance, installation, and recycling concepts, I compute the cost of storing one unit of electricity (MWh) for a battery with different discharge capacities ranging from 0.5 to 4 hours. By separating the levelized cost into different concepts, this proposal makes it possible to observe the change in the levelized cost of these concepts as the discharge capacity ($D_{Hr.}$) increases, finding that for a 4-hour capacity the cost of storing one unit of electricity (MWh) falls by 49% in real terms, with the LCOS reaching $63/MWh.

The main reasons explaining the future reduction in the cost of the lithium battery would be industry learning, which in turn will be driven by an increase in battery-pack demand, more active industrial and fiscal policies on energy storage worldwide, and continuity in public and private R&D investment in these segments. The combination of these elements would allow lithium-battery-derived products to enter a virtuous cycle of growth and learning during the 2020s.

At the same time, commitments to reduce greenhouse gases in the electricity sector would lead to greater penetration of variable renewable energy globally, which would consequently widen the intraday price differences in the electricity market. This would open a larger window of opportunity for more long-duration energy storage projects to become economically attractive on the grid. However, the benefits that can be achieved through energy storage will depend largely on the reduction of its cost.

A plausible greater deployment of energy storage would have the effect of flattening the load curve, which would lead not only to greater reliability of the electricity system but also to greater efficiency in the available energy supply.

The challenges arising from the isolation of the Baja California Electricity System — related to reliability and efficiency — could be addressed with substantial energy-storage capacity, while at the same time accelerating the integration of renewable energy. The co-optimization of ancillary services that can be provided, together with the positive externalities derived from energy storage, should be a necessary part of estimating the potential benefits attainable with the lithium-ion battery, given that current electricity-price differences of approximately $USD 50/MWh compare with the $USD 63/MWh cost expected for 2030.

Based on what has been set out in this research, energy storage could accelerate the adoption of renewable energy without causing curtailment of generation or market distortions. However, even with the cost reduction projected in this research, its deployment in markets with low renewable-energy penetration would still be limited, as is currently the case in Mexico. Further development of the lithium battery, a regulatory framework that rewards the qualities of energy-storage technologies in certain ancillary services, and innovations in other types of technologies will be necessary to further accelerate the decarbonization of the electricity industry.

A Annex

A.1 Abbreviations

BNEF: Bloomberg New Energy Finance

BYD: Build You Dreams

CAISO: California Independent System Operator

CATL: Contemporary Amperex Technology

CNESA: China Energy Storage Alliance

DOE: Department of Energy of the United States of America

EIA: Energy Information Agency

ESS: Energy Storage Systems

EV: Electric Vehicle

GHG: Greenhouse Gases

IEA: International Energy Agency

IPCC: Intergovernmental Panel on Climate Change

IRENA: International Renewable Energy Agency

LCOS: Levelized Cost of Energy Storage

LEM: London Exchange Market

WEM: Wholesale Electricity Market

SDG: Sustainable Development Goals

RES: Renewable Energy System

EU: European Union

VRE: Variable Renewable Energy

A.2 Variable catalog

Table A.1: Variables of the LCOS model

Variable	Concept	Unit
LCOS	Levelized cost of energy storage	$USD 2018/MWh
LCOEC	Levelized cost of the energy component	$USD 2018/MWh
LCOP	Levelized cost of the power component	$USD 2018/MW
CI	Levelized installation cost	$USD 2018/MWh
N_e	Useful life of the energy component	Years
N_p	Useful life of the power component	Years
n	Full battery discharges/charges per year	-
υ_e	Cost of the energy component	$USD 2018/MWh
υ_p	Cost of the power component	$USD 2018/MWh
k_e	Quantity of energy component	MWh
k_p	Quantity of power component	MW
Θ_p	Energy-component degradation factor	-
Θ_e	Power-component degradation factor	-
π_e	Energy-component degradation index	-
π_p	Power-component degradation index	-

Table A.2: Technical parameters of the LCOS model

Adjustment parameter	Unit	Source
Discharge efficiency	91%	Lazard 5.0
Annual degradation rate of the energy component	5%	Lazard 5.0
Annual degradation rate of the power component	1%	Comello&Reichelstein
Capital cost	7%	Author's own assumption
Full cycles per year	360	Author's own assumption
Land	1,100,000	Vivanuncios.com
O&M	5%	Lazard 5.0

A.3 Statistical information

Table A.3: Variables of the log-log regression model for battery packs

Variable	Concept
P_f	Final price of the energy component
P_i	Initial price of the energy component
A_1	Cumulative production of the energy component

Table A.4: Abbreviations by vehicle type

Abbreviation	Segment no.	Concept
PLDV - BEV	1	Battery-electric light passenger vehicle
PLDV - PHEV	2	Plug-in hybrid light passenger vehicle
LCV - BEV	3	Battery-electric light commercial vehicle
LCV - PHEV	4	Plug-in hybrid light commercial vehicle
Bus - BEV	5	Battery-electric bus
Bus - PHEV	6	Plug-in hybrid bus
Truck - PHEV	7	Plug-in hybrid truck

Table A.5: Energy requirement (kWh) by vehicle type

Type	kWh	Flagship vehicle	Source
PLDV- BEV 2005-2012	24	Nissan Leaf	Greentechmaedia - Nissan Leaf
PLDVs - BEV 2013-2018	50	Tesla S, Tesla 3	-
PLDVs - PHEV	16	Prius hibrid	EV- database-Prius
LCVs - BEV	75	BYD Generation 2	-
LCVs - PHEV	20	-	-
Buses - BEV	266	BYD 35 Electric transition	BYD- BUS35
Buses - PHEV	30	-	-
Trucks - BEV	435	BYD 8TT	Insideevs- bydclass-8
Trucks - PHEV	40	-	-

Table A.6: Projected cumulative sales of lithium-battery vehicles 2020–2030 (millions)

Source: IEA, 2019.

Year	PLDVs - BEV	PLDVs - PHEV	LCVs - BEV	LCVs - PHEV	Buses - BEV	Buses - PHEV	Trucks - PHEV
2020	10	6	3	0	2	0	0
2021	17	10	4	0	2	0	0
2022	23	13	6	0	2	0	0
2023	31	17	7	0	3	0	1
2024	41	22	10	1	3	1	1
2025	52	28	12	1	4	1	1
2026	64	33	14	1	5	1	1
2027	79	40	17	1	5	1	2
2028	96	47	20	2	6	1	2
2029	118	56	23	2	7	1	2
2030	139	62	27	10	4	1	2

Table A.7: Historical battery-pack price, 2010–2019
Source: BNEF (2019).

Year	$\frac{\$USD(2018{=}100)}{kWh}$
2010	1116
2011	899
2012	707
2013	650
2014	577
2015	373
2016	288
2017	214
2018	176
2019	156

Table A.8: Cumulative battery-pack production (GWh) by vehicle type, historical and projected
Source: Computed from vehicle energy-requirement and EV sales data (IEA, 2019).

Year	Total	PLDVs - BEV	PLDVs - PHEV	LCVs - BEV	LCVs - PHEV	Buses - BEV	Buses - PHEV	Trucks - PHEV
2005	0.05	0.05	-	-	-	-	-	-
2006	0.1	0.1	-	-	-	-	-	-
2007	0.1	0.1	-	-	-	-	-	-
2008	0.1	0.1	-	-	-	-	-	-
2009	0.2	0.2	-	-	-	-	-	-
2010	0.4	0.4	0.0	-	-	-	-	-
2011	1.5	1.3	0.2	-	-	-	-	-
2012	4.4	2.7	1.7	-	-	-	-	-
2013	15.2	11.3	3.9	-	-	-	-	-
2014	27.9	20.8	7.1	-	-	-	-	-
2015	49.3	36.8	12.4	-	-	-	-	-
2016	79.3	59.9	19.4	-	-	-	-	-
2017	126.1	97.3	28.8	-	-	-	-	-
2018	208.5	164.5	44	-	-	-	-	-
2019	862	350	96	150	-	266	-	-
2020	1,401	500	144	225	-	532	-	-
2021	1,922	850	240	300	-	532	-	-
2022	2,444	1,150	312	450	-	532	-	-
2023	3,321	1,550	408	525	-	798	-	40
2024	4,216	2,050	528	750	20	798	30	40
2025	5,326	2,600	672	900	20	1,064	30	40
2026	6,462	3,200	792	1,050	20	1,330	30	40
2027	7,645	3,950	960	1,275	20	1,330	30	80
2028	9,174	4,800	1,128	1,500	40	1,596	30	80
2029	10,981	5,900	1,344	1,725	40	1,862	30	80
2030	12,065	6,965	1,481	1,995	190	1,091	30	218
96								

Table A.9: Forecast battery-pack price, 2020–2030 ($USD 2018/kWh)

Year	Nieto	BNEF (2019)	Cole&Frazier (2019)	Schmidt et al. (2017)	RMI (2019)	Comello&Reichelstein (2019)
2020	127	142	160	175	175	157
2021	116	128	148	158	148	144
2022	108	115	135	144	120	133
2023	99	104	123	132	113	122
2024	92	94	111	120	105	-
2025	86	87	99	110	98	-
2026	81	81	92	100	90	-
2027	77	76	86	91	83	-
2028	73	71	80	82	75	-
2029	70	66	73	75	68	-
2030	68	62	67	68	60	-

Table A.10: Power-component cost, 2018–2050 ($USD 2018/kWh)
Source: Cole & Frazier (2019).

Year	Low	Medium	High
2018	668	668	668
2019	595	623	668
2020	523	578	668
2021	483	549	668
2022	443	521	668
2023	403	492	668
2024	363	464	668
2025	323	435	668
2026	302	421	668
2027	281	407	668
2028	260	393	668
2029	240	379	668
2030	219	365	668
2031	214	360	668
2032	210	356	668
2033	206	351	668
2034	202	346	668
2035	197	342	668
2036	193	337	668
2037	189	333	668
2038	184	328	668
2039	180	324	668
2040	176	319	668
2041	172	315	668
2042	167	310	668
2043	163	305	668
2044	159	301	668
2045	154	296	668
2046	150	292	668
2047	146	287	668
2048	142	283	668
2049	137	278	668
2050	133	273	668

Table A.11: LCOS table, 2020 ($D = 1$ hr.)

Concept	Value	Unit
LCOEC		
Gross energy cost (X)	125,074	$USD (2018=100)
Annual cycles (A)	360	Days
Useful life (B)	15	Years
Total full cycles (A*B=[C])	5,400	-
Annual degradation rate	0.08	-
Degradation-rate factor (D)	0.5948	-
Discharge efficiency (E)	0.95	-
Discount rate	1.05	-
Discount-rate factor (F)	0.4632	-
LCOEC adjustment factor (D*E*F=[Y])	1413	-
Levelized cost of energy storage (X/Y*C)	**89**	$USD (2018=100)
LCOP		
Power cost (X)	522,818	$USD (2018=100)
Annual cycles (A)	360	Days
Useful life (B)	30	Years
Total full cycles (A*B=[C])	10,800	-
Implicit amortization rate	0.99	-
Amortization factor (D)	0.8676	-
Capital-rate factor (E)	0.4632	-
LCOP adjustment factor (C*D*E=[Y])	4,340	-
Levelized cost of the power component (X/Y)	**120**	$USD/MWh (2018=100)
CI		
Land (Z)	50,000	$USD
Engineering, procurement, and design (W)	60,000	$USD
Total installation costs (Z+W=[X])	110,000	-
LCOP adjustment factor (A)	.4340	-
LCOEC adjustment factor (B)	.1413	-
Average LCOE-LCOP factor ((A+B)/2=[Y])	.2877	
Levelized installation cost (X/Y)	**38**	$USD/MWh (2018=100)
O&M		
O&M rate over capital (A)	0.1	-
Sum of LCOEC and LCOP (X)	210	-
Levelized O&M cost (A*X)	**21**	$USD/MWh (2018=100)
VD		
Battery-pack value (A)	156,000	$USD
Capital rate (B)	0.05	-
Salvage value (A*B=[X])	7,800	-
LCOEC adjustment rate (Y)	1413	-
Real salvage value (X/Y)	**4**	$USD/MWh (2018=100)
LCOS		
Levelized cost of energy storage	**264**	$USD/MWh (2018=100)

Table A.12: Levelized cost of energy storage by discharge capacity, 2020–2030 ($USD 2018/MWh)

	Hourly discharge capacity			
Year	0.5	1	2	4
2020	445	264	169	116
2021	416	245	157	107
2022	389	229	147	100
2023	362	213	136	92
2024	336	198	126	85
2025	311	183	117	79
2026	296	174	111	75
2027	282	166	106	72
2028	269	158	101	68
2029	255	150	96	65
2030	242	142	91	62

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