The Future Cost of Electricity Storage and its Value in Low-Carbon Power Systems

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Declaration of Originality

I declare that this thesis is my own work, and that the work of others is appropriately referenced and acknowledged.

Oliver Schmidt

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Abstract

The energy sector is transforming rapidly to reduce carbon emissions and limit global climate change. Electricity storage can provide the required flexibility to balance intermittent and relatively inflexible power generation with demand in low-carbon power systems. However, falling investment cost, the wide range of technologies with different performance characteristics and the wide range of use cases with different performance requirements lead to uncertainty on its commercial viability. To assess electricity storage against alternatives and enable further investment in low-carbon technologies, policy-makers and industry need certainty on cost reduction potentials and its value in enabling low-carbon power systems.

This thesis creates an experience curve dataset for 11 electricity storage technologies, identifying investment cost reductions to US$325±125/kWh (systems) and US$155±45/kWh (packs) once 1 TWh capacity is installed for each technology. This could be achieved by 2027–2040 based on market growth projections. Expert interviews highlight the importance of production scale-up as cost reduction driver and provide a detailed list of technical and value chain innovations for two prominent storage technologies. The quantification of future application-specific lifetime cost with a novel, comprehensive formula, that accounts for all relevant cost and performance parameters, indicates that lithium ion will be the most cost competitive for most applications by 2030. Lower financing cost, in general, and performance improvements for alternative technologies specifically could challenge this dominance. Matching future lifetime cost to revenue potentials across applications reveals profitable business cases in three distinct application categories with specific requirements. An analysis of modelled flexibility capacity in power system studies reveals two approaches to assess electricity storage capacity requirements in low-carbon power systems. In both approaches, the flexibility capacity requirement relative to peak demand increases linearly with increasing wind, solar and nuclear penetration, albeit at different rates, requiring up to 65% or 115% in a fully decarbonised power system.

These insights combined with the online availability of experience curve dataset and lifetime cost tool increase transparency on the future cost of electricity storage and its value in low-carbon power systems, supporting policy and industry in transforming the energy sector.

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Acknowledgments

My PhD in the last 3.5 years was enriching and enjoyable thanks to a few important people.

I feel extremely lucky to have had the opportunity to work with Iain Staffell, because quality and fun of a PhD depend on your main supervisor. Iain, thank you for giving me the freedom to follow my research ideas and then guiding and supporting me hands-on in implementing them. Your intellect and obsession for detail (fonts for example) gave me the required push to make a real impact within the energy storage community. Thank you for always being available, also in tough moments, and for the great discussions about things that *really* matter in the pub.

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List of Acronyms

ACC	Annuitised capacity cost
AEC	Alkaline electrolysis cell
BEIS	Department for Business, Energy and Industrial Strategy
bn	Billion
BNEF	Bloomberg New Energy Finance
CAES	Compressed air energy storage
CAGR	Compound annual growth rate
CAISO	California independent system operator
CAP	Capacity
CCC	Committee on climate change
CCGT	Combined cycle gas turbine
CI	Confidence interval
CO	Cost of ownership
CRF	Capital recovery factor
CYC	Cycles
DD	Discharge duration
DEG	Degradation
DSR	Demand-side response
EC	Experience curve
EES	Electrical energy storage
EFR	Enhanced frequency response
EL	Electricity
ER	Experience rate
EU	European Union
EV	Electric vehicle
GB	Great Britain
GDP	Gross domestic product
GM	General Motors
GW	Gigawatt
GWh	Gigawatt hour
h	hour
H2	Hydrogen
HHV	Higher heating value
HEV	Hybrid electric vehicle
IAMC	Integrated Assessment Modelling Consortium
ICEV	Internal combustion engine vehicle
IEA	International Energy Agency
IPCC	Intergovernmental Panel on Climate Change
kg	Kilogramms
KOH	Potassium hydroxide
LCOE	Levelised cost of electricity
LCOS	Levelised cost of storage
LFP	Lithium iron phosphate
LMO	Lithium manganese oxide
LSM	Lanthanum strontium manganese
LTO	Lithium titanate
m	Metre
mn	Million
MW	Megawatt
MISO	Midcontinent independent system operator
NaS	Sodium sulphur
NCA	Nickel cobalt aluminium
NMC	Nickel manganese cobalt
NYISO	New York independent system operator
OCGT	Open cycle gas turbine
OECD	Organisation for Economic Co-operation and Development
O&M	Operation and Maintenance
PbA	Lead-acid
PHES	Pumped hydro energy storage
PEMEC	Polymer exchange membrane electrolysis cell
PJM	Pennsylvania New Jersey Maryland
POLES	Prospective Outlook on Long-term Energy Systems
PV	Photovoltaic
R&D	Research and Development
RD&D	Research, Development & Deployment
RV	Residual value
s	Second
SMES	Superconducting magnetic energy storage
SOEC	Solid oxide electrolysis cell
TCO	Total cost of ownership
TSC	Total system cost
UK	United Kingdom
US	United States
VAR	Volt-ampere reactive
VRE	Variable renewable energy
VRFB	Vanadium redox-flow battery
WACC	Weighted average cost of capital
YSZ	Yttria stabilised zirconia

1. Introduction

The widespread use of fossil fuels for electricity generation, transport, heating and industry has driven economic growth since the industrial revolution. However, the consumption of these fuels releases greenhouse gases. With increasing concentration in the atmosphere, these gases affect the earth's climate by causing higher average temperatures, changing living conditions around the planet. A key requirement to limit climate change is the transformation of our global energy system.

1.1 Energy System Transformation

" Pathways limiting global warming to 1.5°C with no or limited overshoot would require rapid and far-reaching transitions in energy […] and industrial systems (high confidence)." [1]

Anthropogenic greenhouse gas emissions have a direct influence on the earth's climate[2]. Annual fossil fuel, industry and land use change emissions are projected to have reached 41.5±3 $GtCO_2$-equivalent in 2018, its highest level in history[3]. As a result, atmospheric CO_2 concentration increased to 407ppm, up from 405ppm in 2017, mirroring the average growth rate for the past decade of 2.24 ppm per year[4]. Global mean surface temperature is also approximately 1°C above pre-industrial levels, increasing at an average rate of 0.2°C per decade[1].

In order to limit climate change, the international community agreed in December 2015 to hold the increase in global mean surface temperature to well below 2°C above pre-industrial levels and to pursue efforts to limit temperature increase even further to 1.5°C[5]. This difference matters, because an increase to 2°C makes the loss of almost all coral reefs and an increase in intensity and frequency of extreme weather events like droughts, heatwaves and heavy precipitation likely[2,6].

Limiting temperature increase to below 2°C requires atmospheric CO_2 concentration to remain below 480ppm (Figure 1.1)[2]. Given that by 2017, total anthropogenic carbon emissions amounted to 2200 ± 320 $GtCO_2$, the remaining carbon budget for a 66% chance to stay below 2°C temperature increase is 700 $GtCO_2$. For a 66% probability to stay below 1.5°C, the respective carbon budget is 420 $GtCO_2$[1].

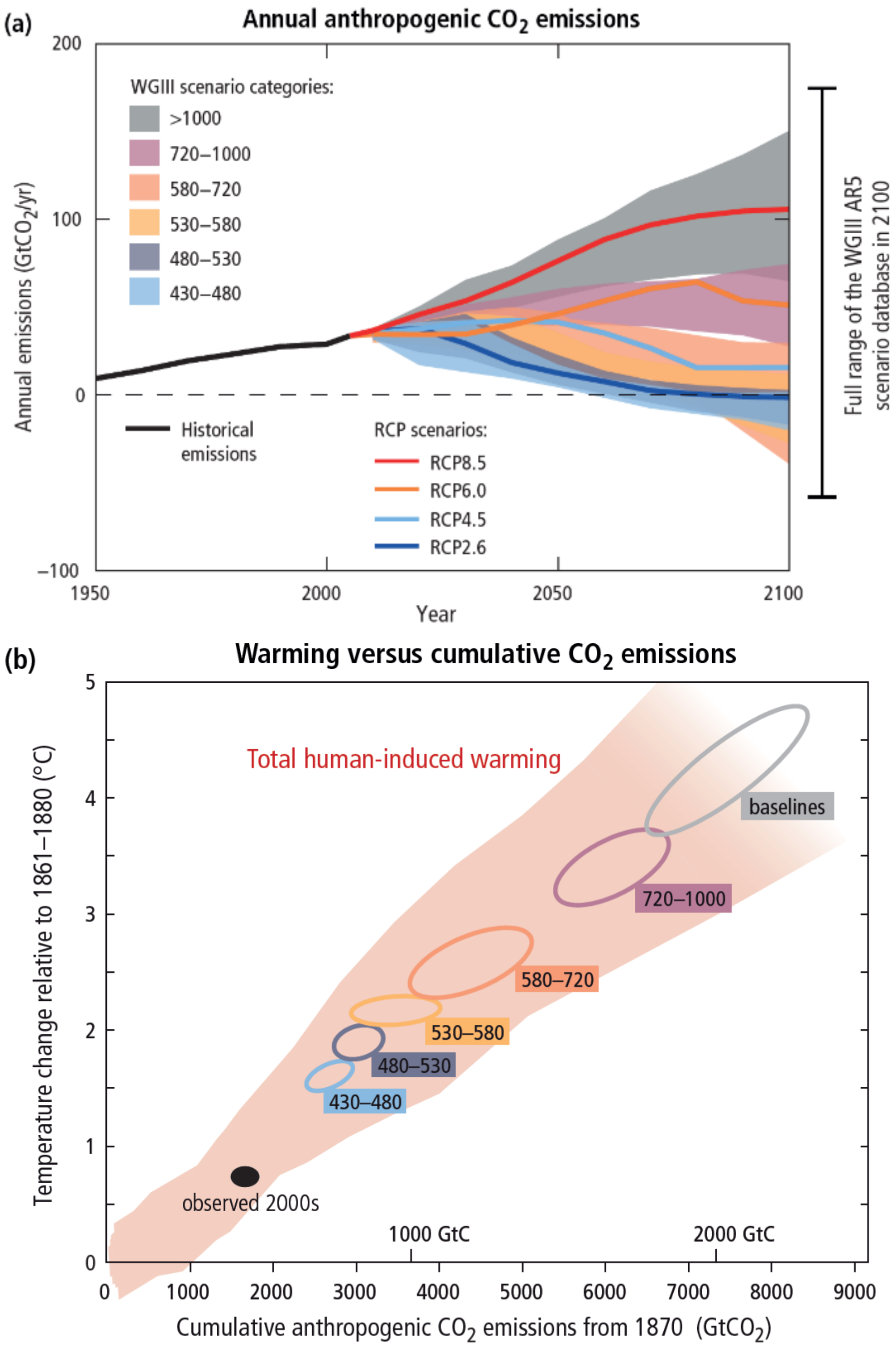


Figure 1.1 – (a) Emissions of carbon dioxide (CO_2) alone in the Representative Concentration Pathways (RCPs) (lines) and the associated scenario categories used in the IPCC 5th Assessment Report (coloured areas show 5 to 95% range)[2]. The scenario categories summarise the wide range of emission scenarios published in the scientific literature and are defined on the basis of $CO_{2\text{-eq}}$ concentration levels (in ppm) in 2100. (b) Global mean surface temperature increase at the time global CO_2 emissions reach a given net cumulative total, plotted as a function of that total, from various lines of evidence. Coloured plume shows the spread of past and future projections from a hierarchy of climate carbon cycle models driven by historical emissions and the four RCPs over all times out to 2100, and fades with the decreasing number of available models. Ellipses show total anthropogenic warming in 2100 versus cumulative CO_2 emissions from 1870 to 2100 from a simple climate model (median climate response) under the scenario categories. The width of the ellipses in terms of temperature is caused by the impact of different scenarios for non-CO_2 climate drivers. The filled black ellipse shows observed emissions to 2005 and observed temperatures in the decade 2000–2009 with associated uncertainties. Source: Figure SPM 5 in Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change[2]. Image reproduced in alignment with copyright rules of the rights holder, Intergovernmental Panel on Climate Change.

For the energy sector this requires a rapid transformation. Annual emissions from electricity generation need to reduce from 12 $GtCO_2$ in 2015 to 5 and 0 $GtCO_2$ by 2030 and 2050 respectively, instead of increasing to 18 and 25 GtCO_2 by 2030 and 2050 as was projected if no change were required[2]. These are median values from a range of energy system modelling scenarios.

To enable this transformation, jurisdictions around the world enacted legislation that mandates a reduction of CO_2 emissions[7] or increase the share of low-carbon electricity[8], both entailing policy instruments that support capacity additions of low-carbon electricity generation technologies like wind, solar and nuclear power plants.

These policy instruments combined with investment cost reductions of wind and solar PV technologies and favourable financing conditions, led to a significant increase in installed renewable energy capacity. Wind and solar PV reached an installed capacity of 495 and 329 GW respectively by the end of 2017, thereby making up 12% of total generation capacity and generating 5% of globally consumed electricity[9,10]. Annual capacity additions of these two renewable technologies are continuously increasing, having overtaken additions of fossil power generation technologies in 2017 at 145 versus 125 GW[11].

In the 28 member states of the European Union (EU), the installed capacity of wind and solar PV increased to 150 and 100 GW respectively at the end of 2016[12]. The share is 25 % of total installed electricity capacity, generating 13% of consumed electricity (Figure 1.2). In contrast to the global electricity generation portfolio, in the EU the absolute capacity of generation technologies based on fossil fuels is reducing since 2012. The highest penetration of variable renewable energy (VRE) produced by wind and solar PV can be found in Denmark and South Australia at more than 40%[11].

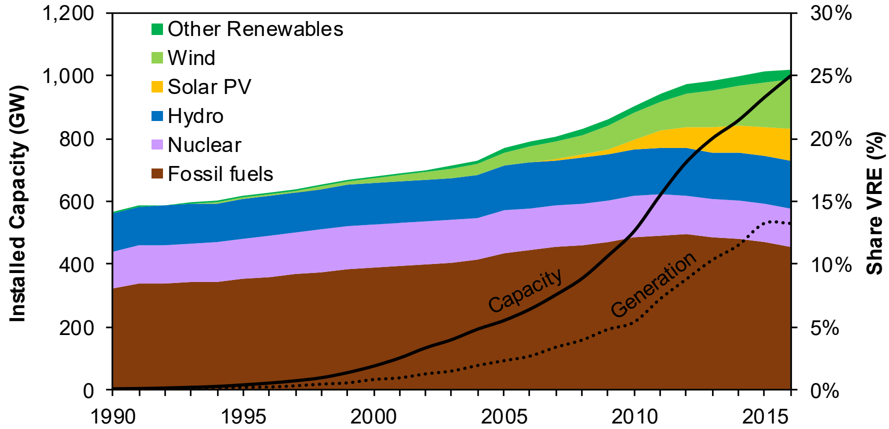


Figure 1.2 – Evolution of installed electricity generation capacity in the 28 members states of the European Union from 1990 to 2016. Left-hand axis displays generation capacity in GW for various fuel categories. Right-hand axis displays share of variable renewable energy (VRE), i.e., wind and solar PV, relative to total capacity (GW) or energy generation (GWh) each year. Total installed capacity of technologies based on fossil fuels is reducing since 2012. Based on data from Eurostat[12].

1.2 Need for Power System Flexibility

The physical characteristics of electricity imply that generation and consumption must be in balance instantaneously and at all times[13]. However, electricity demand varies across a range of timescales (e.g., hourly, daily, weekly). The potential electrification of energy demand for heating and transport with heat pumps and electric vehicles can further increase the variation between minimum and maximum electricity demand within those timescales.

At the same time, low-carbon electricity generation is intermittent or designed for constant power output. Solar and wind power plants generate electricity intermittently, because it fluctuates with the availability of the resource, which can be at various timescales depending on the geography. While technically capable to adjusting power output, nuclear plants are designed to generate electricity constantly at rated power as the most economically efficient operation mode given low fuel and high investment cost[14]. Figure 1.3 highlights the variability of electricity demand as well as the intermittent or relatively inflexible character of low-carbon electricity generation.

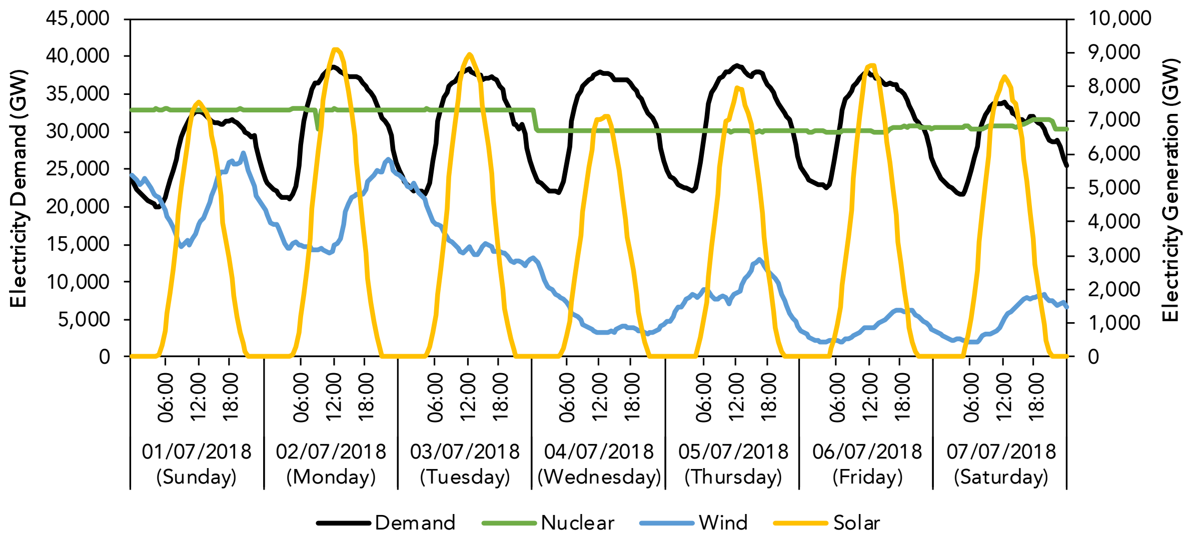


Figure 1.3 – Time series of electricity demand and nuclear, wind and solar generation in Great Britain for the first week of July in 2018. While demand shows a daily pattern, nuclear generation is relatively flat (i.e., constant power output), and wind and solar generation fluctuate (i.e., intermittent power output). Data Source: Electric Insights 2018[15].

The temporal mismatch between the variation of electricity demand and low-carbon generation highlights the need for power system flexibility to balance both instantaneously and at all times. Power system flexibility is defined as "[…] the extent to which a power system can modify electricity production or consumption in response to variability, expected or otherwise."[16] It can be categorised along the timescales needed and the options available to supply it (Table 1.1).

Table 1.1 – Categorisation of power system flexibility types and resources (based on IEA, 2018[17])

Flexibility timescale	**Ultra-short term** (sub- to seconds)	**Very short term** (seconds to minutes)	**Short term** (minutes to hours)	**Medium term** (hours to days)	**Long term** (days to months)	**Very long term** (months to years)
Issues	Ensuring system stability, i.e., keeping voltage and frequency in required range	Ensuring short-term frequency control within required range	Meeting frequent, rapid and non-predictable changes electricity supply and/ or demand	Determining operation schedule of generation capacity to balance electricity supply and demand	Addressing longer periods of surplus or deficit in electricity generation	Balancing seasonal and interannual availability of generation resources with electricity demand
System relevance	Dynamic system stability	Dynamic frequency control	Real-time balancing	Hour-ahead and day-ahead planning	Generation adequacy guarantee	Power system planning
Flexibility resource						
Flexible generation	Mechanic inertia; Synthetic inertia; Shedding;	Governor droop; Synthetic governor response	Ramping; Upward-/ Downward reserves	Unit commitment; Start-up; Forecasting	Unit commitment; Operation criteria; Forecasting	New/ retrofit plants; Reserve generation; Forecasting
Demand-side response	Power electronics for load shedding	Electric (water) heater; Electric vehicle charger; Variable speed electric loads	Air conditioner; Heat pump	Smart meter enabling real-time time-of-use pricing	Demand forecasting	
Network expansion	Synchronous condenser	Network protection relays	Inter-regional transmission lines; Dynamic line rating			
Electricity storage	Supercapacitor, Magnetic coil, Flywheel, Batteries	Supercapacitor, Flywheel, Batteries	Batteries, Pumped hydro, Compressed air		Pumped hydro, Compressed air	Pumped hydro, Compressed air, Power-to-Gas

Ultra-short term to short-term flexibility in the sub-second to minute timescale is driven by technical power system characteristics. It is required to stabilise the power system voltage and frequency in case of an unexpected event leading to an immediate change in electricity supply or demand and to restore the frequency to normal. It is also used to keep frequency under control in general (e.g., in the UK, statutory and operational limits are between 50±0.5 and 50±0.2 Hz respectively[18]). Short to very long-term flexibility is required to ensure the availability of sufficient generation capacity and resource to meet electricity demand on an hour-by-hour, day-by-day, or up to seasonal timescale.

In terms of flexibility resource, four key options are available:

1. Flexible generation
2. Demand-side response
3. Network expansion
4. Electricity storage

Flexible generation is the ability of power plants to deliberately adjust their output. This is the main source of flexibility today with roughly 3,000 GW of the 6,600 GW installed generation capacity worldwide[11]. Of this, largely flexible gas (29%) and hydro power plants (28%) provide the most significant shares. Ultra-short term flexibility is provided by the mechanical inertia of the synchronous generators, where their physical spinning mass resists any change in power system frequency[17]. Very- and short-term flexibility comes from the automated or manual change in power output. Longer term flexibility is ensured by the start-up of plants, improvements to operation criteria enabled through appropriate monitoring equipment, and the general availability of flexible generation capacity (e.g., new-built, retrofit, reserve). Intermittent renewable generators can contribute to power system flexibility requirements through synthetic inertia, curtailment or reserve operation, strategic location and improved output forecasting[17]. However, the vast majority of flexible generation capacity is based on fossil fuels, which are set to reduce to mitigate climate change. Therefore, other flexibility options become more important.

Demand-side response (DSR) affects the pattern and magnitude of end-use electricity consumption, i.e., reducing, increasing or rescheduling demand[19]. It has the potential to be the most cost-effective option to provide flexibility due to limited requirements for new hardware infrastructure[20]. However, there are only about 40 GW of demand-side management capacity installed globally, mostly restricted to large industrial or commercial consumers and night-time tariffs for residential consumers, and further deployment is slow[11,19]. In addition to a lack of required information and communication technology, this option also faces multiple non-technical barriers, namely the implementation of incentive structures like price signals and reluctant behavioural change from domestic consumers[19,20].

The electricity network comprises all assets connecting electricity generation to demand locations. While it is foremost a means of overcoming the geographic mismatch between the two, the aggregation of variable demand and intermittent generation smoothens overall demand and generation patterns, and expands the pool of available flexibility options, thereby reducing the need for active power system flexibility[11,19]. In addition, synchronous condensers and protection relays can make networks more robust to short-term imbalances. Some researchers therefore see network expansion with increased interconnection between regions with different weather patterns as the most cost-effective option to decarbonise power systems[21]. However, global interconnection between countries is only 177 GW and the deployment of further capacity is slow due to significant up-front investment and inter-regional coordination requirements, as well as possible resistance from local residents[11,19].

Electrical energy storage (EES) encompasses all technologies that can consume electricity and return it later. It combines the flexibility characteristics of demand-side response and flexible generation, albeit a temporal limitation given by the storage size. Most EES options can be deployed anywhere in the power network, for example at the generator or consumer site. Different technologies are suitable for different flexibility requirements, with supercapacitors and flywheels most suitable for ultra-short term, and pumped hydro or hydrogen storage best suited for very long-term flexibility. Various types of electrochemical batteries can be used for intermediate timescales. Following flexible generation and interconnection, EES is the third most widely deployed flexibility option with 153 GW of pumped hydro and around 4 GW of other technologies deployed[11,22]. High investment cost and uncertainty around future cost reduction lead to uncertainty on the commercial viability of electricity storage[23,24]. Also, the wide range of technologies with different performance characteristics coupled to the wide range of use cases with different performance requirements make optimal technology choice intransparent today[25–27].

1.3 Project Motivation

The motivation of this PhD project is to decrease uncertainty on the future cost of electricity storage and thereby increase transparency on its role in enabling low-carbon power systems. This is achieved through three main objectives:

A. Identify cost reduction trajectories for electricity storage technologies and underlying cost reduction drivers.

B. Quantify future cost of storage in specific use cases, accounting for differences in technology cost and performance and application requirements.

C. Assess the economic market value of electricity storage in specific use cases and its value in enabling low-carbon power systems.

Chapter 1 introduces the need to transform our energy system and to provide sufficient flexibility in low-carbon power systems. Chapter 2 presents an overview of available electricity storage technologies, cost projection methodologies and the existing literature on future cost and value assessments. The methods used in this thesis are presented in Chapter 3. Chapter 4 derives experience curves for electricity storage technologies and identifies future investment cost trajectories. Chapter 5 presents insights from expert interviews on future cost and performance parameters of two technologies, lithium-ion batteries and water electrolysers, highlighting underlying cost reduction drivers. Future application-specific lifetime cost that account for all relevant cost and performance parameters are quantified in Chapter 6. Chapter 7 matches these lifetime cost projections with the revenue potentials to assess profitability of electricity storage and explores the quantity needed to enable low-carbon power systems. Chapter 8 summarises contributions and concludes.

This PhD thesis makes four main contributions to the literature on the future role of electricity storage in low-carbon power systems:

a) A set of experience curves that enables the methodologically coherent projection of investment cost reduction trajectories for multiple electricity storage technologies (Chapter 4)

b) Identification of the drivers for cost reduction and performance improvement for two key technologies, lithium-ion batteries and water electrolysers (Chapter 5)

c) Quantification of future storage lifetime cost in various power system applications with a novel formula that accounts for all relevant cost and performance parameters and application requirements (Chapter 6)

d) Assessment of the economic market value of electricity storage and the quantity needed to enable low-carbon power systems (Chapter 7)

The thesis builds on the following peer-reviewed journal papers:

1. Schmidt, O., Hawkes, A., Gambhir, A., & Staffell, I. (2017). The future cost of electrical energy storage based on experience curves. Nature Energy, 2, 17110. https://doi.org/10.1038/nenergy.2017.110 (Chapter 2.3.1, 3.1, 4)

2. Schmidt, O., Gambhir, A., Staffell, I., Hawkes, A., Nelson, J., & Few, S. (2017). Future cost and performance of water electrolysis: An expert elicitation study. International Journal of Hydrogen Energy, 42(52), 30470–30492. https://doi.org/10.1016/J.IJHYDENE.2017.10.045 (Chapter 2.3.2, 3.2, 5)

3. Few, S., Schmidt, O., Offer, G. J., Brandon, N., Nelson, J., & Gambhir, A. (2018). Prospective improvements in cost and cycle life of off-grid lithium-ion battery packs: An analysis informed by expert elicitations. Energy Policy, 114, 578–590. https://doi.org/10.1016/j.enpol.2017.12.033 (Chapter 2.3.2, 3.2, 5)[*]

4. Schmidt, O., Melchior, S., Hawkes, A., & Staffell, I. (2019). Projecting the Future Levelised Cost of Electricity Storage Technologies. Joule, 3, 1–20. https://doi.org/10.1016/J.JOULE.2018.12.008 (Chapter 2.2.2, 3.3, 6)

[*] In this study, I contributed to preparation and participated in 9 of the 11 interviews. I also contributed to post-processing and analysis of the interview data. All written text and figures in the relevant chapters are based on the collected data but represent original analysis by me produced exclusively for this thesis.

The following publications were produced as part of this PhD project, but do not provide content for this thesis:

5. Schmidt, O. (2018). Levelised Cost of Storage - The Case of Gravity Storage. London: Storage Lab, Imperial Consultants & Heindl Energy. Retrieved from https://www.storage-lab.com/levelised-cost-of-storage

6. Schmidt, O. (2018). Levelised Cost of Storage for Gravitricity storage systems. London: Storage Lab, Imperial Consultants & Gravitricity.

7. Few, S., Schmidt, O., & Gambhir, A. (2019). Energy access through electricity storage: Insights from technology providers and market enablers. Energy for Sustainable Development, 48, 1–10. https://doi.org/10.1016/J.ESD.2018.09.008

8. Few, S., Schmidt, O., Gambhir, A., Stephenson, E., & DelCore, A. (2018). Energy storage trends for off-grid services in emerging markets Insights from social enterprises. Retrieved from https://shellfoundation.org/app/uploads/2018/10/Shell-Foundation_Energy-Storage-Report.pdf

9. Few, S., Schmidt, O., & Gambhir, A. (2016). Briefing Paper No. 20: Electrical energy storage for mitigating climate change. Grantham Institute - Climate Change and the Environment. Retrieved from https://www.imperial.ac.uk/media/imperial-college/grantham-institute/public/publications/briefing-papers/2526_Energy-storage_BP-20_24p_lores_4.pdf

10. Gardiner, D., Schmidt, O., Staffell, I., Heptonstall, P., & Gross, R. (n.d.). Quantifying the impact of policy on the investment case for residential electricity storage in the UK [*Submitted to Energy Policy*]

11. Varlet, T. Le, Schmidt, O., Gambhir, A., Few, S., & Staffell, I. (2019). Comparative life cycle assessment of lithium-ion battery chemistries for residential application. [*Submitted to Environmental Science and Technology*]

2. Background and Literature Review

This chapter introduces key principles, related concepts and distinct technologies for electricity storage, comparing technologies along their cost and performance parameters. Existing research on future investment and lifetime cost of electricity storage technologies as well as the respective methodologies is presented and studies analysing economic value and storage capacity requirements in low-carbon power systems are reviewed.

2.1 Electricity Storage Technologies

There are five key principles for storing electrical energy (i.e., charging and discharging electricity) with multiple concepts implemented by various technologies (Figure 2.1).

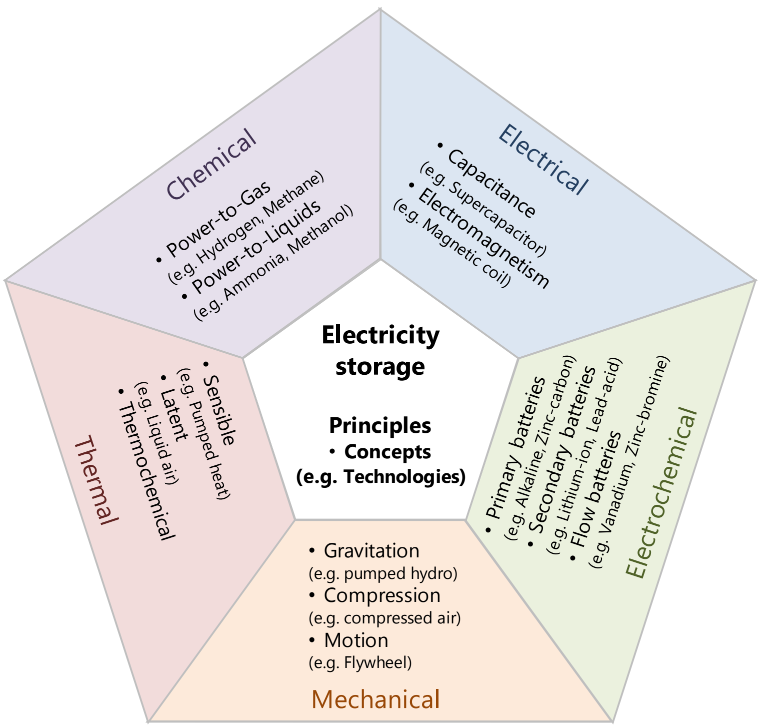


Figure 2.1 – Five key principles of electricity storage with multiple concepts implemented by various technologies. Coloured headings denote principles. Bullet points denote concepts that work based on respective principles. Examples in brackets denote distinct technologies implementing respective concepts.

The first principle relies on converting electrical into mechanical energy. This could be mechanical energy related to the execution of force on mass (i.e., potential energy) or related to the motion of mass (i.e., kinetic energy)[28]. Potential energy concepts are gravitation or compression. Kinetic energy concepts are linear or rotational motion.

Another principle relies on storing electrical energy as the electrochemical potential between two materials that could react to form a new one. The net chemical energy of forming the new material (i.e., Gibbs free energy) is balanced by the electrostatic energy between the two separated materials[28]. This is the underlying principle of battery cells, exemplified in Figure 2.2. Lithium (Li) and iodine (I_2) electrodes are separated by an electrolyte. Both materials naturally want to react to form lithium-iodine (LiI). The net chemical energy of that reaction is directly converted into electrical energy during discharge in the form of electrons that travel through the closed connector from the lithium anode (i.e., releasing electrons during discharge or Oxidation) to the iodine cathode (i.e., consuming electrons during discharge or Reduction). This enables iodine ions to move to the lithium anode through the electrolyte where lithium-iodine is formed. In contrast to primary batteries, the process is reversible for secondary batteries. The application of a higher electrical potential than the battery potential through an outside electrical energy source reverses the electron flow, reducing the cathode and oxidising the anode, which leads to the restoration of the initial electrochemical potential (i.e., charging). The difference between flow batteries and conventional primary and secondary batteries is that the active material is not the electrode itself but two types of liquid electrolyte that can be stored outside of the system[29].

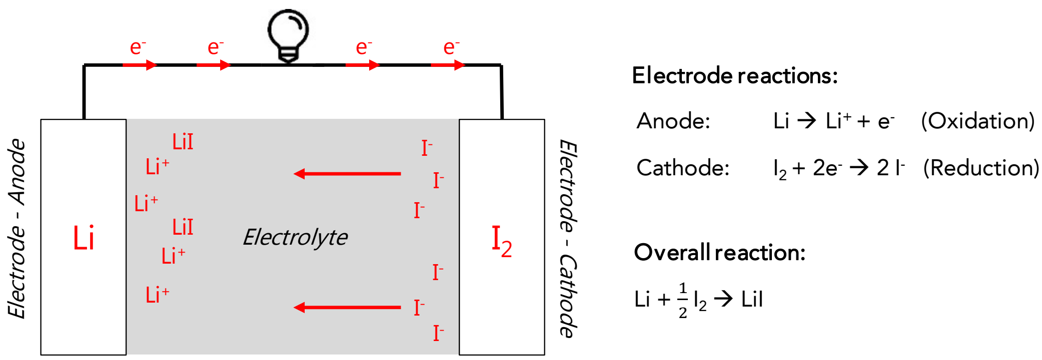


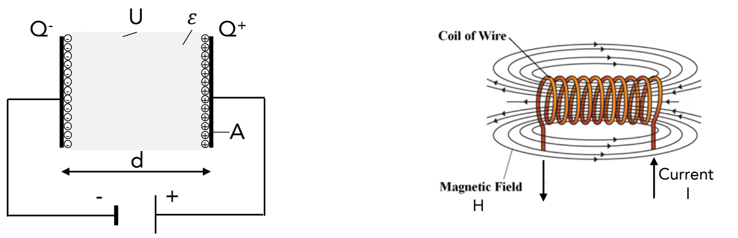
Figure 2.2 – Schematic of primary lithium-iodine battery cell during discharge[30].

The theoretical nominal electrical energy stored in an electrochemical cell (E in kWh) can be calculated as[28]

$$E = z \times F \times U \tag{1}$$

with z the number of charges per reaction (i.e., electrons), F the Faraday constant (96,500 Coulombs) and U the voltage or electrochemical potential between the active materials in Volts.

Another principle is to store electricity directly as electrical energy. This can be done through the concepts of capacitance and electromagnetism. Capacitance separates the positive and negative charges on two plates and stores the electrical energy in the electric field between them. Electromagnetism uses the magnetic field generated by an electric current flowing through a superconducting coil to keep it flowing until needed[28] (Figure 2.3).



$$E_{cap} = \frac{1}{2}\varepsilon A\frac{U^2}{d} = \frac{1}{2}CU^2 = \frac{1}{2}QU \qquad E_{Mag} = \frac{1}{2}\mu H^2 = \frac{1}{2}\mu(4\pi nI)^2$$

E – energy stored in kWh
ε – permittivity of material in F/m
A – area of capacitor plates in m²
C – Capacity of capacitor in F
U – voltage of electric field in V
Q – charge stored in C or A·s
H – intensity of magnetic field in A/m
μ – permeability of material in Vs/Am
n – # turns per unit length of coil in 1/m
I – magnitude of current in A

Figure 2.3 – Schematic of electrical energy storage through the principles of capacitance (left) and electromagnetism (right) and respective formulae to determine electrical energy stored[30,31]. Image reproduced with permission of the rights holder, Springer.

The principle of chemical energy storage relies on converting electrical energy into chemical bonds. These chemical bonds can later be converted back to electricity or used in other energy sectors, such as transport or heating, or in industry[32]. The Power-to-Gas (PtG) concept uses electricity to produce a gas such as hydrogen or methane and thereby couples the power to the gas network, accessing its distribution network and storage capacity[33]. The Power-to-Liquids (PtL) concept uses electricity to produce a liquid fuel such as any hydrocarbon or ammonia and thereby couples the power to the liquid fuel industry, accessing its distribution network and storage capacity. The production of hydrogen from electricity through water electrolysis is the key enabler of both concepts (Figure 2.4).

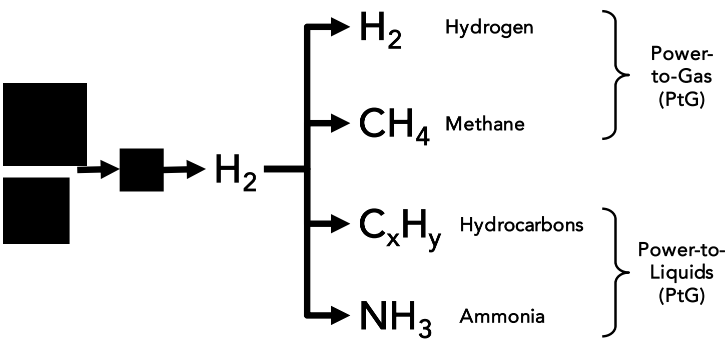


Figure 2.4 – Schematic of electricity storage through conversion into chemical energy, either as gases or liquids. Chemical energy can be used for electricity generation, transport, heating or in industry.

Thermal energy storage is the final principle to store electrical energy. Electricity is used to supply heat or cold to a thermal storage system that can be removed later and used as heat directly or re-converted to electricity. There are three concepts to store thermal energy: sensible heat, latent heat or thermo-chemical reactions[28]. Sensible heat is the thermal energy associated with heating or cooling of a material without changing its physical state. Latent heat is the energy associated with the phase change of a material between the solid, liquid and gaseous state. Thermo-chemical energy is associated with a reversible chemical reaction or sorption process that releases or consumes large amounts of thermal energy (Figure 2.5)[28,34].

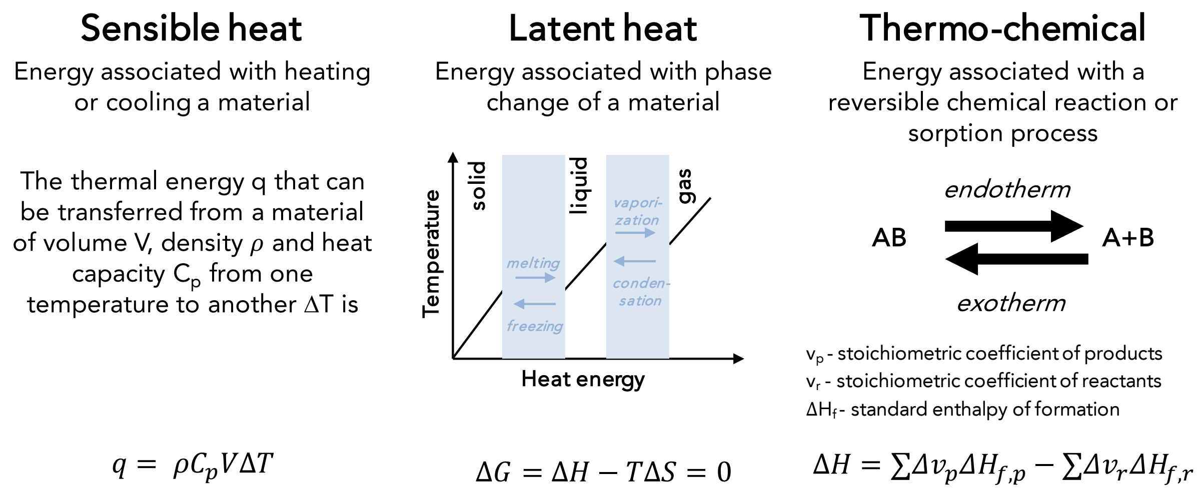


Figure 2.5 – Three concepts of thermal energy storage[28,34].

An assessment of the various electricity storage technologies can be conducted by comparing their different cost and performance parameters (Table 2.1).

Table 2.1 – Performance and cost parameters for assessment of electricity storage technologies.

Performance			Cost		
Nominal power capacity	Maximum amount of power generated / consumed	kW	Investment cost	Cost to construct technology overnight (total vs specific)	\$/kWh \$/kW
Power density - gravimetric	Maximum power relative to system mass	kW/kg	Construction time	Actual duration of technology construction	years
Power density - volumetric	Maximum power relative to system volume	kW/m^3	Replacement cost	Cost to replace technology components	\$/kWh \$/kW
Discharge duration	Duration to discharge energy at maximum power	hours	Replacement interval	Time interval for technology component replacement	years, cycles
Nominal energy capacity	Maximum amount of energy stored	kWh	O&M cost	Cost of operating and maintaining operability of technology	\$/MWh$_{el}$ \$/kW
Energy density - gravimetric	Maximum energy relative to system mass	kWh/kg	Charging cost	Cost for energy to charge technology with energy	\$/MWh$_{el}$
Energy density - volumetric	Maximum energy relative to system volume	kWh/m^3	Disposal cost/ value	Cost or value to dispose of the technology at its end-of-life	\$/kWh

Depth-of-discharge	Share of energy capacity usable without severely damaging the store	%	**Discount rate**	Rate to discount future cost or revenues	%
Usable energy capacity	Usable amount of energy stored	kWh			
State-of-charge	Fraction of energy stored at any moment in time	%			
Cycle life	Number of full charge-discharge cycles before degradation threshold	#			
Calendar life	Number of years before degradation threshold	years			
Degradation	Loss in usable energy capacity	%/year			
Round-trip efficiency	Proportion of energy discharged over energy required to charge	%			
Self-discharge	Unintended discharge of energy while at idle state	%/day			
Response time	Time between idle and maximum power state	seconds			

Note: Total investment cost reflect the cost for the complete storage system in $/kW or $/kWh. Specific investment cost reflect the cost of energy- ($/kWh) or power-components ($/kW) and must be considered in combination to assess total cost.

2.1.1 Pumped Hydro Energy Storage (PHES)

A pumped storage scheme relies on the concept of potential energy difference through gravitation and uses the differential in height between two reservoirs to store energy. During periods when electricity demand is low, electricity is purchased from the grid and used to pump water from the lower reservoir to the higher. During periods of high demand this water is released through the pumps now acting as turbines to generate electricity. Systems can operate using reversible pump-turbines or separate turbines and pumps. Other variations of this technology reflect the type of turbines (e.g., Francis, Kaplan, Pelton), and whether they operate at fixed or variable rotational speeds. Pumped hydro storage can be realised through dedicated pumped hydro plants with two reservoirs, or a pump-back functionality in traditional hydropower plants[35–37].

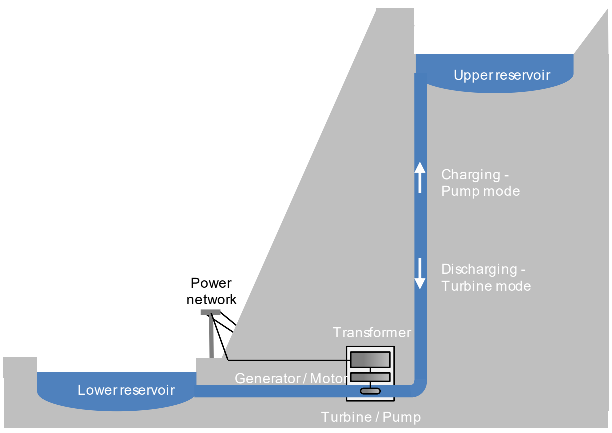


Figure 2.6 – Schematic of pumped hydro energy storage plant, inspired by Roger C. Viadero, Jr., Ph.D., CSE [38].

The nominal electrical energy stored in a pumped hydro energy storage plant (E in kWh) can be calculated as[28]

$$E = V \times \rho \times g \times H \times \eta \quad (2)$$

with H the head height in metres (m), V the reservoir volume in m^3, ρ the fluid density in kg/m^3, g the gravity acceleration in m/s^2 and η the component efficiency in %.

Key advantages of PHES is technical maturity, the large power and energy capacities up to multiple GW and GWh that can be realised and the round-trip efficiency of around 80% and response time of above 10 seconds, which are sufficiently good for most power system applications. Disadvantages relate to the low energy density of this technology at only 1.25 kWh/m^3, geographical constraints and possible environmental impacts (Table 2.3)[35–37].

2.1.2 Compressed air energy storage (CAES)

Compressed air energy storage plants rely on the concept of potential energy difference due to pressure by compressing and storing air, either using geological underground voids or purpose made vessels. When electricity is available, the air is compressed. When electricity is needed, the air is expanded, driving a turbine. Since compressed air cools down during expansion, diabatic CAES plants combust natural gas to heat it and generate additional electricity. A diabatic CAES plant thereby produces three times the electricity than a gas-fired power station with the same gas input[39]. Technology variations are adiabatic and isothermal CAES plants. Adiabatic plants store the thermal energy generated during compression to heat the gas during expansion, thereby eliminating the requirement for fuel[35]. Isothermal CAES plants compress and expand the gas at constant temperature, for example through the injection of a liquid[40].

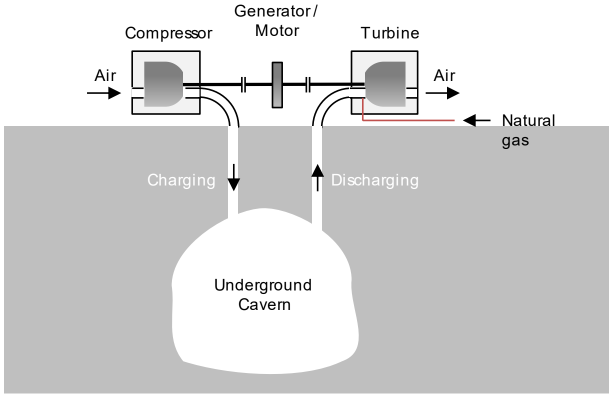


Figure 2.7 – Schematic of compressed air energy storage plant, inspired by Arup[35].

The nominal electrical energy stored in a compressed air energy storage plant (E in kWh) can be calculated as[28]

$$E = p_2 V_2 \ln\left(\frac{p_1}{p_2}\right) + (p_2 - p_1) V_2 \eta \tag{3}$$

with P the pressure in N/m^2 (N = kg m/s^2), V the volume in m^3, η the component efficiency in % and subscript 1 denoting ambient state and 2 compressed state of the gas.

Key advantages of CAES plants are also technological maturity and the large power and energy capacities at multiple hundred MW and GWhs that can be realised. In addition, the technology is more flexible regarding nominal power and energy capacity design. However, underground CAES plants are also geographically limited to the availability of caverns and by low energy density of only around 4 kWh/m^3. Diabatic CAES plants have low round-trip efficiencies of below 50% and require fuel for discharge (Table 2.3)[35–37].

2.1.3 Flywheel energy storage

Flywheel energy storage makes use of the mechanical inertia contained within a rotating mass and thereby relies on the concept of kinetic energy. Electricity is used in an electric motor to spin the flywheel (i.e., charging) and the process is reversed with the motor that accelerated the flywheel acting as a generator extracting energy from the rotating flywheel (i.e., discharging). To reduce friction losses, it is common to place flywheels inside a vacuum with the flywheel magnetically levitated. Variations of the technology refer to the material used as the spinning mass (e.g., steel, aluminium, carbon fibre) and whether it rotates at high (<10,000 rpm) or low speed (>10,000 rpm)[35–37].

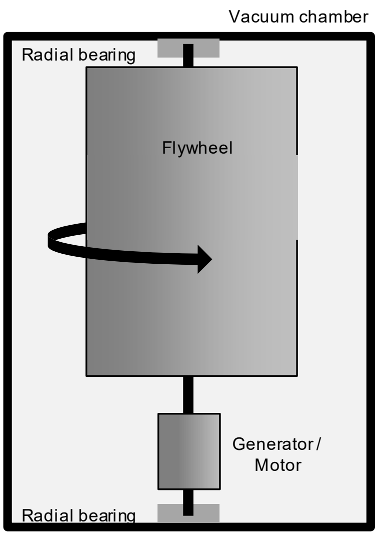


Figure 2.8 – Schematic of a flywheel for stationary energy storage, inspired by Beacon Power[41].

The nominal electrical energy stored in a flywheel (E in kWh) can be calculated as[28]

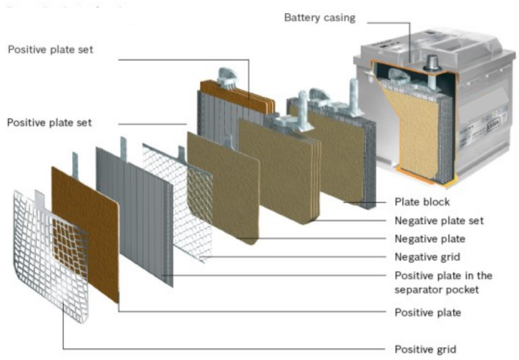
$$E = \frac{1}{2} \times I \times \omega^2 = m \times \frac{\sigma_{max}}{\rho} \times K_m \quad (4)$$

with I the moment of inertia in kg m^2, ω the angular velocity in 1/s, m the mass in kg, σ_{max} the maximum stress in N/m^2, ρ material density in kg/m^3 and K_m the shape factor of the rotating mass.

Flywheels respond rapidly below 1 second and sustain more than 100,000 charge-discharge cycles. They have high power density of about 3,000 kW/m^3 and round-trip efficiency of about 90% and are modular in design. These advantages are contrasted by a relatively low energy density of only 50 kWh/m^3 and high self-discharge of up to 20% capacity per idle hour. Engineering is complex to minimise losses and contain the spinning mass in case of a failure (Table 2.3)[35–37].

2.1.4 Lead-acid battery storage

Lead-acid battery cells have an anode of elemental lead (Pb) in sponge-like form and a cathode of powdered lead dioxide (PbO_2) in a grid. During discharge, the aqueous sulphuric acid electrolyte (HSO_4^-) is converted to water (H_2O), while each electrode turns to lead sulphate ($PbSO_4$). When recharging, lead sulphate is converted back to sulphuric acid, leaving a layer of lead dioxide on the cathode and pure lead on the anode[28]. These batteries are widespread as engine starters, back-up power or for power supply in remote locations. Variations of the technology refer to the electrolyte, which can be a liquid mixture of water and sulphuric acid (i.e., flooded) or either a gel or special acid-saturated fiberglass mat (i.e., sealed). While some systems are designed for shallow depth-of-discharge operation, others tolerate deep discharge cycles.



Half-cell reactions:

Anode: $Pb + HSO_4^- \rightarrow PbSO_4 + H^+ + 2e^-$

Cathode: $PbO_2 + 3H^+ + HSO_4^- + 2e^- \rightarrow PbSO_4 + H_2O$

Overall reaction:

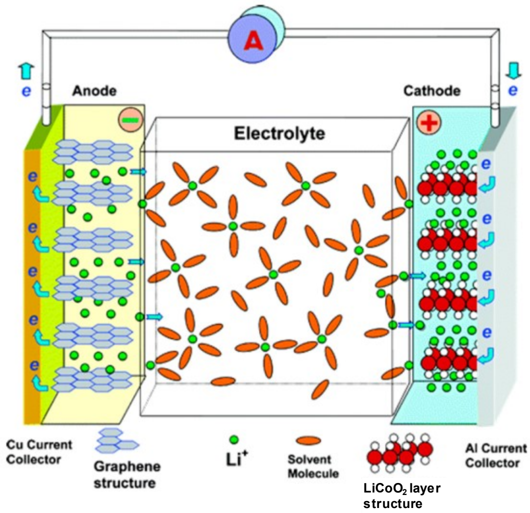
$Pb + PbO_2 + 2H_2SO_4 \rightarrow 2PbSO_4 + 2H_2O$

Figure 2.9 – Schematic of lead-acid battery module[42].

Lead-acid batteries have the advantage of high technological maturity, high efficiency of around 85% and low self-discharge, and fast response times below 1 second. However, they also have low energy density compared to other electrochemical storage technologies of about 70 kWh/m^3, are sensitive to deep discharge cycles and contain toxic materials, albeit established recycling processes in developed countries (Table 2.3)[35–37].

2.1.5 Lithium-ion battery

In a lithium-ion battery, lithium ions (Li^+) move from anode to cathode when discharging and back when charging. The cathode is made of a lithium metal oxide (e.g., $LiCoO_2$) and the anode is made of graphitic carbon (C_6) with lithium intercalated between carbon layers (LiC_6). The electrolyte is normally a non-aqueous organic liquid containing dissolved lithium salts, such as lithium hexafluorophosphate ($LiPF_6$) in ethylene carbonate. Variations include the cathode chemistry (e.g., LMO: lithium manganese oxide, NMC: nickel manganese cobalt, NCA: nickel cobalt aluminium, LFP: lithium iron phosphate), anode chemistry (e.g., pure Graphite, Graphite-silicon mix, lithium titanite oxide), electrode structure (e.g., layered, olivine, spinel) and the form factor (e.g., cylindrical, prismatic, laminate/ pouch)[43,44]. These batteries are commonly used in consumer electronics and electric vehicles.



Half-reactions are:

Anode: $LiC_6 \rightarrow C_6 + Li^+ + e^-$

Cathode: $CoO_2 + Li^+ + e^- \rightarrow LiCoO_2$

Overall reaction:

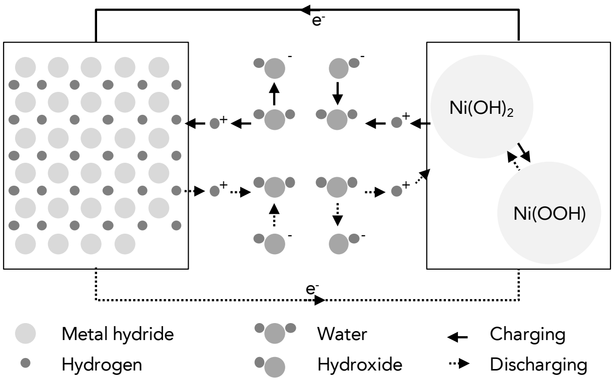
$LiC_6 + CoO_2 \rightarrow C_6 + LiCoO_2$

Figure 2.10 – Schematic of lithium-ion battery cell with lithium cobalt oxide ($LiCoO_2$) cathode and pure graphite anode[44]. Image reproduced with an Attribution-NonCommercial-NoDerivatives 4.0 International (CC BY-NC-ND 4.0) license.

Lithium-ion batteries have become popular due to their relatively high energy and power densities at around 6000 kW/m^3 and 300 kWh/m^3 respectively, modularity, high efficiency at around 85% and fast response below 1 second. Degradation affecting cycle life, safety risks through thermal runaway and potential resource scarcity are frequently cited disadvantages (Table 2.3)[35–37].

2.1.6 Nickel-metal hydride battery

A nickel-metal hydride battery consists of an hydrogen-absorbing intermetallic alloy (anode), nickel hydroxide (cathode) and 30% by weight potassium hydroxide in water as electrolyte[45]. During charging, nickel hydroxide is oxidised to nickel oxyhydroxide, releasing hydrogen ions, which react with the metal in the intermetallic electrode to form metal hydride[46]. During discharge, these hydrogen ions are released again, and the process is reversed. The intermetallic alloys can be grouped into two classes. So-called AB_5 alloys combine rare earth elements like lanthanum, cerium, neodymium with Nickel[45]. AB_2 alloys combine titanium, vanadium, or zirconium with modified zirconium or nickel.



Half-reactions are:

Anode: $MH + OH^- \rightarrow M + H_2O + e^-$

Cathode: $NiOOH + H_2O + e^- \rightarrow Ni(OH)_2 + OH^-$

Overall reaction:

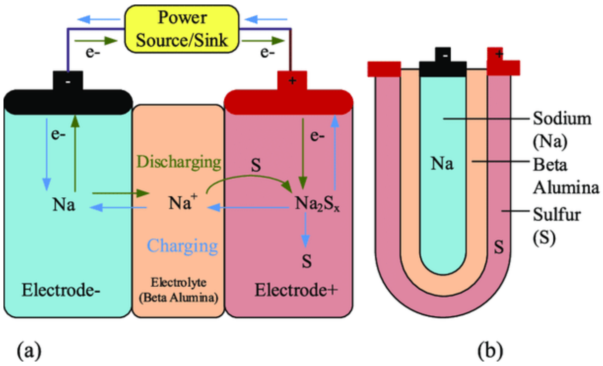
$NiOOH + MH \rightarrow Ni(OH)_2 + M$

Figure 2.11 – Schematic of nickel-metal hydride battery cell. Image inspired by Duraman et al.[45].

Nickel-metal hydride batteries have high energy and power densities of around 170 kWh/m^3 and 300 kW/m^3 respectively. A key advantage is high electrolyte conductivity, which allows for high power applications such as acceleration of hybrid vehicles. Key disadvantages are self-discharge up to 10% per day and high cost due to the high nickel content[47].

2.1.7 Sodium-sulphur battery

A sodium-sulphur battery is a molten state battery constructed from molten sodium (Na) and sulphur (S). The sulphur is absorbed in a carbon sponge. The battery casing is the cathode while the molten sodium core is the anode. The battery operates at high temperatures of between 300-350°C. During charging, sodium ions are transported through the beta-aluminium solid electrolyte to the sulphur reservoir. Discharge is the reverse of this process. Once running, the heat produced by charging and discharging cycles is sufficient to maintain operating temperatures[35]. Sodium-nickel chloride is an alternative high-temperature battery based on sodium.



Electrode reactions:

Anode: $2Na \rightarrow 2Na^+ + 2e^-$

Cathode: $xS + 2e^- \longrightarrow S_x^{2-}$

Overall reaction:

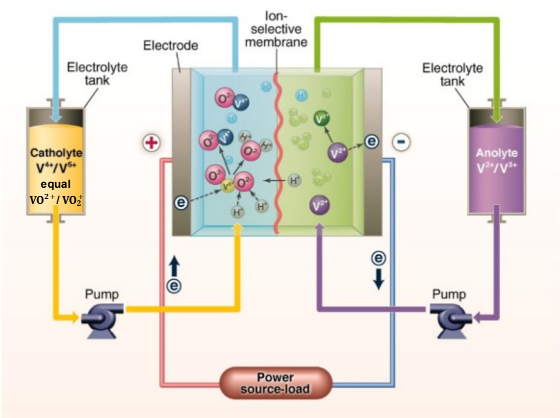
$Na_2 + S_x \rightarrow Na_2S_x$

Figure 2.12 – Schematic of sodium-sulphur battery cell[48]: (a) during discharging and charging, (b) tubular design battery. Image reproduced with permission of the rights holder, Elsevier.

Advantages of high energy density at around 200 kWh/m^3, inexpensive and non-toxic materials and fast response below 1 second, are countered by the thermal energy required to maintain the high temperature of around 300°C in idle state, relatively low discharge rates, and the high reactivity of sodium with water (Table 2.3)[35–37].

2.1.8 Vanadium redox-flow battery

Flow batteries use two liquid electrolytes as energy carriers (i.e., active materials), which are separated with an ion-selective membrane. Electrodes are carbon based. This design allows the dissociation of power and energy as the electrolyte is stored in separate tanks and pumped into the power cell when required. Storage capacity is increased with larger tanks. The most common electrolyte is a vanadium redox couple (anolyte: V^{2+}/V^{3+}; catholyte: VO^{2+}/VO_2^{+}), prepared by dissolving vanadium pentoxide (V_2O_5) in sulphuric acid (H_2SO_4). Alternative chemistries are zinc-bromine, polysulfide-bromine and iron-chromium[36,37].



Electrode reactions:

Anode: $V^{2+} \rightarrow V^{3+} + e^-$

Cathode: $VO_2^+ + 2H^+ + e^- \rightarrow VO^{2+} + H_2O$

Overall reaction:

$V^{2+} + VO^{+2} + 2H^+ \rightarrow VO^{2+} + V^{3+} + H_2O$

Figure 2.13 – Schematic of vanadium redox-flow system[49]. Image reproduced with permission of the rights holder, PNNL.

The key advantage of flow batteries is the independent sizing of energy and power capacity, as well as a relatively long cycle life of more than 8,000, full depth-of-discharge and scalability of the technology. This is contrasted by relatively low energy density of only about 25 kWh/m^3 compared to other battery types, an immature industry and higher system complexity (e.g., pumps) (Table 2.3)[35–37].

2.1.9 Supercapacitors

Supercapacitors or electric double-layer capacitors utilise an electrochemical double-layer of charge to store energy. As voltage is applied, charge accumulates on the electrode surfaces. Ions in the electrolyte solution diffuse across the separator into the pores of the electrode of opposite charge. However, the electrodes are engineered to prevent the recombination of the ions. Thus, a double-layer of charge is produced at each electrode (Figure 2.14)[37]. Alternative supercapacitor types are pseudocapacitors and hybrid capacitors. Pseudocapacitors feature fast redox reactions at the electrode surface, which means there is not only capacitive, but also electrochemical energy storage. Hybrid capacitors combine electric double-layer or pseudocapacitor with battery electrodes[19].

The nominal electrical energy stored in a supercapacitor (E in kWh) can be calculated as[28]

$$E = \frac{1}{2}\varepsilon A\frac{U^2}{d} = \frac{1}{2}CU^2 = \frac{1}{2}QU \quad (5)$$

With ε the permittivity of the material in Farad/m, A the area of capacitor plates in m^2, C the capacity in Farad, U the voltage of the electric field in Volts and Q the charge stored in Coulomb.

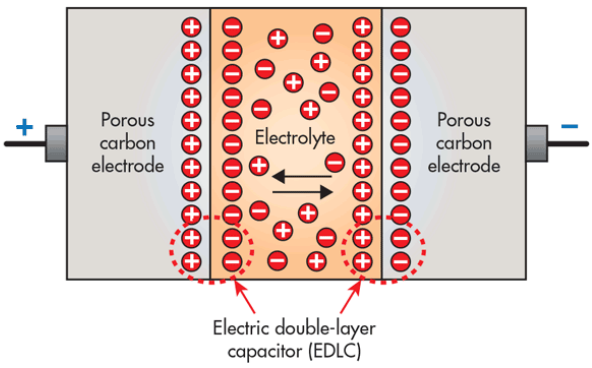


Figure 2.14 – Schematic of an electric double-layer capacitor (i.e., supercapacitor)[50]. Image reproduced with an Attribution 3.0 Unported (CC BY 3.0) license.

The key advantages of are high power density at around 100,000 kW/m^3, round-trip efficiency of more than 90% and cycle life of multiple hundred thousand cycles, and nearly instantaneous response. Disadvantages are low energy density of only 20 kWh/m^3, limited discharge duration of usually only a few seconds or minutes and potential voltage changes during discharge (Table 2.3)[35–37].

2.1.10 Power-to-Gas (Hydrogen)

The enabling technology for storing electricity in chemical bonds, such as the Power-to-Gas concept, is the conversion of electricity into hydrogen. Hydrogen can be produced through electrolysis of water by imposing a voltage between two electrodes, such that water exceeds its thermodynamic stability range. As a result, water splits into oxygen and positively charged hydrogen ions. These migrate through the membrane to the anode to form hydrogen gas.

There are three water electrolysis technologies: Alkaline Electrolysis Cells (AEC), Proton Exchange Membrane Electrolysis Cells (PEMEC) and Solid Oxide Electrolysis Cells (SOEC). Figure 2.15 depicts the technology set-up and Table 2.2 summarises component materials and performance and cost parameters.

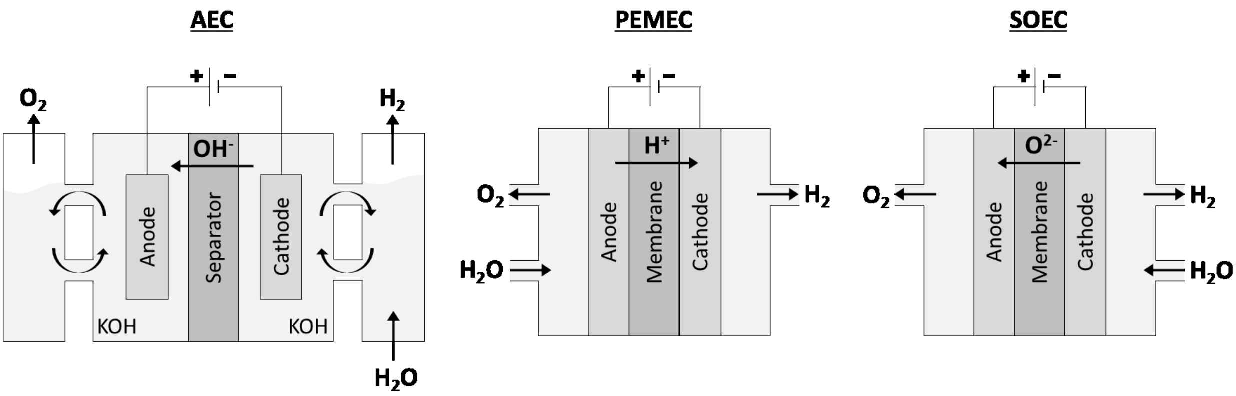


Figure 2.15 – Conceptual set-up of three electrolysis cell technologies[51].

AEC is the incumbent water electrolysis technology and widely used for large-scale industrial applications since 1920[52]. AEC systems are readily available, durable and exhibit relatively low investment cost due to the avoidance of noble metals and relatively mature stack components[53–55]. However, low current density and operating pressure negatively impact system size and hydrogen production costs. Also, dynamic operation (frequent start-ups and varying power input) is limited and can negatively affect system efficiency and gas purity[54]. Therefore, development is focussed on increasing current density and operating pressure, as well as system design for dynamic operation[53,55], to allow operation with intermittent renewable sources, for example. Previous analyses suggest that future cost reductions are most likely driven by economies of scale[51,54,56].

PEMEC systems are based on the solid polymer electrolyte concept for water electrolysis that was first introduced in the 1960s by General Electric to overcome the drawbacks of AECs[52]. The technology is therefore less mature than AEC and mostly used for small-scale applications[54]. Key advantages are high power density and cell efficiency, provision of highly compressed and pure hydrogen, and flexible operation[54,55,57]. Disadvantages include expensive platinum catalyst and fluorinated membrane materials, high system complexity due to high pressure operation and water purity requirements, and shorter lifetime than AEC at present. Current development efforts are therefore targeted at reducing system complexity to enable system scale-up and reducing investment cost through less expensive materials and more sophisticated stack manufacturing processes[51,54,55].

SOEC is the least developed electrolysis technology. It is not yet widely commercialised, but systems have been developed and demonstrated in laboratory scale[52] and individual companies are currently aiming to bring this technology to market[58]. SOECs use solid ion-conducting ceramics as electrolyte, enabling operation at significantly higher temperatures. Potential advantages include high electrical efficiency, low material cost and the options to operate in reverse mode as a fuel cell or in co-electrolysis mode producing syngas ($CO+H_2$) from water steam (H_2O) and carbon dioxide (CO_2)[54,59]. A key challenge is severe material degradation because of the high operating temperatures. Thus, current research is focussed on stabilising existing component materials, developing new materials and lowering the operation temperature to 500-700°C to enable the commercialisation of this technology[54,60].

Table 2.2 – Main materials and performance characteristics of AEC, PEMEC and SOEC systems.

	AEC	PEMEC	SOEC*
Electrolyte	Aq. potassium hydroxide (20-40 wt.% KOH)[51,53,54]	Polymer membrane (e.g., Nafion)[54,55]	Yttria stabilised Zirconia (YSZ)[59,60]
Cathode	Ni, Ni-Mo alloys[51,53,54]	Pt, Pt-Pd[55]	Ni/YSZ[59,60]
Anode	Ni, Ni-Co alloys[51,53,54]	RuO_2, IrO_2[55]	LSM**/YSZ[59,60]
Current density (A/cm^2)	0.2 – 0.4[55]	0.6 – 2.0[55]	0.3 – 2.0[51,60]
Cell voltage (V)	1.8 – 2.4[55]	1.8 – 2.2[55]	0.7 – 1.5[60]
Voltage efficiency (%$_{HHV}$)	62 – 82[55]	67 – 82[55]	<110[54]
Cell area (m^2)	<4[54]	<0.3[54]	<0.01[54]
Operating Temperature (°C)	60 – 80[55]	50 – 80[55]	650 – 1000[59,60]
Operating Pressure (bar)	<30[54]	<200[54]	<25[54]
Production Rate*** (m$^3_{H2}$/h)	<760[54]	<40[54]	<40[54]
Stack energy*** (kWh$_{el}$/m$^3_{H2}$)	4.2 – 5.9[55]	4.2 – 5.5[55]	>3.2[54]
System energy*** (kWh$_{el}$/m$^3_{H2}$)	4.5 – 6.6[56]	4.2 – 6.6[56]	>3.7 (>4.7)$_{kWh\_energy}$
Gas purity (%)	>99.5[53]	99.99[54]	99.9
Lower dynamic range**** (%)	10 - 40[54,55]	0 - 10[55]	>30
System Response	Seconds[54]	Milliseconds[54]	Seconds

Cold-start time (min.)	<60[56]	<20[56]	<60
Stack Lifetime (h)	60,000-90,000[56]	20,000-60,000[56]	<10,000
Maturity	Mature	Commercial	Demonstration
Investment Cost ($US\$_{2018}/kW_{el}$)	1,400 – 1,700[56]	2,600 – 3,200[56]	>2,800[56]

*Unreferenced data derived during expert elicitations
**Perovskite-type lanthanum strontium manganese ($La_{0.8}Sr_{0.2}MnO_3$)
***Refers to norm cubic metre of hydrogen (at standard conditions) and respective electrical energy consumption (kWh_{el}) if applicable
****Minimum operable hydrogen production rate relative to maximum specified production rate

The requirements for electrolysers to operate with intermittent power sources are: fast response of system components enabling dynamic operation, operation at lower dynamic range (Table 2.2) without negative impacts on gas purity, and short cold-start times or energy efficient stand-by operation[57]. While PEMEC electrolysers appear to be best-suited to meet these requirements with lifetime potentially benefitting from intermittent operation[61], AEC and SOEC are also suitable and their system components can be successfully engineered to operate with an intermittent power supply[56,62].

Overall, a complete hydrogen storage system for electricity storage is composed of an electrolyser, storage tank or cavern, and fuel cell or gas turbine for re-electrification. Key advantages are fully independent power and energy capacity sizing, potential access to gas infrastructure and storage capacity, and high gravimetric energy density of up to 10 kWh/kg. These advantages are contrasted by the low volumetric energy density of around 0.1 kWh/m^3 when unpressurised, low round-trip efficiency around 40%, because of losses in the electrolysis and re-electrification stage, and the lack of a dedicated hydrogen infrastructure.

Hydrogen is typically stored as pressurised gas either in geological formations (i.e., underground caverns) or in stainless steel tanks[63]. The investment cost in US$/kWh of electricity storage capacity depend on which of these technologies is used and the conversion efficiency of the fuel cell that reconverts hydrogen to electricity. Assuming a fuel cell efficiency of 60% and investment cost for 28,000 kg nominal hydrogen storage capacity of US$ 7.8 million for geological storage and US$ 30.7 million for steel tanks (both including compressor subsystems) returns specific energy investment cost of 11.5 US$/kWh and 45.5 US$/kWh respectively[63].

The cost and performance parameters of hydrogen-based energy storage systems are shown in Table 2.3[35–37].

Table 2.3 – Technology input parameters for 2015. Table shows cost and performance parameters of the nine most widely deployed electricity storage technologies[64]. Parameters are based on a review of studies by research institutes, international organisations, industry and academia (bottom row: *Sources*). They reflect the mean of the median upper and lower range values of the reviewed studies. Values in brackets show standard deviation of mean based on median upper and lower range values.

			Pumped hydro	Compressed air	Flywheel	Lithium-ion	Sodium-sulphur	Lead-acid	Vanadium redox-flow	Hydrogen	Supercapacitor
Power density	kW/m^3	p	1 (50%)	1.25 (60%)	3,000 (67%)	5,750 (74%)	160 (13%)	205 (95%)	1 (99%)	0.01 (98%)	100,000 (0%)
Energy density	kWh/m^3	e	1.25 (60%)	4 (50%)	50 (60%)	325 (54%)	225 (33%)	70 (29%)	26 (37%)	0.06 (0%)	20 (50%)
Nominal power	MW	$Cap_{nom,P}$	2,550 (96%)	650 (54%)	10 (99%)	10 (90%)	17 (99%)	20 (99%)	25 (99%)	500 (99%)	0.15 (99%)
Nominal energy	MWh	$Cap_{nom,E}$	4,250 (88%)	1,720 (66%)	2.5 (99%)	5 (99%)	123 (99%)	20 (99%)	31 (94%)	84,000 (94%)	0.0005 (0%)
Discharge duration	hours	d	8 (50%)	16 (88%)	0.55 (82%)	4.25 (88%)	7 (14%)	5.25 (90%)	5.5 (82%)	86 (95%)	0.03 (67%)
Depth-of-discharge	%	DoD	100% (0%)	100% (0%)	100% (0%)	85% (6%)	100% (0%)	55% (45%)	100% (0%)	100% (0%)	100% (0%)
Round-trip efficiency	%	η_{RT}	78% (9%)	44% (16%)	88% (3%)	86% (7%)	81% (6%)	84% (0%)	73% (9%)	40% (13%)	91% (6%)
Self-discharge	%/day	$\eta_{self,idle}$	0%	0%	480%	0%	20%	0%	0%	1%	30%
Lifetime (100% DoD)	cycles	Cyc_{life}	33250 (43%)	16250 (20%)	143402 (30%)	3250 (38%)	4098 (29%)	1225 (35%)	8272 (13%)	20000 (0%)	300000 (67%)
Shelf life	years	T_{shelf}	55 (9%)	30 (33%)	18 (14%)	13 (38%)	14 (20%)	10 (50%)	13 (20%)	18 (14%)	14 (33%)
Response time	seconds		>10	>10	<10	<10	<10	<10	<10	<10	<10
Time degradation	%/year	T_{deg}	0.4%	0.7%	1.3%	1.7%	1.6%	2.2%	1.7%	1.3%	1.6%
Cycle degradation	%/cycle	Cyc_{deg}	0.0007%	0.0014%	0.0002%	0.0069%	0.0054%	0.0182%	0.0027%	0.0011%	0.0001%
Investment cost - Power	$/kW	C_P	1129 (45%)	871 (35%)	641 (17%)	678 (17%)	657 (27%)	675 (23%)	829 (21%)	5417 (48%)	296 (31%)
Investment cost - Energy	$/kWh	C_E	80 (63%)	39 (58%)	5399 (67%)	802 (24%)	738 (12%)	471 (38%)	760 (17%)	31 (60%)	13560 (19%)
Operation cost - Power	$\$/kW_{year}$	$C_{P\text{-}OM}$	8 (26%)	4 (23%)	7 (8%)	10 (35%)	11 (50%)	8 (31%)	12 (52%)	46 (30%)	0 (0%)
Operation cost - Energy	$/MWh	$C_{E\text{-}OM}$	1 (60%)	4 (60%)	2 (60%)	3 (60%)	3 (60%)	1 (60%)	1 (60%)	0 (60%)	0 (60%)
Replacement cost	$/kW	$C_{P\text{-}r}$	116 (5%)	93 (5%)	199 (44%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	1637 (48%)	0 (0%)
Replacement interval	cycles	Cyc_r	7300	1460	22500	3250	4098	1225	8272	6388	69320
End-of-life cost	%	F_{EOL}	0%	0%	0%	0%	0%	0%	0%	0%	0%
Discount rate	%	DR	8%	8%	8%	8%	8%	8%	8%	8%	8%
Construction time	years	T_c	3	2	1	1	1	1	1	1	1
Sources			36,65–70	36,65–69,71,72	36,65–69,73	36,67–69,74,75	36,65,67–69,74,75	36,65–69,76,77	36,65,67–69,74	36,63,67–69,78–81	36,66–69

Note: Cycles refers to full equivalent charge-discharge cycles. Investment and operation cost reflect specific cost for energy and power components.

Electricity storage technologies vary in suitability to application requirements (Figure 2.16). The reason are the different cost and performance parameters, which are ultimately defined by the underlying energy storage principle. Direct storage as electrical energy (capacitors, coils) means the energy can be discharged rapidly and frequently due to high cycle life of the technologies. However, storing large amounts of energy is challenging because of high energy capacity cost. In contrast, chemical energy storage (power-to-gas) is suitable for long discharge durations and large energy capacities due to low cost for additional energy capacity. The same is true for mechanical energy storage technologies (pumped hydro, compressed air), although to a lesser extent. Better cycle life and round-trip efficiency, and lower power capacity cost make the technology suitable for more frequent operation throughout the year. Flywheels are an extreme example for that. Electrochemical battery technologies (lithium ion, sodium sulphur, lead acid, redox flow) are in between electric and chemical / mechanical technologies. That is because their power and energy capacity cost are more balanced, making them suitable for applications that require a couple of hours discharge duration. Heat storage is of similar size in terms of energy capacity, but suitable for longer discharge durations.

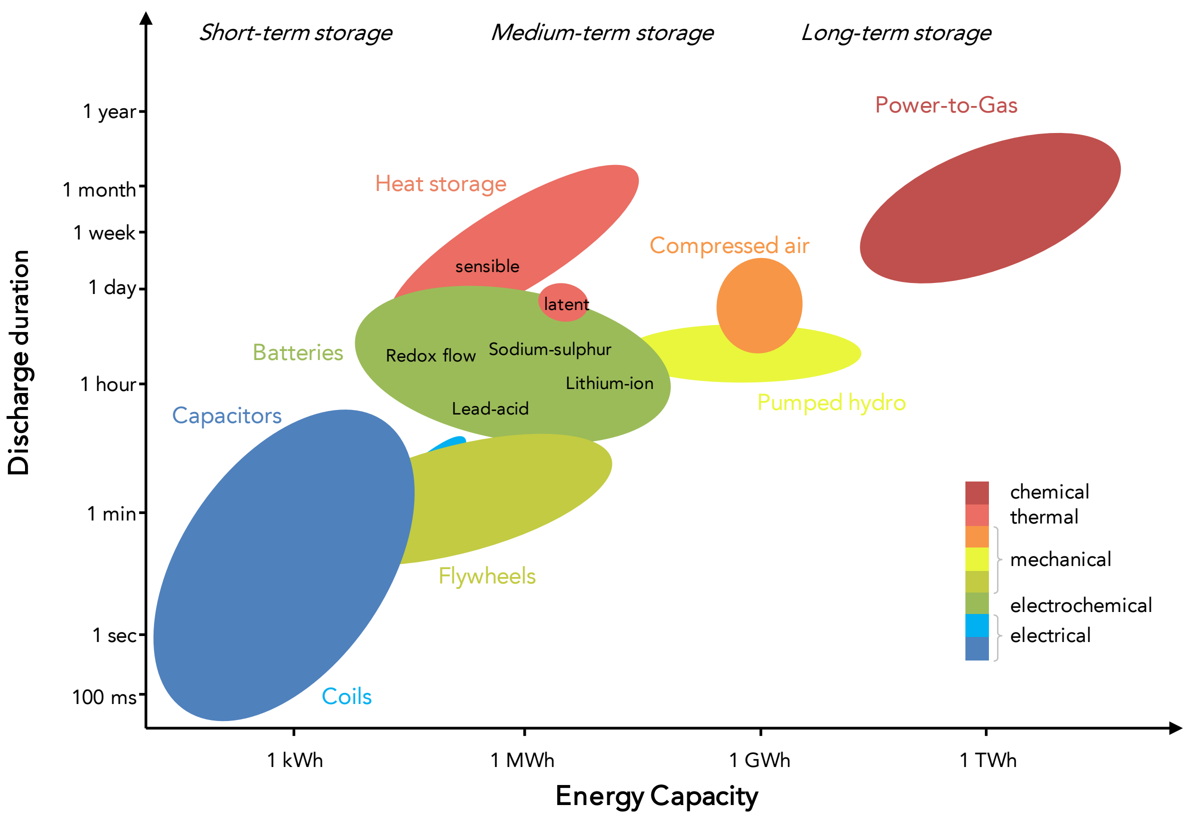


Figure 2.16 – Suitability of various electricity storage technologies of the five energy storage principles to the application requirements discharge duration and energy capacity. Adapted from Sterner et al.[82].

In terms of installed capacity, pumped hydro is by far the most widely deployed electricity storage technology with more than 170 GW operational in 2018[64] (Figure 2.17). This capacity has grown in parallel with the deployment of nuclear power stations during the second half of the 20th century, mostly to shift electricity supply during the night at low demand to peak demand periods during the day[83]. The need for power transformation to mitigate climate change renews the interest in stationary electricity storage because of the increase in renewable, and potentially nuclear, generation capacity (Chapter 1.2). As a result, more than 30 GW of pumped hydro were commissioned globally in the last ten years with another 50 GW projected until 2025[84].

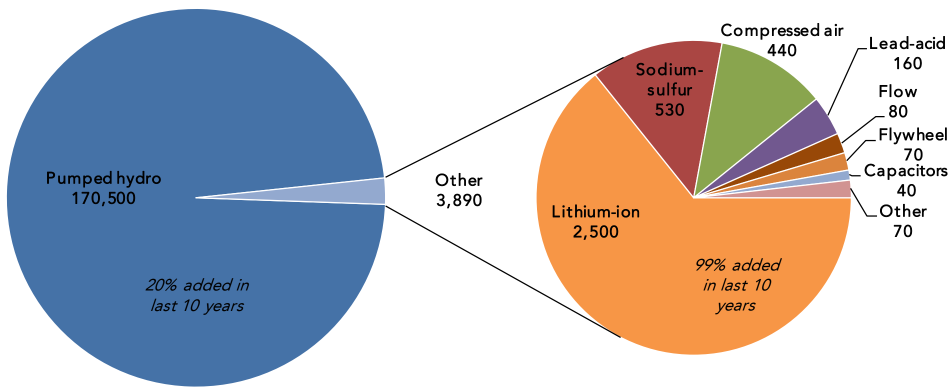


Figure 2.17 – Global installed electricity storage capacity in GW in 2018 based on data from the US Department of Energy global database[64,85,86].

At the same time, the distributed character of renewable generation technologies paired with falling cost for batteries leads to an increase in the deployment of these technologies. 99% of the 2.5 GW of stationary lithium-ion battery systems were deployed in the last 10 years. In 2017, nearly half of that was at the customer site in so-called behind-the-meter applications[11].

However, despite the likely need for more electricity storage capacity, ongoing deployment and falling cost, the future role of electricity storage in the power system is still perceived as highly uncertain[22]. This is due to a wide range of technologies available, all with different cost and performance parameters, the uncertainty about future cost reductions for each one of them, and the lack of a comprehensive metric that allows for an objective comparison between storage technologies and to alternatives.

2.2 Cost of Electricity Storage

This section reviews existing literature on the current and projected investment and lifetime cost of electricity storage technologies.

2.2.1 Investment Cost

Investment cost is the most common parameter to assess cost of electricity storage technologies. It is widely used to compare technologies and project future cost improvements. Table 2.4 displays current and projected investment cost for electricity storage technologies, including the methodologies used to project future cost.

Table 2.4 – Review of total investment cost for electricity storage technologies today and projected in the future. Method / Comment column qualifies values if applicable and indicates the underlying methodology and reference for the future value. The values for electrolysers, fuel cells and supercapacitors are given in US$/kW. These technologies are not explicitly designed to store energy and cost estimates are only available in terms of power capacity.

Technology	Today ($\$_{2018}$/kWh)	Future ($\$_{2018}$/kWh)	Year of Study	Method/Comment
Pumped hydro	181 - 415[87]	148 - 244	2014	Long-term estimate for 90% renewables system[88]
Compressed air	130 - 188[89]	-	-	Reported investment cost for compressed air plants built in 1978 and 1991 are 134 and 22 US$_{2018}$/kWh[90].
Flywheel	550 - 10,000[65,89]	-	-	-
Lead acid	550 - 1,832[89,91]	206 - 260 127 - 180	2014 2014	Bottom-up engineering model for 'Future State Price'[92] Long-term estimate for 90% renewables system[88]
Lithium ion (Cell)	154 - 196[93,94]	105 105	2014 2015	Experience curve analysis for 2020[95] GM forecast for 2022 for pack-grade cells[94]
Lithium ion (Pack)	160 - 227[96]	169 - 318 224 - 483 180 - 333 219 - 328 215 - 754 62	2015 2012 2012 2012 2013 2018	Literature Review for 2030[23]; Bottom-up Engineering Model for 2030[97]; Bottom-up Engineering Model for 2030[97]; Literature Review for 2030[98]; Expert Elicitation for 2030[99]; Experience curve analysis for 2030[96]
Lithium ion (System)	692 - 1,420[91,100]	196 - 217 255 - 337 261 - 648 470 - 575 309 - 526 227 - 390	2015 2014 2016 2016 2018 2018	Bottom-up engineering model for high manufacturing[101] Bottom-up engineering model for 'Future State Price'[92] Analyst projections for 2030[102]; Experience Curve Analysis for 2030[102] Experience Curve Analysis for 2030[100] Experience Curve Analysis for 2040[100]
Sodium sulphur	304 - 886[100]	-		-
Redox flow	313 - 840[103]	157 - 275 191 - 265 185 - 196	2014 2014 2015	Bottom-up engineering model for 'Future State Price'[92] Bottom-up engineering model for 2GWh demand p.a.[104] Bottom-up engineering model for high manufacturing[101]
Hydrogen Electrolyser in $/kW Fuel cell in $/kW Hydrogen tank	 1,600 - 2,900[51,56] 10,000 - 12,000[105] 11 - 45[63]	 520 - 1,111 4,040 - 5,630 -	 2014 2015 -	 Expert Elicitation for 2030[56] Consultancy report for mass-market production[106] -
Supercapacitor (in $/kW)	1,755 - 2,340[107]	-	-	'Today' cost based on 2009 study.

Five observations can be made. First, current cost covers a wide range from as low as 130 US$/kWh for compressed air plants to 10,000 US$/kWh for flywheels and potentially higher for supercapacitors if converted to US$/kWh. Similarly, future cost estimates for lithium-ion battery packs alone range from 62 to 754 US$/kWh (2030). Second, future cost estimates are focussed on lithium-ion technologies. Third, there is a wide range of methodologies used to project future cost, but none are consistently used across a range of technologies. Fourth, the studies do not always make clear, which electricity storage system components are included in the cost estimates. And fifth, many studies are outdated already. The 2030 lithium-ion estimates of studies from 2012 and 2013 are above today's cost, highlighting the long lag times in science and the inability of static studies to cope with the fast-moving developments observed in electricity storage technologies.

These observations are the reason for the high uncertainty associated with the future role of electricity storage in low-carbon energy systems[108]. The wide range of future cost estimates, lack of detailed estimates of technologies other than lithium ion and lack of consistent methodology across technologies make future cost estimates uncomparable. This is aggravated by common intransparency regarding the technological scope (i.e., inclusion of selected vs all cost components) of often outdated cost estimates[89].

Therefore, to improve transparency on future investment cost, studies should apply a consistent, easily updatable methodology across a meaningful selection of electricity storage technologies, clearly highlighting the system components included in the estimates.

2.2.2 Lifetime Cost

Adequate cost assessments for electricity storage solutions are challenging due to the diversity of technologies possessing different cost and performance characteristics and the varying requirements of storage applications[25]. Recent studies on future cost are limited to investment cost of storage technologies only[109,110]. This is also a driver of why the future role of electricity storage is still perceived as highly uncertain[108], despite remarkable growth in deployment for distinct technologies and applications[26,111].

To account for the various cost and performance characteristics of electricity storage technologies and the varying requirements of applications, a different metric must be used. The levelised cost of storage (LCOS) quantifies the discounted cost per unit of discharged electricity for a specific storage technology and application. It can be described as the total lifetime cost of the investment in an electricity storage technology divided by its cumulative delivered electricity[112,113]. Delivered electricity can refer to electrical energy (LCOS) or electric power[114]. The metric accounts for all technical and economic parameters affecting the lifetime cost of discharging stored electricity. It reflects the internal average price at which electricity can be sold for the investment's net present value to be zero (i.e., its revenue requirement)[115], and thereby represents an appropriate tool for cost comparison of electricity storage technologies[113,114,116].

The concept is analogous to the levelised cost of electricity (LCOE) for generation technologies. The LCOS for storage technologies and LCOE for generation technologies can be directly compared; however, different concepts of providing electricity and resulting differences in cost calculation methodology suggest the use of different names. The suitability of the LCOS method to compare storage technologies for specific applications among each other, and to generation technologies, explains the recent increase in LCOS studies[68,89,112,117,118].

For applications that value the provision of active power instead of energy, measuring LCOS per unit of delivered electrical energy is unsuitable[27]. In this context, the LCOS in power terms (i.e., annuitised capacity cost or ACC) is determined as the discounted lifetime cost per unit of power capacity. It describes the minimum payment required for each kW available for power provision for an entire year to achieve a net present value of zero. This metric also indirectly applies to applications that value the provision of reactive power since reactive power provision requires low active power output from storage devices.

Despite an increasing number of LCOS studies[65,68,89,117–119], there is not yet a common definition of this metric. While some studies neglect cost parameters like replacement or disposal[68,117,118], others exclude relevant performance parameters, such as capacity degradation[65,89,119] (Table 2.5).

Table 2.5 – Varying consideration of economic and technical parameters in LCOS studies.

	LCOS components	Zakeri et al.[68]	Jülch et al.[112]	Lazard[89,103]	Lai et al.[117]	Pawel[113]
Economic	Investment cost	x	x	x	x	x
	Replacement cost	x	x	x		
	Operating cost	x	x	x	x	x
	Power cost	x	x	x	x	x
	End-of-life cost	x	x			x
	Discount rate	x	x	x	x	x
	Taxes			x		
Technical	Nominal capacity	x	x	x	x	x
	Depth-of-discharge	x	x	x		x
	Round-trip efficiency	x	x	x	x	x
	Cycle life	x	x			
	Shelf life	x	x		x	x
	Construction time					
	Degradation rate				x	x
	Self-discharge		x			

Investment cost should include overnight investment cost, construction time and replacement cost. While most studies consider overnight investment and replacement cost, they neglect the impact of construction time. Also, most studies combine operating and replacement cost and thereby annualise replacement cost[68], which distorts the impact of discounting on this cost element. The end-of-life cost or value of a storage technology at the end of the investment period should also be accounted for, which is not the case for some studies.

Electricity discharged incorporates the technologies nominal charge capacity, depth-of-discharge, efficiency, annual cycles, self-discharge and time and cycle degradation. Some studies neglect the impact of varying depth-of-discharge[117] and most studies neglect the impact of self-discharge and degradation[68,89,103,112].

Some studies do not explicitly consider the lifetime of the technology, but rather assume a fixed investment period[89,103]. This approach is suitable for specific project proposals, but ill-suited to compare technologies based on their cost and performance characteristics.

Considering the impact of taxes is important in a country-specific context, but not relevant for the location-independent character of this thesis.

Some studies differentiate between net internal costs of storing electricity, which excludes electricity price and storage efficiency, and cost per unit of discharged electricity, which includes both[117]. All other studies include power price and round-trip efficiency in their lifetime cost assessment of storage technologies.

This lack of common methodology is reflected in the different names that are used to describe LCOS, such as levelised cost of storage[89,103,112], levelised cost of stored energy[113], life cycle cost[68,115,119], levelised cost of delivery[117] or levelised cost of electricity[117,118].

In addition, academic publications are often limited to a small selection of storage applications[68,112,117,118], while industry reports lack transparency on LCOS methodology[65,89]. Both focus only on current LCOS and do not project cost to the future[65,68,89,117–119].

Figure 2.18 to Figure 2.21 review LCOS or ACC of various studies for four power system applications: arbitrage, network investment deferral, primary response and seasonal storage.

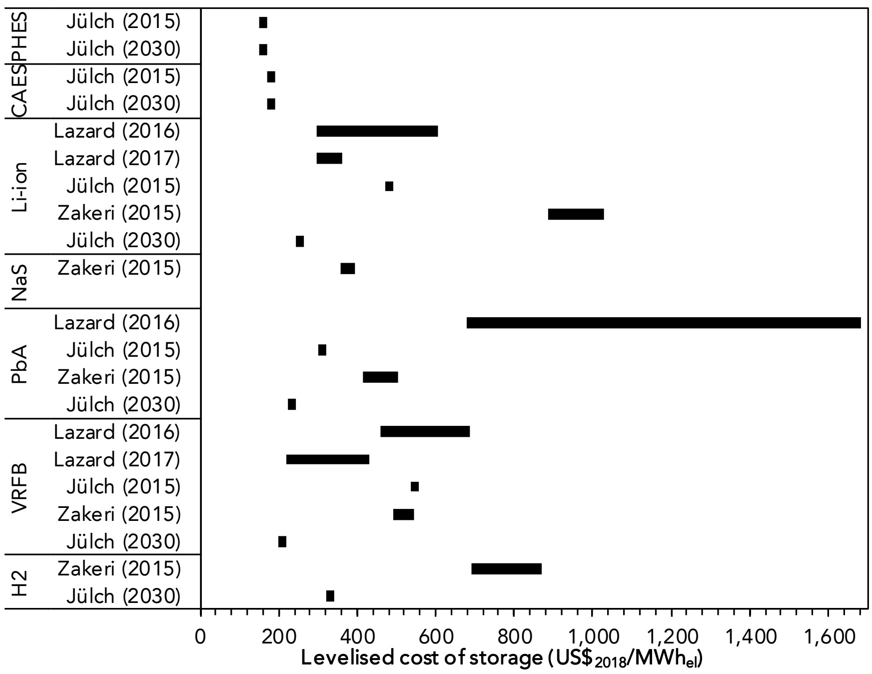


Figure 2.18 – Literature review of LCOS studies for energy arbitrage. Application requirements are 4 hours discharge duration and 365 annual cycles, or 2 hours discharge duration and 400 annual cycles for Zakeri. Number in brackets indicates year for which LCOS are determined. Studies: Jülch[112], Lazard[89,103], Zakeri[68]. PHES – pumped hydro energy storage, CAES – compressed air energy storage, Li-ion – lithium ion, NaS – sodium sulphur, PbA – lead acid, VRFB – vanadium redox flow, H2 – Hydrogen storage.

For energy arbitrage, the most cost-effective technologies seem to be pumped hydro storage and compressed air energy storage at around 200 US$/MWh, albeit no cost improvement towards 2030. The LCOS for lithium ion vary significantly across the studies, although there is a continuous trend of cost reduction from 2015 (Zakeri & Jülch) to 2016 and 2017 (Lazard). By 2030, the cost could approach those of pumped hydro and compressed air, according to Jülch et al.[112]. Similarly, the cost for lead acid vary widely across the studies but could approach the 200 US$/MWh mark by 2030. Vanadium redox-flow batteries appear to be the most cost-competitive electrochemical storage technology for energy arbitrage.

Also, for network investment deferral, pumped hydro and compressed air are the most cost-competitive storage technologies at cost below 200 US$/MWh. The lower LCOS compared to energy arbitrage is a result of the longer discharge duration requirement of this service, enabling those technologies to benefit more from low energy-specific investment cost. While lithium-ion cost range between 350 and 390 US$/MWh, vanadium redox-flow batteries are again the most cost-effective battery technology at a range of 200 to 370 US$/MWh according to Lazard's 2016 study[89].

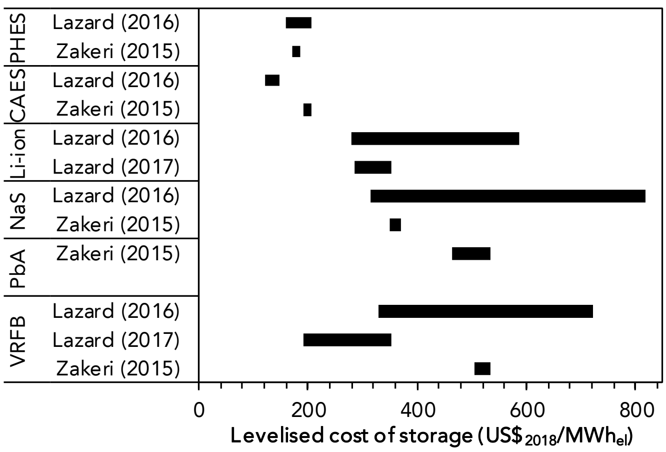


Figure 2.19 – Literature review of LCOS studies for network investment deferral. Application requirements are 6-8 hours discharge duration and 350-365 annual cycles for Lazard and 8 hours discharge duration and 250 annual cycles for Zakeri. Number in brackets indicates year for which LCOS are determined. Studies: Lazard[89,103], Zakeri[68]. PHES – pumped hydro energy storage, CAES – compressed air energy storage, Li-ion – lithium ion, NaS – sodium sulphur, PbA – Lead-acid, VRFB – Vanadium redox flow, H2 – Hydrogen storage.

For primary response the appropriate lifetime cost metric is ACC in US$/$kW_{year}$ as this service reimburses the availability of power capacity for a certain period. Lithium ion is the cheapest technology for this service at 150-250 US$/$kW_{year}$, closely followed by flywheels and lead-acid batteries, both below 500 US$/$kW_{year}$, according to Zakeri et al.[68].

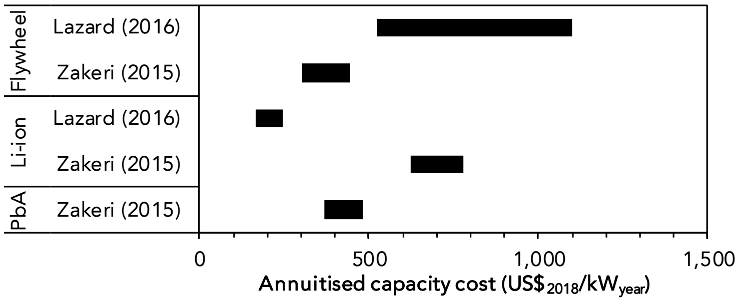


Figure 2.20 – Literature review of ACC studies for primary response. Application requirements are 0.5 hours discharge duration and 1,700 annual cycles for Lazard and 0.25 hours discharge duration and 1,000 annual cycles for Zakeri. Number in brackets indicates year for which LCOS are determined. Studies: Jülch[112], Lazard[89,103], Zakeri[68]. PHES – pumped hydro energy storage, CAES – compressed air energy storage, Li-ion – lithium ion, NaS – sodium sulphur, PbA – Lead-acid, VRFB – Vanadium redox flow, H2 – Hydrogen storage.

LCOS for seasonal storage are only modelled by Jülch et al.[112]. Since pumped hydro and compressed air are unlikely to experience cost reductions from the high level of above 2,000 US$/MWh, hydrogen storage seems to be the only viable technology option to enable costs below 1,000 US$/MWh after 2030.

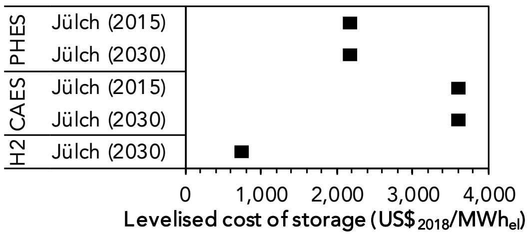


Figure 2.21 – Literature review of LCOS studies for seasonal storage. Application requirements are 700 hours discharge duration and 1 annual cycle[112]. Number in brackets indicates year for which LCOS are determined. PHES – pumped hydro energy storage, CAES – compressed air energy storage, Li-ion – lithium ion, NaS – sodium sulphur, PbA – Lead-acid, VRFB – Vanadium redox flow, H2 – Hydrogen storage.

2.3 Cost Projection Methods

The principal methodologies to estimate future cost trends are learning or experience curves, expert interviews and bottom-up engineering assessments[120,121]. Some studies stress that expert opinions should be used to inform technical assumptions in bottom-up engineering assessments[120], however Table 2.4 shows that expert elicitations are also commonly used to directly estimate future cost values. This section introduces the two cost projection methods used in this PhD project, experience curves and expert elicitations.

2.3.1 Experience Curves

Learning curves depict the improvement of a technology parameter (e.g., cost, size) as a function of experience (e.g., cumulative capacity, time). More specifically, learning curves based on Wright describe the development of manufacturing cost in relation to increased cumulative production[122]. They have been described as the most objective method to project future cost of technologies[123]. Instead of manufacturing cost, experience curves depict product price development (i.e., investment cost) to account for all cost factors (e.g., R&D, sales, depreciation) and, while more uncertain than learning curves, are also suitable to explore future cost[124,125]. The rate at which product prices change is termed the experience rate (ER). Cumulative production has been identified as the predictor of technology cost that performs best compared to other variables[126].

There are a range of milestones in the development of the experience curve methodology and its application in the energy sector, which are listed below:

- 1936: Theodore Wright describes the effect of learning on manufacturing cost in the aircraft industry and proposes a mathematical model[122]
- 1962: Kenneth Arrow finds that the model holds true for whole "capital goods industry" (i.e., industrial sector) and coins "learning-by-doing" as the specific cost reduction in the manufacturing stage[127]
- 1968: The Boston Consulting Group extends the cost inputs to the model to include all manufacturing inputs as well as any other costs required to deliver the product to the end user and coins the term "experience curve"[124]
- 2000: The International Energy Agency publishes learning curves for the most prominent energy generation technologies[128]

- 2000+: A rich body of literature evolves on learning curves for energy technologies, with individual curves, reviews and comparisons[128–132]

2.3.1.1 *Strengths of experience curve analysis*

The experience curve model is appealing, because the idea that firms learn from experience in the past seems intuitive, testing of the model with empirical datasets is doable, the high goodness-of-fit shows it works and, by reducing the complex process of innovation into a single parameter, the model is simple[120].

The underlying reasons for cost reductions as a result of learning-by-doing in manufacturing are identified as spreading overhead cost over larger volumes, reducing inventory cost, cutting labour cost with process improvements, achieving greater division of labour and improving efficiency through greater familiarity with the process[133]. Similar models were developed to account for these underlying reasons more specifically, like Moore's Law (power law of time), Goddard's law (power law of annual production), Sinclair, Klepper and Cohen (power law of annual and cumulative production) and Nordhaus' Law (power law of time and cumulative production)[126].

2.3.1.2 *Weaknesses of experience curve analysis*

A common critique of experience curve analysis is the lack of causation and accountancy to the various cost reducing factors. Experience curves show how cost may reduce over time, but provide no explanation for the underlying reasons beyond its relationship to cumulative output (in the case of one-factor curves)[134]. Additional cost reducing factors are R&D expenditures (learning-by-searching)[135], improvement of product characteristics via user feedback (learning-by-using)[131] and network relationships between research laboratories, industry, end-users and polical decision-makers that can lead to spill-over effects (learning-by-interacting)[131]. Some authors suggest that experience curves largely reflect economies of scale[136]. While it has been shown that cumulative production is a suitable predictor for costs of solar PV modules, other factors than experience in manufacturing are responsible for this, namely plant size (economies of scale), efficiency improvements and commodity costs[137]. It has also been argued that individual experience effects of single component improvements together may explain an aggregated form of experience for a product[138]. Component-specific ERs could account for these individual effects, but separate production and cost data are difficult to obtain[125].

Two-factor experience curves aim to disentangle two important learning factors: cumulative output (learning-by-doing) and knowledge stock (learning-by-searching)[139]. They have been used to explain cost reductions for wind, solar and conventional generation technologies as well as the recent plunge in lithium-ion battery prices[110,131,140]. However, it has been argued that this approach is less robust than the proven concept of one-factor experience curves due to challenges in resolving the collinearity between cumulative output and knowledge stock and choosing a proxy for knowledge stock (e.g., patents, R&D investment) as well as obtaining respective data (e.g., private R&D investment)[125,139].

The use of price data as a proxy to reflect all cost input factors makes the analysis sensitive to pricing policies (i.e., the rationale behind determining product prices within a company based on product costs, customer demand, and market competition)[133]. Four stages of product pricing relative to product cost as a result of pricing policy at different levels of market and product maturity have been observed:[124]

- Development: Prices are below cost to compete with existing alternatives
- Umbrella: Early commercialisation leads to price increase above cost
- Shakeout: Strong price reductions due to increasing competition
- Stability: Price movements reflect cost in mature markets

High data variance can lead to significant variations of ERs across studies and datasets. Depending on the spread of the data, it is possible to calculate different learning rates by changing the start and end point of the analysis and by including or excluding outliers[125]. In particular when price data is used, a period of at least ten years' worth of historical data should be available for price trends to be reliably reflective of cost trends[120].

Experience curves are incapable of predicting step-change innovations or accounting for product changes that might improve performance at same cost[133,137]. It has been argued that radical product changes constitute new products that exhibit new ERs[125]. Moreover, in situations with significant product changes, other indicators than the specific investment cost may be more appropriate to reflect learning outputs, such as product functionality or levelised cost of electricity for a power generation technology[139,141].

The idea of experience improvement at a constant rate is also critiqued. Some argue that cost reduce stronger during the R&D phase due to radical discontinuity (i.e., innovations leading to new technology features)[138,142]. Others argue that learning might be stronger in the commercial phase due to competition[143]. What is clear though, is that ERs cannot project cost indefinitely and cost floors exist. Following the logic that relative cost shares of components with high ERs decrease over time, a reduction of the aggregated rate for products over time appears feasible[138]. This can be represented in energy systems models with "kinked" (i.e., piece-wise linear) curves or ERs that depreciate with time[144–146].

Finally, a distinction between products that require extensive on-site construction and those mass-produced in centralised factories must be made, due to the often highly specific, custom-built nature of the former resulting in lower ERs[134].

2.3.2 Expert Elicitations

Expert elicitations use structured discussions to elicit scientific and technical judgments in the form of subjective probability distributions around uncertain variables from experts in a particular field[147]. They are a valuable tool to support investment and policy decision-making in conditions of uncertainty and limited data availability[147,148]. Accordingly, both the US National Research Council and the 2010 Inter Academy Council review of the IPCC climate change assessment recommend the use of expert elicitations to inform funding decisions in the energy field[149,150]. As a result, this method has been used to investigate the impact of research, development and deployment funding (RD&D) on cost reductions for low-carbon generation technologies[151–157] and electric vehicle batteries[99,158]. These studies also compare the impact of additional funding between technologies[99,152,153] or funding type[157], and identify the underlying technical innovations[151,157] or possible deployment scenarios[154,155].

It has been argued that this method can be a valuable addition to other forms of evidence in support of public-policy decision-making. If so, expert elicitation should not be viewed as low-cost, low-effort alternative to other research methods, but elicitation protocols must be developed through careful iterative refinement and the elicitation itself must be conducted diligently to minimise cognitive bias and overconfidence[147].

Expert elicitations have gained increasing popularity in research on future cost and performance of energy supply and energy storage technologies[99,153,158,159]. While many studies exist on carbon capture and storage, solar PV, biomass and nuclear technologies, expert elicitations on energy storage are limited to transport applications[99,153,158].

2.3.2.1 Strengths of expert elicitations

Experts have information that may not be available elsewhere[160]. Therefore, experts' judgements based on their knowledge and experience can at least partly overcome the lack of empirical or modelling data[99]. It also gives energy systems modellers opportunities to consult technical experts on exogenous technological progress for deterministic models, which is typically informed by engineering cost estimates. The method allows experts to account for the fact that the future is not a projection of the past, which clearly distinguishes it from other methods like experience curves[160]. Elicitations can therefore help modellers to identify and avoid potential blind spots, which is particularly useful for energy and cost modelling that features nascent technologies[161]. Here, expert elicitations allow the explicit characterisation of uncertainty by not only providing a range of possible outcomes, but also their associated probabilities[160]. Finally, expert elicitations enable the identification of the drivers for performance improvements, a key information to qualify future cost and performance estimates and useful input for bottom-up engineering modelling as well.

2.3.2.2 Weaknesses of expert elicitations

Expert elicitations are subject to heuristics and biases[162]. Experts use simple, efficient rules (heuristics) to form judgments on complex tasks, such as assessing probabilities and predicting values. This leads to biases with the most common types being:[147,162]

- Representativeness – judgement based on not sufficiently representative information
- Availability – judgement based on more easily imaginable circumstances
- Anchoring & Adjustment – judgement relying too heavily on first piece of information
- Overconfidence – judgement resulting from insufficient accountancy of uncertainty

Such biases highlight the need for care in the design of elicitation protocols. Methods to minimise the impact of such biases are:[147]

- providing detailed background information on the field in question
- asking experts under which circumstances estimated values lie outside given range
- asking experts to state ranges for estimates before estimating a median value,
- asking experts to justify estimates

In addition, it has been argued that, while coherence or adherence to formal probability theory is an unreasonable expectation of any person intuitively, it can be achieved through appropriate questioning, training in probability calculus and the use of computational aids to check assessments, and further recommendations have been developed to minimise heuristics and bias[163].

Finally, the careful choice of topics for expert elicitations and of the experts themselves is essential to obtaining meaningful results. Expertise with predictive capability is less likely to exist where individual and social behaviour determine the outcomes of interest compared to matters of fact that depend on empirical natural or social science and well validated models[147]. Where expertise exists, it is not the number of experts interviewed, but the suitability of experts to make relevant predictions that is of value[147].

2.4 Value of Electricity Storage

The increasing penetration of low-carbon generation capacity requires more power system flexibility (Chapter 1.2). Therefore, electricity storage can add value in low-carbon power systems as a flexibility option. This section reviews literature on the economic value of electricity storage in distinct applications (market value) and its role in integrating low-carbon electricity in the power system (system value).

2.4.1 Market Value

There is a wide range of applications for electricity storage in the power system. A review of reports from research institutes[27,64,65,73,164,165], international organisations[24], industry[89,166] and academia[26,167] reveals 27 unique electricity storage applications referred to with more than 100 different names (Figure 2.22, Appendix C.3). In all of these applications, electricity storage creates economic value through four fundamental services[168]:

1. **Power Quality:** Keeping frequency and voltage within permissible limits
2. **Power Reliability:** Providing electricity in case of supply reduction or interruption
3. **Increased utilisation:** Optimising use of existing assets in the power system
4. **Arbitrage:** Exploiting temporal price differentials

The value creation behind these fundamental services as well as the ideal location for electricity storage in the power system is directly or indirectly related to key characteristics of intermittent, renewable generators that pose a challenge for their integration in the power system[13]:

- **Uncertainty**: Availability of resource cannot be predicted with absolute certainty
- **Variability**: Power generation fluctuates with availability of renewable resource
- **Low short-run cost**: Once built, electricity is generated at very low operating cost
- **Location-constraint**: Resource is not equal in all locations and cannot be transported
- **Modularity**: Scale of individual generators is relatively small

Similar characteristics apply to other low-carbon generation technologies like nuclear, for example: uncertainty of an outage, output inflexibility instead of variability, low short-run cost, location-constraint for cooling and very large sizes instead of modularity[14].

Figure 2.22 matches the 27 identified unique-purpose electricity storage applications with the fundamental, economic value creating services and possible locations in the power system. The shading indicates their relation to the integration of intermittent renewable electricity and the respective characteristics are displayed in italics.

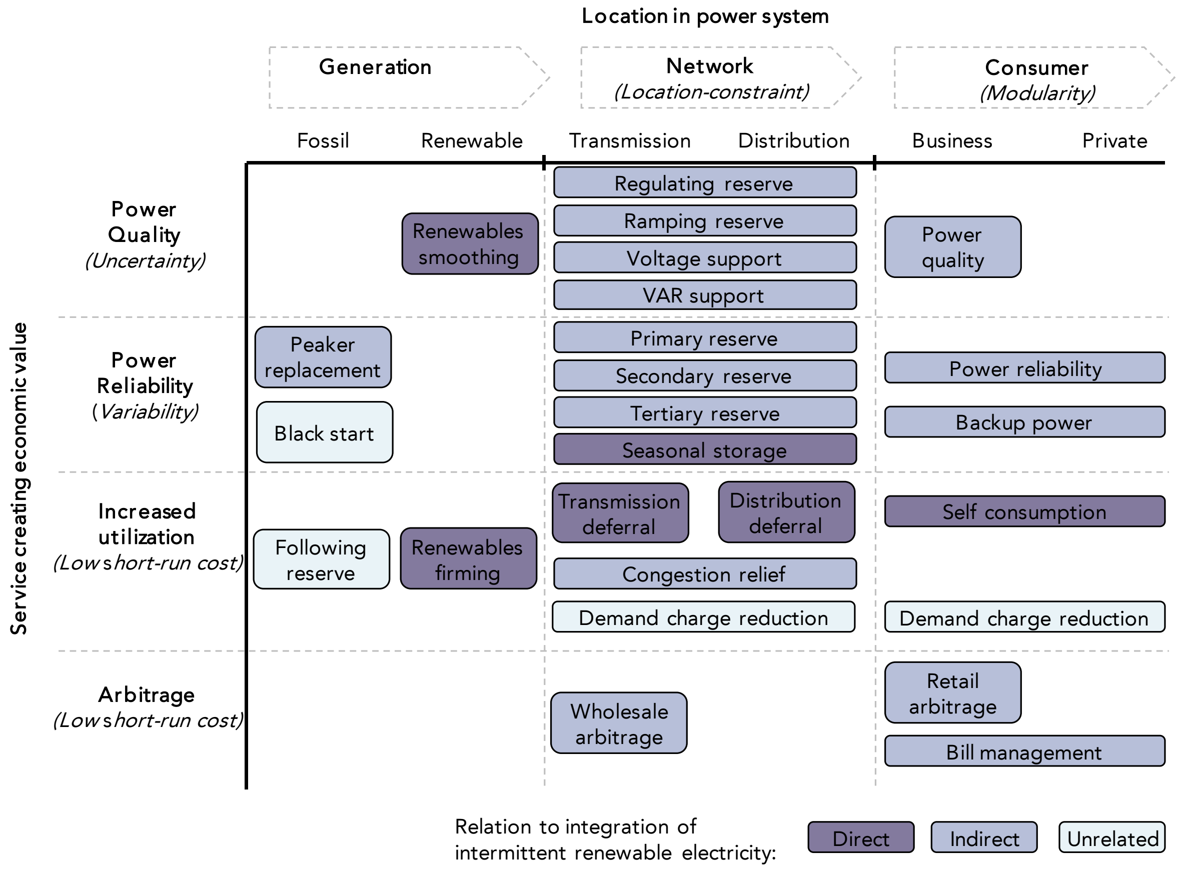


Figure 2.22 – Allocation of identified unique-purpose electricity storage applications to source of economic value and possible location in the power system. Colouring indicates relation to characteristics of intermittent renewable electricity generation (direct, indirect, unrelated). Terms in italic indicate intermittent renewable generation characteristics that drive economic value potential or power system location for electricity storage. 27 services identified, but 25 services displayed, because spinning and non-spinning reserve are summarised as secondary reserve and transmission and distribution demand charge reduction as demand charge reduction. Description of all applications in Appendix C.3. Schematic is inspired by Battke et al., 2015[119]. VAR – volt-ampere reactive power

The requirement to ensure power quality is affected by the uncertainty associated with intermittent renewable generation or the inertia of thermal generators. In contrast, power reliability is associated with the variability of resource availability for intermittent renewable generators, the sudden loss of a conventional generator or variation in electricity demand. Low short-run cost of renewable or nuclear power generation enable electricity storage to create economic value by increasing the utilisation of existing generation or network assets or through electricity price arbitrage, which capitalises on differences in electricity supply at low cost and demand. The location-constraint and modularity of renewable generators drive the need for electricity storage applications for increased asset utilisation in the power network and at the end-customer site more generally. A detailed description of all applications is in Appendix C.3.

Historically, pumped hydro storage plants were built to meet demand peaks and use low short-run cost nuclear generation for wholesale arbitrage (Chapter 2.1). Stationary battery systems are most commonly used to provide power quality in applications like regulating reserve or for arbitrage at the consumer site[26]. Future projections indicate that the majority of electricity storage capacity will be deployed for applications at the consumer site in combination with solar PV, followed by renewables firming and reserve applications[169].

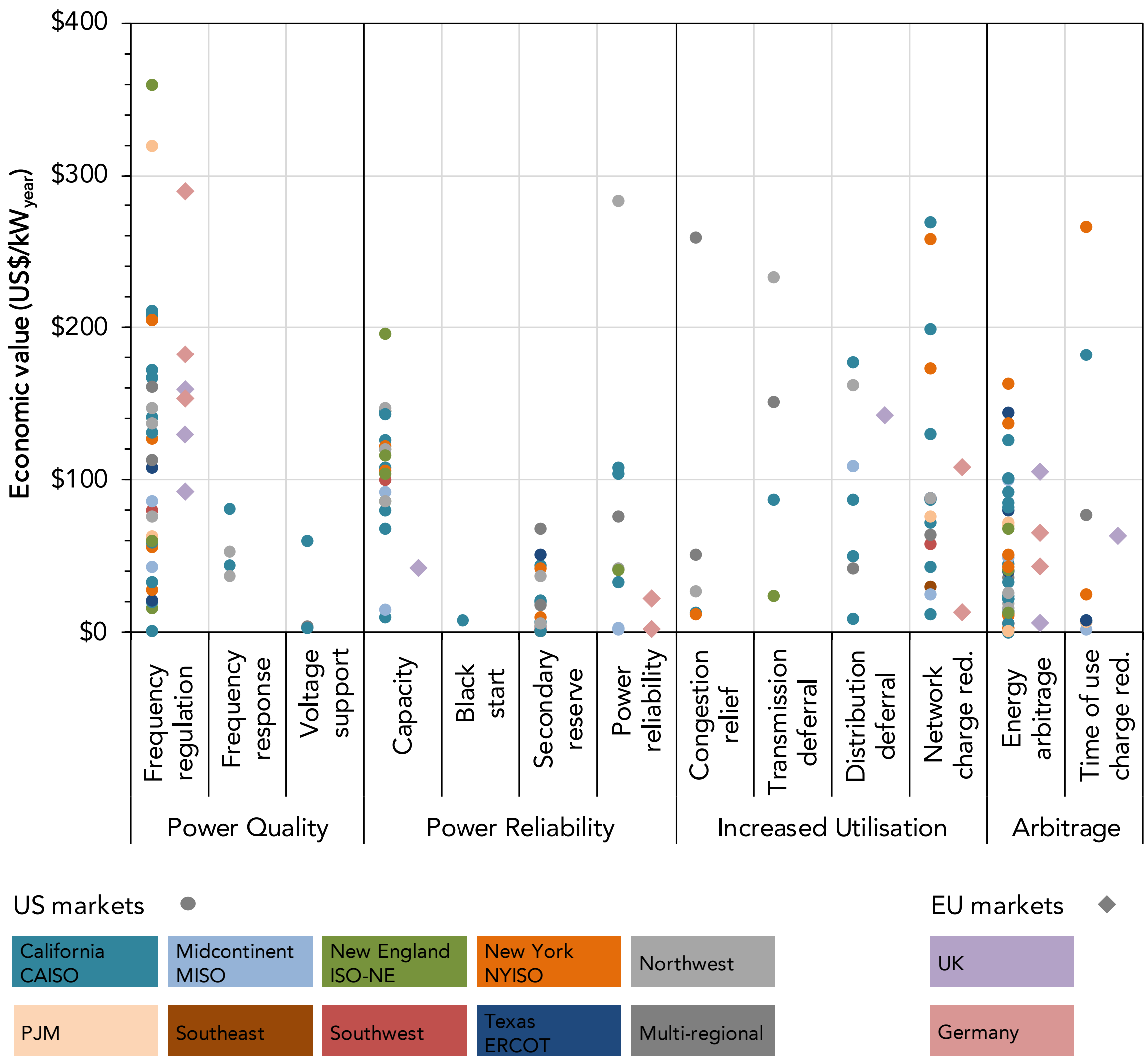


Figure 2.23 – Review of energy storage valuation studies and transactions in the United States (US) and two countries of the European Union (EU), Germany and the UK. US data are taken directly from Balducci et al., 2018[170]. EU data are taken from a range of studies[168,171–176]. Comparison of application names to Figure 2.22: Capacity = Peaker replacement, Frequency response = Primary reserve, Network charge reduction = Demand charge reduction, Time of use charge reduction = Bill management.

Figure 2.23 compares the economic value (i.e., revenue potential) of electricity storage from a review study for various applications and power markets in the US[170] to values achieved in the EU[168,171–176]. In both geographies, there is a wide spread for nearly all applications. For the US, highest revenues above 200 US$/kW$_{year}$ are achieved in regulation, transmission network and customer services (charge reduction, power reliability). Secondary reserve, voltage support, black start and frequency response are consistently below 100 US$/kW$_{year}$. Arbitrage values are mostly below 100 US$/kW$_{year}$, while Capacity revenues are well distributed around that threshold.

The comparison with potential revenues in European markets resembles these findings. The value of arbitrage is also mostly below 100 US$/kW$_{year}$, ranging from 44 to 66 in Germany (70-80% round-trip efficiency)[168] and 8 to 107 in the UK (40-100% round-trip efficiency)[173]. Power reliability in the German market is valued at only 3 to 23 US$/kW$_{year}$, confirming most samples in the US. Similarly, values for demand charge reduction and regulation cover the spectrum also observed in US markets. The value for distribution upgrade deferral in the UK is estimated at 144 US$/kW$_{year}$ with the assumption of a 7% discount rate and 20 year asset lifetime[174], confirming the relatively high value in the US.

Current research on the market value of electricity storage is also focussed on benefit-stacking, a concept that refers to the combination of multiple applications by one storage device, either sequentially or simultaneously with different portions of its capacity. While not yet widely applied, there is a consensus that this approach can capitalise on the versatility of electricity storage and thereby increase its economic value[167,175,177]. However, the concept is not investigated here to ensure appropriate assessment of market values for single-application use cases as baseline.

2.4.2 System Value

LCOE for generation technologies or LCOS for electricity storage technologies are an intuitive metric for technology-specific cost and useful to determine market values when combined with application-specific revenues. From a system perspective, however, both metrics are ambiguous, because they do not account for output variability or the impact of a technology's operation on the electricity system in terms of reliability and operability[178]. The system value concept was defined to determine the value of a technology to the power system as a whole as the difference in total system cost (TSC) caused by the deployment of a technology[179]. The concept therefore explicitly accounts for levelised cost and the impact on power system reliability and operability, but it requires comprehensive energy system models to determine this value. The value itself can be given as the absolute difference in TSC (%), normalised per annual energy demand ($/MWh$_{el}$), normalised per installed capacity of the technology ($/kWh$_{cap}$), or normalised and annuitised per installed capacity ($/kW$_{year}$).

A range of studies analyse the TSC of low-carbon power systems with variable renewable and flexibility technologies compared to systems with conventional, dispatchable generators. For the US, Denholm et al.'s detailed grid simulation model of the balancing areas in Colorado and Missouri reveal a system value of 145 US$$_{2011}$/kW$_{year}$ for electricity storage with 8 hours discharge duration, highlighting that the reduction of operational costs is more significant when the device provides capacity (i.e., frequency regulation) rather than energy services (i.e., following reserve)[180]. These results are in line with a similar model for the Texas power system, which reveals system values of 55-85, 120-200 and 160-270 US$$_{2017}$/kW$_{year}$ for 1, 4 and 8 hour discharge duration respectively[181]. More broadly, the capacity expansion model of the same power system by de Sisternes et al. identifies a 7 to 12% reduction in electricity generation investment and operation cost for 90% emission reduction as a result of electricity storage deployment through increased utilisation of installed resources and greater penetration of lowest cost low-carbon resources[182]. This translates to a value range of 286-572 and 103-257 US$$_{2016}$ per kWh of installed electricity storage capacity for the first 10 GW of a 2 or 10-hour discharge duration technology respectively. In contrast, MacDonald et al.'s study focussed on improved regional interconnection in the US found that decarbonisation of 80% could be achieved, at least cost, without any electricity storage, using 55% renewable and 15% nuclear generation[21]. Jacobson et al. quantify electricity system cost of a fully renewable US energy system covering all end-use sectors in 2050 at 87-133 US$$_{2015}$/MWh$_{el}$ (compared to a conventional system at 172-544 US$/MWh$_{el}$) and include electrical storage capacity at less than 0.1% of annual electricity demand and 30% of peak power demand[183].

In a set of European power supply scenarios by Scholz et al., similar TSC for a system with 0% intermittent renewable electricity and one with 85% combined with electricity storage capacity at 23% of peak demand were found[184]. An integrated assessment model of 24 European countries quantifies the system value of electricity storage as a 3 to 5 US$$_{2016}$/MWh reduction in the integration cost of variable renewable electricity[185]. Weitemeyer et al.'s more simplified power system model based on long-term meteorological and load data and a 90% share of variable renewable electricity found long-term storage with an energy capacity equivalent to 168 average load hours to reduce total system cost by 10%, while more efficient short-term storage equivalent to 4 load hours achieves 20%[186].

Table 2.6 lists studies that model the Great Britain (GB) power system up to 2050 and include electricity storage. The penetration of variable renewables ranges from 0 to 87% of annual electricity demand and 0 to 91% generation capacity. Electricity storage capacity is included at 0.004 to 0.027% of annual demand (energy) or 3 to 57% of peak demand (power). The storage technologies modelled range from one generic proxy for all technologies to a full suite of seven different technologies. While all studies consider storage and interconnection, other flexibility options like demand-side response (DSR) and hydro are not always included, and some studies are unclear whether open cycle gas turbines (OCGT) are included in the broader 'gas' capacity.

Table 2.6 – Overview of studies investigating the system impact of electricity storage and other flexibility options on a low-carbon power system in Great Britain. System value in some studies reported explicitly for electricity storage. Other studies report system value for deployment of flexibility options in general. VRE – Variable renewable energy

Study, Year (Institution)	Time horizon	VRE share*	Storage capacity**	System value	Flexibility options	Storage options
BEIS, 2017 (Government)[187]	2015-2035	25-55% 32-62%	0.007-0.023% 5-18%	-	Storage, Interconnection	-
BNEF, 2018 (Industry)[188]	2030, 2040	43-75% 56-85%	0.011-0.027% 12-57%	2% TSC reduction or 0.7 £/MWh_{el} (67% VRE, 16.5 GW vs 11.7 GW electricity storage)	OCGT, Storage Interconnection, Hydro, DSR, Other	Pumped storage, Small-scale batteries, Utility-scale batteries
Carbon Trust, 2016 (Government)[20]	2020, 2030, 2050	25-34% 37-48%	0.005-0.020% 4-23%	1.4-2.4 £bn/pa (net) (100g_{CO2}/kWh_{el} target, deployment of flexibility options)	OCGT, Storage Interconnection, DSR	Pumped storage, Bulk storage, Distributed storage
CCC, 2015 (Government)[189]	2030	0-83% 0-75%	0.004-0.024% 3-20%	3-3.8 £bn/pa (gross) (100g_{CO2}/kWh_{el} target, deployment of flexibility options)	OCGT, Storage Interconnection, Hydro	Pumped storage, Other dedicated storage
Edmunds, 2014 (Academic)[190]	2020-2030	16-39% 24-54%	0.009-0.027% 4-6%	-	Storage, Interconnection, Hydro	Pumped storage
Heuberger, 2017 (Academic)[179]	2035	- 49-60%	- 0-10%	15% TSC reduction or 515 £/kW_{EES} (70 £/t_{CO2}, 9.5 GW vs 0 GW electricity storage)	OCGT, Storage Interconnection	Compressed air
Heuberger, 2018 (Academic)[191]	2015-2050	14-76% 27-86%	0.007-0.023% 5-18%	-	OCGT, Storage Interconnection	Pumped storage, Battery
National Grid, 2018 (Industry)[192]	2020-2050	26-63% 35-74%	0.007-0.019% 10-38%	-	Storage Interconnection, Hydro, DSR	Pumped storage, Decentral battery, Grid-scale battery, Fuel cells, Liquid air, Vehicle to grid, Compressed air
Pfenninger, 2015 (Academic)[193]	-	- 85%	- 5-25%	50-130 £/MWh_{el} (90% VRE, scenarios with vs without storage)	OCGT, Storage Interconnection, Hydro, Tidal	Pumped storage, Grid-scale batteries
Price, 2018 (Academic)[194]	2050	52-87% 68-85%	0.006-0.024% 6-24%	-	OCGT, Storage Interconnection,	Pumped hydro, Sodium sulphur
Zeyringer, 2018 (Academic)[195]	2050	49, 76% 73, 91%	0.009-0.015% 8-14%	-	OCGT, Storage Interconnection	Pumped hydro, Sodium sulphur

*Upper: Energy generation, Lower: Power capacity
**Upper: Energy capacity relative to annual electricity demand, Lower: Power capacity relative to peak demand

In terms of system value, BNEF finds a 2% reduction in total system cost by 2030 in a scenario where an additional 4.8 GW of electricity storage capacity is deployed because of 10% lower cost[188]. This translates to a reduction of £0.7 per MWh produced in the system. In comparing two scenarios with and without electricity storage, Heuberger et al. identify a reduction of 15%[179]. However, it is highlighted that the first GW of storage already leads to a reduction of 13%, thereby putting the result in line with the previous study. The analyses by the Committee on Climate Change and the Carbon Trust determine annual TSC savings for a power system with a carbon intensity of $100g_{CO2}$/kWh with flexibility technologies at £1.4-2.4 or 3-3.8 billion in 2030 compared to no flexibility options. While the former refers to net savings, which include investment cost of the flexibility technologies, the latter uses gross savings, which does not[20,189]. At 90% VRE penetration, the value of electricity storage specifically is identified by Pfenninger et al. at 50-130 £/MWh_{el} system-wide electricity cost (32-35% of respective TSC), when adding electricity storage at a cost of 350 £/kWh_{cap} to a range of scenarios[193].

However, not all studies quantify the system value of electricity storage explicitly. The system value originates from the ability of electricity storage to increase the utilisation of power system assets like intermittent generators and thereby increase their penetration[182]. Therefore, some studies only focus on exploring this capability without quantifying its financial value. They investigate the quantity of electricity storage needed to enable low-carbon power systems.

Figure 2.24 compares the findings of 31 existing studies across the US, EU, Germany and Great Britain (GB), regarding the required electricity storage energy and power capacity in low-carbon power systems with increasing variable renewable energy. The capacity requirements are displayed relative to annual energy and peak power demand. Most studies appear to agree that across developed countries for up to a VRE penetration of 50% only 0-0.02% relative energy and 0-20% relative power capacity are required. At 90% penetration, this requirement increases to 0.02-1% and 20-100%. Taking GB as example of a system with approximately 50 GW peak and 300 TWh annual demand, a 90% VRE penetration would suggest the need for 60-3,000 GWh and 10-50 GW of electricity storage energy and power capacity respectively. The study by Sinn et al. at the high end of capacity requirements discounts the possibility of VRE output constraint[196]. The separate analysis by Pietzcker et al. modelling electricity storage power capacity requirements as a function of VRE penetration in various integrated assessment models finds similar results of 0-20% at 55% and 5-40% at 80% penetration[197]. The study highlights the impact of the dominant renewable energy source, which is confirmed in a review by Cebulla at al. identifying higher storage capacity requirements for systems based on solar rather than wind energy[198]. This study also found that power and energy capacity requirements seem to increase linearly and exponentially respectively, an insight that is evident above 50% VRE penetration from the higher number of studies shown in Figure 2.24. Linearity for power capacity can be attributed to the instantaneity of a power requirement. Additional intermittent power capacity needs to be backed-up by a constant amount of reliable capacity (e.g., electricity storage) to ensure power demand is met at any specific point in time. However, the combined impact of additional intermittent power capacity and the time it is supposed to generate electricity, means that energy capacity requirements increase exponentially to ensure sufficient electricity is available at all times.

Overall, this literature review shows that there is still substantial uncertainty on the system value of electricity storage, and on the drivers that influence the results. Quantitative estimates span a wide range (from <1 to 130 £/MWh_{el}) and are often subject to very specific assumptions (i.e., carbon price, storage cost). While Figure 2.24 shows some overarching trends regarding the power and energy capacity requirement of electricity storage in low-carbon power systems, the studies focus on renewable electricity and storage capacity only, masking the impact of alternative low-carbon generation sources with limited flexibility (i.e., nuclear) and alternative flexibility options (i.e., demand-side response, interconnection, flexible generation).

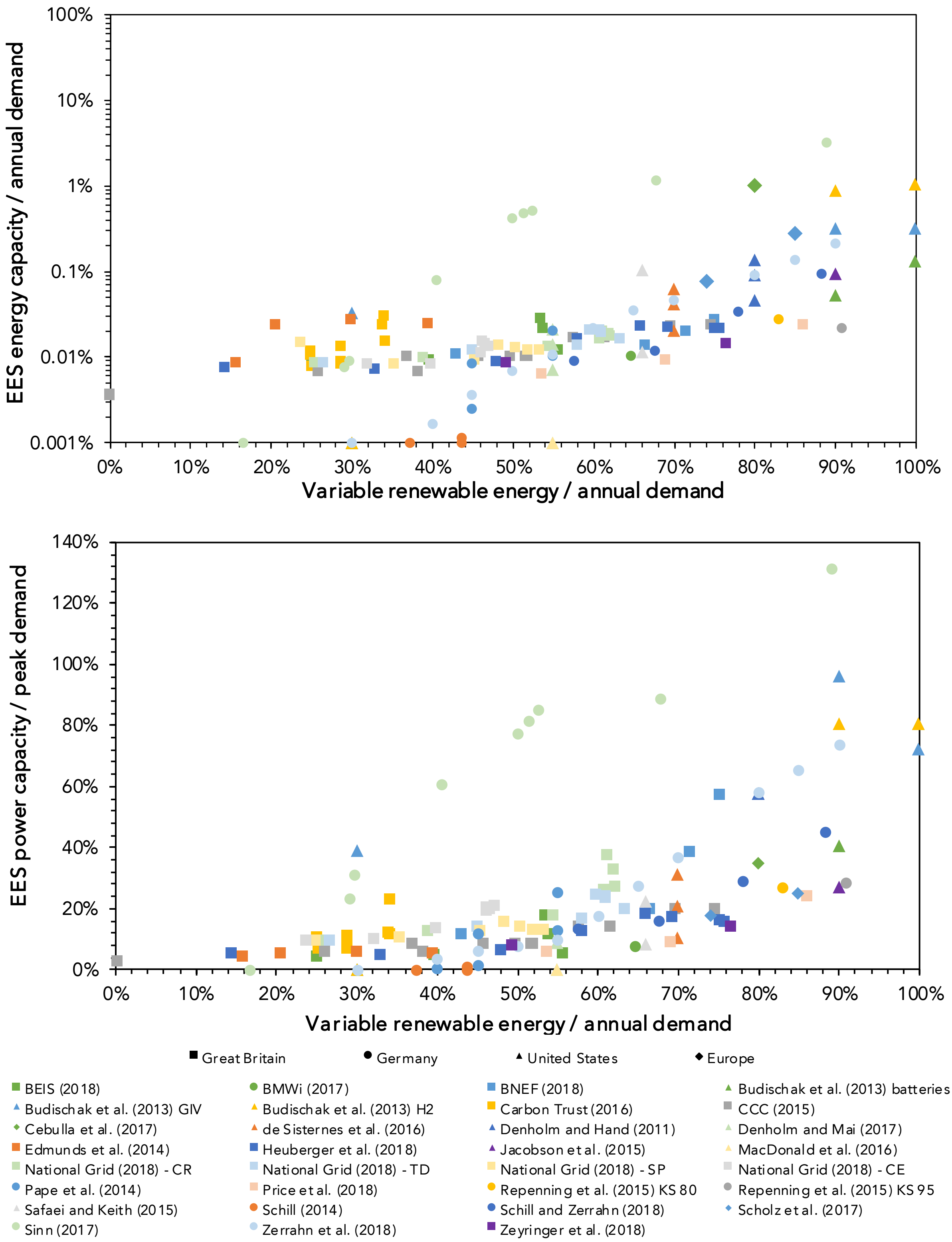


Figure 2.24 – Electrical storage energy (top) and power capacity requirements (bottom) as a function of variable renewable energy penetration. Capacity requirements displayed relative to annual energy or peak power demand. Data based on literature review of 31 studies modelling EES requirements in future low-carbon power systems in Germany, Great Britain, the US and the EU. Budischak scenarios: GIV – Grid-integrated vehicles, National Grid scenarios: CE – Community Renewables, TD – Two Degrees, SP – Slow Progression, CE – Consumer Evolution. Repenning: KS 80 – 80% emission reduction, KS 95 – 95% emission reduction. Studies: BEIS (2018)[187], BMWi (2017)[199], BNEF (2018)[188], Budischak et al. (2013)[200], Carbon Trust (2016)[20], CCC (2015)[189], Cebulla et al. (2017)[198], de Sisternes et al. (2016)[182], Denholm and Hand (2011)[201], Denholm and Mai (2017)[181], Edmunds et al. (2014)[190], Heuberger et al. (2018)[191], Jacobson et al. (2015)[183], MacDonald et al. (2016)[21], National Grid (2018)[192], Pape et al. (2014)[202], Price et al. (2018)[194], Repenning et al. (2015)[203], Safaei and Keith (2015)[204], Schill (2014)[205], Schill and Zerrahn (2018)[206], Scholz et al. (2017)[184], Sinn (2017)[196], Zerrahn et al. (2018)[207], Zeyringer et al. (2018)[195]. Figure based on Zerrahn et al. (2018)[207] and updated with GB power system studies.

3. Methods for Cost Projection and Value Estimation

This thesis uses experience curve analysis and expert elicitations to project future investment cost for electricity storage technologies. The levelised cost of storage (LCOS) methodology is further refined to assess application-specific lifetime cost and statistical algorithms extrapolate reviewed revenue data to any electricity storage application. A meta-analysis investigates the electricity storage capacity required in low-carbon power systems.

3.1 Investment Cost – Experience Curves

Experience curve analysis identifies a relationship between historic technology prices and cumulative capacity additions and can be used to extrapolate observed trends to the future.

3.1.1 Data

This thesis draws on peer-reviewed literature, research and industry reports, news items, energy storage databases and interviews with manufacturers to identify price and cumulative deployment data or already published experience rates (ERs) for electrical energy storage technologies (EES). In the literature, learning (based on manufacturing cost) and ERs (based on product price) are sometimes used interchangeably. The sources in the referenced literature are double-checked to ensure the use of actual product price data.

By performing linear regression of the identified product price and cumulative deployment data (Appendix A.1), ERs are derived according to Wright's law[122]

$$P(x) = A\,X^{-b} \tag{6}$$

$$ER = 1 - 2^{-b} \tag{7}$$

with *P(x)* the price per energy or power capacity of a storage technology (US$/kWh, US$/kW) at the cumulatively installed energy or power capacity X (kWh, kW) of that technology. The normalisation factor *A* and ER *b* are obtained with a regression analysis of the logarithms of the given price and capacity data. Using the ER *b*, the price reduction for each doubling of installed capacity can be calculated as *ER* (%).

The geographic scope of this analysis is global. Where cumulative deployment data is available on company or country level, the data is scaled to global level with validated assumptions on the respective global market share. Regarding price data, it is assumed the global marketplace ensures that these are globally applicable[139] and technologies where prices are more likely to vary by geography are highlighted.

Technology scope is differentiated into cell, battery, module, pack, ex-works system and system level. While ex-works system refers to the factory-gate price of complete EES systems, system includes the cost for transportation, installation and commissioning if applicable. Electrolysers and fuel cells that consume or generate direct current and are not yet containerised or equipped with other balance-of-system components are usually referred to as electrolyser or fuel cell stacks. For simplicity, they are referred to as ‘packs’ in this thesis as the technology scope is comparable to battery packs. Additional information on the cost components included at each level can be found in Appendix A.2.

Three application categories are distinguished in this analysis with subgroups to indicate technology size and power-to-energy ratio (P/E): portable (<1kWh, P/E≈1), transport (hybrid electric vehicle: <5kWh, P/E>1; electric vehicle: >25kWh, P/E>1) and stationary (residential: <30kWh, P/E<1; utility: >100kWh, P/E<1).

ER uncertainty is calculated for the 95% confidence interval based on standard error using the mean μ and standard error σ of the tabulated ER in

$$\mu \pm 1.96\,\sigma \tag{8}$$

Currency conversions are performed in two steps. First, historic prices are deflated in local currency with OECD Consumer Price Indices[208] and then converted to US$$_{2018}$ with OECD exchange rates based on Purchasing Power Parities for GDP[209].

Conversions from energy-based to power-based data (US$/kWh, GWh vs. US$/kW, GW) are performed using the reported power-to-energy ratio for each technology.

Technical[66] and economic[24] maturity assessments of EES technologies in the literature are compared to the cumulative installed capacities in our analysis. It is found that those technologies termed ‘Research & Development’ or ‘Developing’ have less than 1 GWh installed (flow batteries, fuel cells), ‘Demonstration & Deployment’ or ‘Developed’ less than

100 GWh (sodium sulphur) and 'Commercialisation' or 'Mature' more than 100 GWh (pumped hydro, lead acid, lithium ion). If applicable, the economic maturity assessment is prioritised. Maturity categories are renamed to 'emerging', 'maturing' and 'mature'.

3.1.2 Future cost

Equation (6) is used to project product prices as a function of increased cumulative installed capacity. ER uncertainty is accounted for by projecting future prices using upper and lower rates of the identified 95% confidence interval while ensuring that the ER variations only apply to future projections and not retrospectively.

The raw material cost for each storage technology is calculated by multiplying reported material inventories[210–214] with commodity prices. Commodity prices are drawn from peer-reviewed literature[215], the Bloomberg database[216], a bottom-up engineering model[217] and a range of commercial and academic websites (Appendix A.3). For the majority of commodities, price data are identified for the past ten years and average, minimum and maximum prices are determined. For those with insufficient data, only a single price figure is used. Raw material cost uncertainty is based on variations in reported material inventories and commodity prices. While special care has been taken to identify commodity prices for the required input form of the raw materials (e.g., high-purity nickel sulfate vs metallic nickel), it should be noted that this was not always possible and prices for related commodities had to be used as proxy.

Additional cost factors for cost floors of electrochemical storage technologies beyond material cost include direct labour, variable overhead, general, sales, administration, R&D, depreciation, warranty and profit[217]. These are determined using the bottom-up engineering model BatPac Version 3.0[217], setting annual production to 1 million units, and from the literature[218]. Additional cost factors for cost floors of mechanical storage technologies beyond material cost include electrical connection, infrastructure & logistics, civil works and planning, and are determined from the literature[219]. The potential cost impact of high-volume production for these usually large-scale projects is neglected.

3.1.3 Timeframe

To obtain potential EES technology diffusion curves, sigmoid functions (i.e., S-curves) for EES application subgroups (i.e., consumer electronics, hybrid and battery electric vehicles, residential and utility storage) are derived with the logistic growth function:

$$A_n = \frac{\mathrm{A}_{sat}}{1 + \frac{(A_{sat} - A_{base})}{A_{base}} e^{-r\,n}} \tag{9}$$

where A_n (GWh) is the annual market capacity in a particular year, A_{base} (GWh) the initial capacity and A_{sat} (GWh) the maximum annual market capacity that will be reached long-term, the saturation capacity. r is the growth rate and n the number of periods after the start period. A_{base} and A_{sat} are based on the literature or own assumptions. r is then fitted to annual market capacity forecasts and saturation capacities from the literature by non-linear regression. The non-linear regression also yields the standard error of r to measure goodness-of-fit. Growth rate uncertainty is based on the maximum and minimum r determined in a Monte Carlo analysis of the non-linear regression.

The resulting annual market growth projections relate future cumulative capacities to time to interpret projected cost reductions. Henceforth, it is assumed that each EES technology obtains 100% market share in its respective application subgroup.

The impact of ER uncertainty is modelled with maximum and minimum ERs of the 95% confidence interval. The impact of additional market growth uncertainty is modelled using maximum and minimum growth rates in combination with maximum and minimum ERs respectively.

3.1.4 Cumulative Investment

Calculating the integral of equation (6) determines the cumulative spend required to go from the current installed capacity X_1 to some future amount X_2 – thus installing the amount $X_2 - X_1$ while product prices reduce:

$$Cumulative\ Spend\ (X) = \int_{X_1}^{X_2} \left(A\,X^{-b}\right) dx \tag{10}$$

Calculating this integral, while subtracting a target price (P_{target}) from the product (e.g., what consumers are willing to pay), returns the cumulative subsidy required to deploy a defined amount of storage capacity at a subsidised target price.

The compound annual growth rate (*CAGR)* of global clean energy investments is calculated for 2004 to 2018 and then used to project clean energy investments from 2019 to 2030.

3.1.5 Levelised Cost

To assess the competitiveness of an electricity storage technology in a specific application relative to existing alternatives, all cost and performance parameters relevant throughout its lifetime must be considered and the respective lifetime cost calculated. For mobility and stationary applications this metric is cost of ownership and LCOS respectively.

Cost of ownership for the energy inputs and storage components of internal combustion engine (ICEV) and electric vehicles (EV) are based on the formula for total cost of ownership (TCO)[220]:

$$TCO = \frac{\left(Capex - \frac{RV}{(1+r)^N}\right) CRF + \frac{1}{N} \sum \frac{Opex}{(1+r)^n}}{Mileage} \qquad (11)$$

with *RV* as residual value at the end of life, *r* as discount factor, *N* as lifetime in years, mileage as the distance travelled per year and *CRF* as the capital recovery factor; itself a function of *N*:

$$CRF = \frac{r\,(1+r)^N}{(1+r)^N - 1} \qquad (12)$$

The capital recovery factor converts a present value into a constant rate of cash flows over a given timeframe (i.e., annuity), accounting for the discount factor *r* and the total payment periods N (lifetime in years in this case). In mathematical terms, it reflects the reciprocal of the annuity factor, itself the sum of the geometric series that constant, discounted cash flows represent.

By considering only fuel tank or battery pack and gasoline or power price, the formula for cost of ownership (CO) is specified as:

$$CO = \frac{\left(capex - \frac{RV}{(1+r)^N}\right) CRF}{mileage} + \frac{\left(\frac{P_{fuel}}{\eta} DoD\right) \frac{1}{CRF}}{\eta_{fuel}\, N \sum_{n=1}^{N} (1 - DEG\, n)} \qquad (13)$$

with P_{fuel} as gasoline or power price, η_{fuel} the fuel efficiency, η the round-trip efficiency of the energy storage device, *DoD* the depth of discharge and *DEG* the annual degradation of the storage device, defined as the fraction of usable storage content lost per year. All parameters can be found in Appendix A.5. By comparing average US gasoline prices[221] to crude oil spot prices[222] from 1990 to 2016, the reference price of 2.36 US$/gallon is determined as the average gasoline price observed when crude oil is between 45 and 55 US$/barrel. A reference crude oil price of around 50 US$/barrel is chosen as it is the average price over the last 20, 30 and 40 years (US$54, US$45 and US$47)[222]. The US is chosen for this example to complement studies that focus on electrification of personal vehicle transportation in this country[223].

LCOS for residential storage are calculated based on Chapter 3.3 of this thesis with the parameters in Appendix A.5. Charging cost are modelled as the LCOE for a residential solar PV installation. The 2016 German retail power price is taken as reference power price up to 2040, with Germany chosen for this example, because recent growth in residential storage installations suggest that it could be a promising market for this application[224].

In both applications (EV transportation, residential storage) recent deployment data shows lithium ion as the most common technology, the reason for calculations performed for this technology[225,226].

3.2 Investment Cost – Expert Elicitations

Expert elicitations were conducted for two prominent electricity storage technologies, lithium ion and water electrolysers. The method is based on structured discussions with experts to obtain estimates for uncertain parameters. The estimates rely on cognitive heuristics and are therefore subject to bias[147].

3.2.1 Measures to reduce bias

A number of methods recommended in the literature aim to minimise the use of heuristics and resulting biases in expert elicitations. While the comprehensive, visual presentation of all necessary evidence can minimise availability bias, asking for extreme values first and allowing for refining these before making a best guess can help to avoid anchoring bias[147]. It appears more challenging to minimise overconfidence bias. Here, neutrally formulated questions and diligent interview conduction with probing questions that allow the expert to justify estimates are useful tools[147,163]. Face-to-face interviews as opposed to telephone interviews or online surveys facilitate this evaluation of given probabilities and may ensure the elicitation is taken more seriously by experts[161]. These best-practice recommendations from the literature are implemented to obtain representative results and minimise cognitive heuristics and bias (Table 3.1).

Table 3.1 – Cognitive heuristics and bias and recommended countermeasures[147,162]

	Description	Countermeasure
Anchoring	Tendency to rely too heavily on a first piece of information (the "anchor") and adjust relatively conservatively from this when making probabilistic decisions, rather than fully considering factors which may influence a quantity of interest, leading to overconfident estimates (i.e., too narrow ranges).	Informing interviewee about heuristic. Asking for extreme estimates first (90^{th}, 10^{th} percentiles), then for median estimate (50^{th} percentile). Asking for reasons for estimates to lie outside of indicated range.
Availability	Heuristic procedure of making a decision according to the ease with which one can imagine an event occurring, which may for example bias judgements towards recent trends or events.	Informing interviewee about heuristic. Asking for reasons for estimates to lie outside of indicated range.
Overconfidence	Heuristic procedure of making confidence intervals according to the span of ad-hoc imaginable outcomes that are too narrow due to limited information availability.	Neutrally formulated questions. Probing questions allowing expert to justify estimates.
Representativeness	Judgement based on not sufficiently representative information.	Providing background material to compile latest data and research insights from multiple sources.

3.2.2 Elicitation procedure

Before the interview, potential experts were contacted and, upon agreement of participation, an elicitation protocol was sent two weeks before the interview. The elicitation protocol outlines the motivation for the study, compiles background material on technological and economic aspects of the technology, describes the expert elicitation technique, and contains the elicitation questionnaire. Iterating this protocol with experts of Imperial College London allowed for capturing the latest available and relevant information, phrasing unambiguous questions and identifying academic and industry experts in the field.

Table 3.2 – Elicitation procedure

Phase	Interactions with expert	Timeline / Duration
Before interview	1. Making initial contact 2. Sending elicitation protocol (background material, questionnaire)	- 2 weeks before interview
During interview	3. Discussing background material 4. Eliciting values of interest with questionnaire	1 hour during interview 1 hour during interview
After interview	5. Sending elicited values and possible implications for final approval	1 week after interview

During the interview, the first hour was spent discussing the background material to minimise any availability bias. The second hour was spent introducing the case studies to limit technical ambiguity (Table 3.3 and Table 3.4) and eliciting the values of interest:

- Investment cost for 2020 and 2030 under three R&D funding scenarios (1x, 2x, 10x current) in situations without (R&D) and with production scale-up (RD&D) due to increased deployment
- Cycle life for 2020 and 2030 under three R&D funding scenarios (1x, 2x, 10x current)
- Efficiency for 2020 and 2030 under three R&D funding scenarios (1x, 2x, 10x current)
- Environmental impact of technology manufacturing and operation
- Technical and value chain innovations driving the cost or performance improvements

Experts were asked for 10th, 50th and 90th percentile estimates with extreme values being identified first to minimise any anchoring bias[147]. Using probing questions, they were supported in critically assessing, refining and verifying the given values. By eliciting distinct parameters (e.g., investment cost), instead of aggregate parameters that require implicit calculations (e.g., levelised cost), uncertainty was further minimised[147,152]. Audio recordings were made with the experts' permission to ensure all responses were captured correctly. For lithium ion, cycle life estimates were elicited for 80% depth-of-discharge and efficiency estimates refer to round-trip efficiency.

Table 3.3 – Electrolysis case study for energy storage system that injects hydrogen to gas grid for later re-electrification

Power Source	Intermittent Renewables (e.g., Wind, Solar PV)
System Size	10 MW_{el}
H_2 output pressure	20 – 30 bar

Table 3.4 – Lithium ion case study for battery packs used in stationary off-grid systems

Power Source	Intermittent Renewables (e.g., Wind, Solar PV)
System Size	15 kWh_{cap}
Discharge rate	< 1 C

After the interview, responses were transcribed into a spreadsheet and potential implications were derived based on the elicited values in a separate document. Both were sent to the expert to allow for adjustments, point out potential inconsistencies, ask for additional comments and receive final approval of the elicited values. These elicited values are anonymised and reported and discussed in Chapter 5.

3.2.3 Interviewed experts

Table 3.5 and Table 3.6 lists the ten and eleven experts that were interviewed on water electrolysers and lithium-ion battery packs respectively. While ten is a common number of experts to interview[227], there is no one rule for the correct number of interviewees required. However, it is important to select a set of experts who adequately represent the diversity of expert opinion in the area[148,161]. As such, equal numbers of experts were selected from academia and industry. To represent the diversity of water electrolysis technologies, experts on AEC, PEMEC and SOEC systems were interviewed. They come from the UK, Denmark, Germany and Belgium, representing the European perspective on future water electrolysis development potential. For lithium ion, all industry experts come from the UK, limiting the represented industry perspective of that technology to the UK. The interviews lasted for two hours and were conducted face-to-face (15), via Skype (5) or by phone (1) to ensure attentiveness, enable the interviewees to fully convey their expertise, and to allow for spontaneous interviewer questions to fully capture that expertise[147,148]. They took place between October 2015 and June 2016.

Table 3.5 – Water electrolysis experts interviewed (ordered alphabetically and by category)

Name	Institution	Role	Category
Dan Brett	University College London	Professor, Electrochemical Engineering	Academic
Jens Oluf Jensen	Technical University Denmark	Professor, Energy Conversion and Storage	Academic
Mogens Bjerg Mogensen	Technical University Denmark	Professor, Energy Conversion and Storage	Academic
Tom Smolinka	Fraunhofer Institute - ISE	Head, Chemical Energy Storage Department	Academic
Stephen Skinner	Imperial College London	Professor, Materials Chemistry	Academic

Franz Lehner	E4Tech Ltd	Senior Consultant	Industry
Ben Madden	Element Energy Ltd	Director	Industry
Marcus Newborough	ITM Power Ltd	Development Director	Industry
Christian von Olshausen	SunFire GmbH	Chief Technology Officer	Industry
Filip Smeets	Hydrogenics Europe N.V.	General Manager On-site Generation	Industry

Table 3.6 – Lithium-ion battery experts interviewed (ordered alphabetically and by category)

Name	Institution	Role	Category
Shane Beattie	Warwick Manufacturing Group	Technical Manager	Academic
Nigel Brandon	Imperial College London	Professor, Sustainable Energy Development	Academic
Michael Brunell	Warwick Manufacturing Group	EngD Candidate	Academic
Nikita Hall	Warwick Manufacturing Group	Project Engineer	Academic
Dave Howey	University of Oxford	Professor, Engineering Science	Academic
Greg Offer	Imperial College London	Senior Lecturer, Engineering	Academic
Celine Cluzel	Element Energy Ltd	Associate Director	Industry
Tom Cleaver	Oxis Energy	R&D Programme Manager	Industry
Allan Paterson	Johnson Matthey	Chief Electrochemist	Industry
John Perry	Denchi Power	Technical Director	Industry
Ian Whiting	AGM Batteries	Business Development Director	Industry

3.2.4 Data analysis

The method chosen to analyse the relative impact of increased R&D funding and production scale-up is to take the median 50th percentile estimate at current R&D funding scenario (1x) without production scale-up (R&D) for 2020 and 2030 and deduct the median percentage reduction of experts' estimates based on these drivers. Recent work highlights the suitability of the median as aggregation method for small sample sizes[148,228]. However, it should be noted that any single measure must be treated with caution when aggregating elicitation results[229]. Previous studies also used the arithmetic mean to analyse results[99,156–158,230].

The identified innovations are categorised along three dimensions:

- Technology: AEC, PEMEC, SOEC or lithium-ion
- Impact: Reduced investment cost, longer lifetime, higher efficiency
- Innovation area:
    - Cell: Catalyst, Electrolyte, Electrodes, Membrane, Binder, Separator, Multiple
    - Stack or Module: Bipolar Plates, Sealing, Battery / Thermal Management
    - System: Balance-of-Plant, Operation, New set-up/chemistry, Multiple
    - Manufacturing: Automation, Design, Experience, Method, Scale
    - Supply Chain: Volume, Competition

The number of experts that mention innovations along each dimension and the frequency of innovations within each sub-category mentioned overall are recorded.

3.2.5 Comparison to experience curve projections

Finally, investment cost estimates for 2020 and 2030 (1x R&D funding) are compared to projections based on previously identified experience curves for electrolysis and lithium-ion batteries.

Two scenarios for future capacity additions are investigate for both technologies, in line with the scenarios used for the expert elicitations:

- R&D only: continued average annual market size of 0.36 GW_{el}[231] for water electrolysers or 12 GWh_{cap}[96] (2015) for lithium-ion battery packs
- RD&D: annual market grows to 1 GW_{el} (2020) and 2.5 GW_{el} (2030) for water electrolysers[56] and to 80 GWh_{cap} (2020) and 800 GWh_{cap} (2030) for lithium-ion packs

The R&D only scenario for water electrolysis is based on the average annual market size of 0.36 GW_{el} between 1956-2002[231]. For lithium-ion battery packs, 12 GWh_{cap} was the estimated market size in 2015 when expert elicitations were conducted[225]. The RD&D scenario for water electrolysis is based on stakeholder assessment for the EU and the assumption that the EU electrolysis market comprises 20% of the global market (EU share in global GDP[232])[56]. For lithium-ion battery packs, increased deployment is based on a sigmoid function that models technology diffusion for EV battery packs (Chapter 3.1.3).

The ER for alkaline electrolysis systems is 17±6% (Chapter 4). Global cumulative produced capacity is around 24 GW_{el} in 2015[231]. The experience curve is projected forwards from 2016 to 2030 using the two market growth scenarios.

PEM and solid oxide electrolysis are immature technologies and no published ERs could be found. However, PEM and solid oxide fuel cells are more mature with published ERs. Due to the technological similarity between electrolysers and fuel cells, fuel cell ERs are used as a proxy for the respective electrolysis technology.

Published PEM fuel cells ERs are 19.1-21.4%[233], 16%[142], 18%[234] and 16±2% (Chapter 4), of which the latter one is used for PEM electrolysis. Experience curve starting point is set at 2016 with respective investment cost (Table 2.2) and the assumption of 1 GW_{el} cumulative produced PEM electrolyser capacity.

The ER range of between 12-44%[235] based on data from 1996-2008 for solid oxide fuel cells is used for solid oxide electrolysis. Experience curve starting point is set at 2016 with respective investment cost (Expert H's 2020 estimate in 1x R&D scenario, based on expert's rationale of no cost reduction from 2015) and assumption of 0.1 GW_{el} capacity in 2016.

For lithium-ion battery packs an ER of 16 ± 4% is used. This ER is based on price and cumulative deployment data from 2010 to 2015[96] and thereby reflects the available information at the time of expert elicitation interviews. Cumulative capacity in 2015 was 30 GWh_{cap}, which is the starting point for the R&D only and RD&D deployment scenarios.

Estimates were elicited in € (2016) or € (2015). The conversion to US$ (2018) is performed using Eurozone consumer price index inflation and GDP-based power purchase parity exchange rate for 2018[208,209].

3.3 Lifetime Cost

The equation below depicts the approach for calculating LCOS as derived in this study. LCOS is defined as the discounted cost per unit of discharged electrical energy, in line with recent publications[89,103,112].

$$LCOS\left[\frac{\$}{MWh}\right]=\frac{Investment\ cost+\sum_{n}^{N}\frac{O\&M\ cost}{(1+r)^{n}}+\sum_{n}^{N}\frac{Charging\ cost}{(1+r)^{n}}+\frac{End\_of\_life\ cost}{(1+r)^{N+1}}}{\sum_{n}^{N}\frac{Elec_{Discharged}}{(1+r)^{n}}} \tag{14}$$

3.3.1 Equation components

The equation incorporates all elements required to determine the full lifetime cost of an electricity storage technology: Investment, operation and maintenance (O&M), charging and end-of-life cost divided by electricity discharged during the investment period. It assumes all investment cost are incurred in the first year and sums ongoing cost in each year (n) up to the system lifetime (N), discounted by the discount rate (r). The lifetime is the minimum of shelf life (T_{shelf}) or cycle life (Cyc_{life}) when compared to annual cycles (Cyc_{life}/Cyc_{pa}) and includes construction time.

Discharged electricity accounts for annual cycles (Cyc_{pa}), nominal energy capacity ($Cap_{nom,E}$), depth-of-discharge (DoD), round-trip efficiency (η_{RT}), cycle degradation (Cyc_{Deg}), time degradation (T_{Deg}), self-discharge (η_{self}) and construction time of the technology (T_c).

$$\sum_{n}^{N}\frac{Elec_{Discharged}}{(1+r)^{n}}[MWh] = Cyc_{pa}\cdot DoD\cdot Cap_{nom,E}\cdot\eta_{RT}\cdot(1-\eta_{self})\cdot\sum_{n=1}^{N}\frac{\left(1-Cyc_{Deg}\right)^{(n-1)\cdot Cyc_{pa}}\cdot\left(1-T_{Deg}\right)^{(n-1)}}{(1+r)^{n+T_c}} \tag{15}$$

Investment cost account for nominal power ($Cap_{nom,P}$) and energy capacity ($Cap_{nom,E}$), specific power (C_P) and energy cost (C_E), replacement cost relative to power capacity ($C_{P\text{-}r}$) and interval (T_r), and number of replacements throughout technology lifetime (r). The replacement interval is determined based on full equivalent cycles requiring replacement relative to annual cycles (Cyc_r/Cyc_{pa}).

$$Investment\ cost\ [\$] = C_P\cdot Cap_{nom,P} + C_E\cdot Cap_{nom,E} + \sum_{r=0}^{R=\frac{T_r}{N}}\frac{C_{P-r}\cdot Cap_{nom,P}}{(1+r)^{T_c+r\cdot T_r}} \tag{16}$$

O&M cost account for power and energy specific operation and maintenance cost ($C_{P\text{-}OM}$, $C_{E\text{-}OM}$) relative to nominal power capacity and annual charged electricity.

$$\sum_{n}^{N}\frac{O\&M\ cost}{(1+r)^n} = \sum_{n=1}^{N}\frac{C_{P-OM}\cdot Cap_{nom,P} + C_{E-OM}\cdot\left(Cyc_{pa}\cdot DoD\cdot Cap_{nom,E}\right)\cdot\left(1-Cyc_{Deg}\right)^{(n-1)\cdot Cyc_{pa}}\cdot\left(1-T_{Deg}\right)^{(n-1)}}{(1+r)^{n+T_c}} \tag{17}$$

Charging cost account for the electricity price (P_{el}) and round-trip efficiency.

$$\frac{\sum_{n}^{N}\frac{Charging\ cost}{(1+r)^n}}{\sum_{n}^{N}\frac{Elec_{Discharged}}{(1+r)^n}}\left[\frac{\$}{MWh}\right] = \frac{P_{el}}{\eta_{RT}} \tag{18}$$

End-of-life cost are calculated as a fraction of investment cost (F_{EOL}).

$$\frac{End\_of\_life\ cost}{(1+r)^{N+1}}[\$] = \frac{\left(C_P\cdot Cap_{nom,P} + C_E\cdot Cap_{nom,E}\right)\cdot F_{EOL}}{(1+r)^{N+1}} \tag{19}$$

The parameters nominal energy capacity ($Cap_{nom,E}$), discharge duration (DD), annual cycles (Cyc_{pa}), response time and electricity price (P_{el}) are pre-defined for each application. The electricity price assumed in all applications is 50 US$/MWh, except for the behind-the-meter applications *bill management*, *power reliability* and *power quality* which use 100 US$/MWh. These generic values are broadly representative of wholesale electricity prices relevant to network / system applications (i.e., front-of-the-meter), and end-customer applications (i.e., behind-the-meter). They are similar to values used in previous LCOS studies and thereby ensure comparability of results[68,112,119,236]. In the sensitivity analysis it is also shown that electricity prices only have a minor contribution to LCOS in most applications.

While the response time requirement only influences which technologies are modelled per application, all other factors affect the quantitative LCOS result. Where applicable, depth-of-discharge and thus cycle life is optimised per technology and application to minimise LCOS (Appendix C.1).

Self-discharge (η_{Self}) for each technology and application is approximated by accounting for the daily self-discharge at idle state of the technology, and the application's annual cycle and discharge duration (DD) requirement.

$$\eta_{Self} = \eta_{Self,idle}\cdot\left(1-\frac{2\cdot Cyc_{pa}\cdot DD}{8760\ hours}\right) \tag{20}$$

This equation describes the maximum influence of self-discharge, assuming the device is always fully charged when idle between cycles, which are always made at full power. The other extreme of zero self-discharge would occur if the device either remains fully discharged between cycles, or cycles occur gradually to eliminate idle time. As the actual operating strategy of a storage device cannot be known without high-resolution dispatch modelling, the latter is assumed for simplicity.

Cycle and temporal degradation parameters (Cyc_{Deg}, T_{Deg}) are modelled as geometric sequences representing degradation of energy storage capacity to an end-of-life value of 80% relative to initial capacity ($Cap_{nom,E}$). For cycle degradation relative to cycle life (Cyc_{Life}):

$$Cap_{nom,E} * \left(1 - Cyc_{Deg}\right)^{Cyc_{Life}} = 80\% * Cap_{nom,E} \tag{21}$$

$$Cyc_{Deg}\left[\frac{\%_{capacity}}{cycle}\right] = 1 - exp\left(\frac{\ln(0.8)}{Cyc_{Life}}\right) = 1 - 80\%^{\left(\frac{1}{Cyc_{Life}}\right)} \tag{22}$$

For temporal degradation relative to shelf life (T_{shelf}):

$$T_{Deg}\left[\frac{\%_{capacity}}{year}\right] = 1 - 80\%^{\left(\frac{1}{T_{Shelf}}\right)} \tag{23}$$

Where applicable, the relationship between cycle life and depth-of-discharge (DoD) for a technology is taken from recent technical studies and applied to the cycle life value (at 100% DoD) identified in the literature review for each technology (Appendix C.2). The impact of system size on investment cost of any technology is neglected.

The LCOS in power terms, or annuitised capacity cost (ACC), is calculated by dividing annuitised lifetime cost over power capacity ($Cap_{nom,P}$) instead of annual discharged electrical energy ($Elec_{Discharged}$).

$$ACC\left[\frac{\$}{MW_{yr}}\right] = \frac{Investment\ cost + \sum_n^N \frac{O\&M\ cost}{(1+r)^n} + \sum_n^N \frac{Charging\ cost}{(1+r)^n} + \frac{End\_of\_life\ cost}{(1+r)^{N+1}}}{\sum_n^N \frac{Cap_{nom,p}}{(1+r)^n}} \tag{24}$$

ACC is derived by multiplying the LCOS in energy terms with the annual discharged electricity and dividing by power capacity. The result reflects the internal average price at which power capacity can be provided per year for the investment's net present value to be zero (i.e., its revenue requirement). This metric also indirectly applies to applications that value the provision of reactive power since reactive power provision requires low active power output from storage devices. A direct metric measuring LCOS per unit of reactive power is conceivable, but not explored in this study as are reactive power applications. A metric measuring lifetime cost per unit of reactive power output would be best suited for these services.

3.3.2 Application requirements and technology parameters

27 unique electricity storage applications referred to with more than 100 different names (Appendix C.3) are identified by reviewing reports on storage applications by research institutes[27,64,65,73,164,165], international organisations[24], industry[89,166] and academia[26,167]. Excluding reactive power services leaves 25 applications. Albeit serving different purposes, these applications often have similar technical requirements. Comparing size (MW), annual cycle (#), discharge duration (hours) and response time requirements (seconds), 12 core applications are identified that are sufficiently differentiated according to these metrics (Table 3.7). The distinct annual cycle and discharge duration requirements for each application are chosen from within these ranges and such that the entire spectrum for these parameter combinations is represented.

Table 3.7 – Technical requirements for electricity storage applications.

Application	Size (MW)	Duration (hours)	Cycles (per year)	Response Time (seconds)
Energy arbitrage	0.001-2,000 [24,65]	1-24 [24,65]	50-400 [24,65,73]	>10 [24]
Primary response	1-2,000 [24]	0.02-1 [24,65]	250-15,000 [24,65]	<10 [164]
Secondary response	10-2,000 [24]	0.25-24 [24,65]	20-10,500 [24,65]	>10 [164]
Tertiary response	5-1,000 [24,164]	>1.5 [164]	20-50 [65]	>10 [164]
Peaker replacement	1-500 [65]	2-6 [65]	5-100 [65]	>10 [24]
Black start	0.1-400 [24]	0.25-4 [24,65]	1-20 [24,65]	>10 [24]
Seasonal storage	500-2,000 [24]	24-2000 [24]	1-5 [24]	>10 [24]
T&D upgrade deferral	1-500 [24]	2-8 [65]	10-500 [24,65]	>10 [24]
Congestion management	1-500 [24,65]	1-4 [65]	50-500 [24,65]	>10 [24]
Bill management	0.001-10 [65]	1-6 [65]	50-500 [65]	>10 [24]
Power quality	0.05-10 [65,73]	0.003-0.5 [65,73]	10-200 [65]	<10 [65]
Power reliability	0.001-10 [73]	2-10 [73]	50-400 [73]	>10 [65]

Note: *Cycles* refers to full equivalent charge-discharge cycles. Superscripts refer to references.

With respect to electricity storage technologies, values for 17 cost and performance parameters for 9 technologies are identified using 21 sources. Special focus is placed on using industry validated sources that are based on manufacturer quotes and have a track record for realistic data. The resulting values are cross-checked via e-mail exchanges with 6 industry experts. The final input range is based on the median of all maximum and minimum values of the ranges identified in the literature. Its central estimate and standard deviation are shown in Table 2.3.

The choice of which technologies to model in each application is based on the match between technical requirement ranges of applications (Table 3.7) and technical performance ranges of technologies (Table 3.8) in terms of size, annual cycles / cycle life, discharge duration and response time. Technology-application combinations without overlap of technology performance and application requirement ranges are not modelled.

Table 3.8 – Electricity storage technology performance characteristics.

Technology	Power range (MW)	Discharge (hours)	Cycle life (# cycles)	Response time (seconds)
Pumped hydro	10-5,000 [68]	1-24 [68]	20,000-50,000 [68]	> 10 [68]
Compressed air	5-400 [68]	1-24 [68]	>13,000 [68]	> 10 [68]
Flywheel	0.01-20 [36]	< 0.5[68]	20,000-225,000 [65,68]	< 10 [68]
Lead acid	0.005-100 [65]	0.25-10 [65]	< 5,500 [65]	< 10 [68]
Lithium ion	0.001-35 [74]	0.25-5 [65]	2,000-3,500 [74]	< 10 [68]
Sodium sulphur	0.05-50 [68,74]	0.0167-8 [65,74]	2,500-4,500 [74]	< 10 [85]
Redox flow	0.02-50 [65]	0.0167-10 [68]	5,000-13,000 [68,74]	< 10 [68]
Hydrogen	0.3-500 [68]	0.0167-24 [68]	<20,000 [68]	< 10 [68]
Supercapacitor	<4 [237]	<1 [237]	>100,000 [68]	< 10 [68]

Note: *Cycles* refers to full equivalent charge-discharge cycles. Superscripts refer to references.

3.3.3 Future cost improvement

The modelled lifetime cost projections account for future investment cost improvements. These are determined using experience curve analysis for the total investment cost of specific electricity storage systems in Chapter 4.3. The resulting relative investment cost reductions and uncertainty (Appendix C.4) are applied to the 2015 specific investment cost input parameters identified from the literature (Table 2.3). To combine the uncertainty of investment cost parameters and relative future reduction, combined standard deviations are derived (Appendix C.5).

$$\sigma_{a\pm b} = \sqrt{{\sigma_a}^2 + {\sigma_b}^2} \tag{25}$$

For technologies without experience curve data and resulting cost projections, the relative cost reductions and standard deviations are taken either from a related technology, such as compressed air for which pumped hydro data is used, or from hydrogen storage for sodium sulphur, flywheel and supercapacitors. Hydrogen storage is chosen as proxy for these technologies, because of its moderate cost reduction, less aggressive than projections for lithium ion but more than for lead acid.

3.3.4 Monte Carlo and probability analysis.

Monte Carlo simulations generate random samples from a given probability distribution to estimate or simulate expectations of mathematical functions under that distribution[238]. This method was first used systematically during the 1940s to investigate properties of neutron travel through radiation shielding as part of the Manhattan project[239]. It is said to be named after the Monte Carlo Casino in Monaco, drawing a comparison between the random sampling for mathematical simulations and the random sampling in gambling games like roulette. The method is now used as scientific tool for mathematical problems that are analytically intractable and for which experimentation is too time-consuming or costly[239].

To perform a Monte Carlo analysis, a subjective probability distribution must be assigned to the given, uncertain parameters. The distribution can be uniform (where data is limited but uncertainty is low), triangular (when a midpoint exists) or log-uniform or log-normal (when uncertainty exceeds a factor of 10)[240]. However, other distributions such as normal, lognormal, or empirical are also common, because they often reflect the distribution of real-world data. Various other distributions like Poisson, Weibull or discrete ones can be used as well.

In this thesis, Simple Random Sampling is used as Monte Carlo method. That means for each iteration, a random sample is taken from within the distribution that is specified for an uncertain parameter. Other methods like Latin Hypercube Sampling can be more efficient, in terms of required iterations for a meaningful result, but are less straightforward to understand[240].

For the lifetime cost calculation, a Monte Carlo simulation is conducted for each technology and application to account for the uncertainty of technology input parameters, in line with previous studies[68,118,119]. A normal distribution is attributed to a technology parameter (x) based on its central estimate (μ) and standard deviation (σ) or combined standard deviation ($\sigma_{combined}$) (Table 2.3 and Appendix C.5). A normal distribution is assumed to best reflect the variation of input parameters within the value ranges identified in literature sources.

$$f(x; \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \cdot e^{\frac{-(x-\mu)^2}{2\sigma^2}} \tag{26}$$

The Monte Carlo analysis simulates 500 lifetime cost calculations per technology and application with random values from an 80% confidence interval of the attributed normal distribution of the parameter, corresponding to 1.285 standard deviations from the mean.

The probability (P) of a technology exhibiting lowest lifetime in each application reflects the frequency with which each technology exhibits minimum cost when accounting for uncertainty in the Monte-Carlo simulation.

If LCOS for technology A, B and C are {a_1; a_2; …; a_{500}}, {b_1; b_2; …; b_{500}}, and {c_1; c_2; …; c_{500}} respectively, up to N technologies, then

$$P(a_i = \min LCOS) = P(a_i < b_k, k \in [1;500]) \cdot P(a_i < c_k, k \in [1;500]) \cdot \ldots \qquad (27)$$

$$P(A = \min LCOS) = \frac{1}{500^N} \cdot \sum_{i=1}^{500} |a_i < b_k, k \in [1;500]| \cdot |a_i < c_k, k \in [1;500]| \cdot \ldots \qquad (28)$$

with $|X|$ the cardinality of set X.

So, if the maximum of the LCOS distribution for a technology A is below the minimum of all other technologies, technology A is set as the cheapest option with 100% probability by the simulation (Figure 3.1 - left). However, if the intersection between the LCOS distributions is not an empty set, the probability is lower (Figure 3.1 - right). The approach then counts the occurrences when technology A exhibits lower LCOS than all other technologies and divides by all occurrences (500^N) to arrive at the probability for a technology to exhibit lowest LCOS. The same applies to ACC.

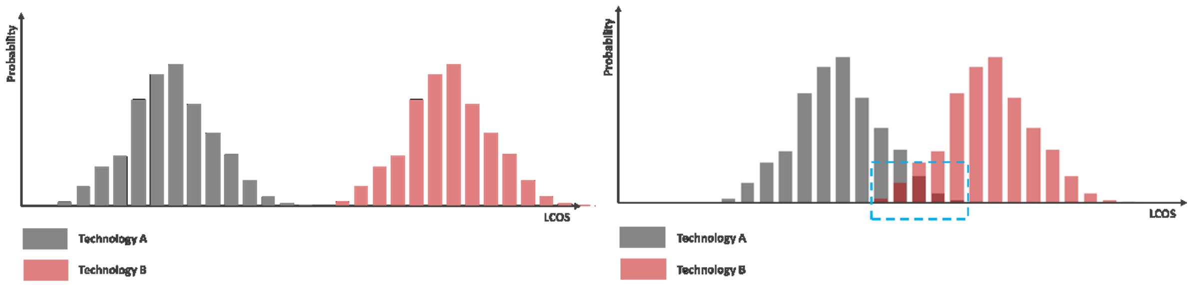


Figure 3.1 – Schematic for probability assessment. Left: 100% probability. Right: <100% probability to exhibit lowest LCOS.

3.3.5 Sensitivity analyses

To explore the sensitivity of lifetime cost to discharge duration and annual cycles, the LCOS or ACC of each technology is determined for each year between 2015 and 2050 using the central estimate for technology inputs, fixed electricity price (50 US$/MWh), discount rate (8%) and size (10 MW), while varying discharge duration and annual full equivalent discharge cycle requirements. Discharge duration and cycle requirements are varied in 490 steps on a logarithmic scale between 0.25 to 1,024 hours and 1 to 10,000 cycles respectively.

To explore the sensitivity to technical performance parameters, the most sensitive parameters are identified by comparing the impact of a constant percentage change for each parameter on lifetime cost. The presented sensitivity results are chosen such that the respective technology becomes competitive with the prevalent technology by varying its most sensitive parameters.

3.4 Market and System Value

This section outlines the methodology to assess the economic market value for electricity storage in various power system applications and the capacity required to integrate intermittent or relatively inflexible low-carbon generation.

3.4.1 Market value for any application

The review data for the economic market value of electricity storage in various power markets for 13 applications in the US[170] is verified with respective values in European markets[168,171–176], namely Germany and the UK (Chapter 2.4.1).

The US values are matched to the discharge duration and annual cycle requirement ranges that were used in the review to differentiate between applications[170,241]. Due to the lack of data for long-term storage applications, its value is modelled using the storage dispatch algorithm developed by Ward et al.[242] based on wholesale price data of the last ten years for the US PJM (hourly) and GB power markets (half-hourly). The algorithm develops a profit-maximising dispatch schedule by pairing maximum and minimum prices to notional charge-discharge pairs, subject to capacity, efficiency and charge rate constraints. It is run for an 80% and 30% efficient technology with discharge durations of 512, 768 and 1,024 hours, returning discharge frequencies between 1.75 to 4.65 and a value range of 1-179 US$/kW$_{year}$.

The ranges of economic values, duration and frequency requirements for each application are used to determine the economic value of any potential application with a discharge duration between 0.25 to 1,024 hours and 1 to 10,000 annual discharge cycles. Duration and frequency are varied in 490 steps on a logarithmic scale to obtain this spectrum. A Monte-Carlo simulation with 1,000 trials samples across three dimensions of uncertainty: (i) the identified economic values[170] and within the (ii) discharge and (iii) frequency ranges for each application[241]. Thus, for each trial there are 14 applications with a unique economic value, discharge duration and frequency requirement. Each point on the duration-frequency matrix is then assigned the value of its nearest application, using a nearest neighbours' algorithm.

The discrete nature of the results from individual Monte Carlo trials lead to sharp discontinuities between the values of adjacent cells, so the resulting data across the frequency-duration space is smoothed using a Gaussian smoothing kernel (i.e., applying a convolution matrix to the original image / underlying data, thereby accounting for the data surrounding a specific cell with a Gaussian function).

Finally, mean, 25th and 75th percentiles are determined for the entire spectrum based on the 1,000 Monte-Carlo trials.

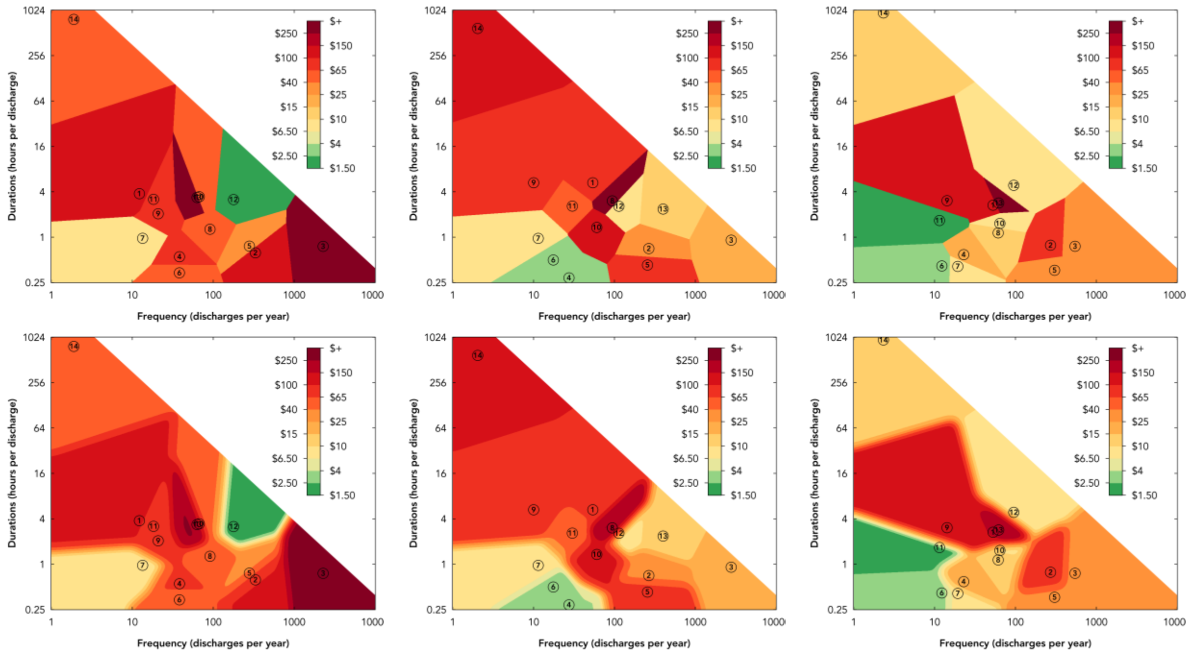


Figure 3.2 – Allocation of market values to the entire frequency-duration space based on the variation in value, duration and frequency requirements of specific applications and a nearest neighbours' algorithm. Top: Three sample Monte Carlo trial results where each of the 14 applications is assigned an economic value, discharge duration and frequency from within their given range and each point on the duration-frequency matrix is assigned the value of its nearest application. Bottom: Gaussian smoothing kernel applied to Monte Carlo trial result. Note: Service 14 is not taken from the literature but modelled explicitly.

This analysis is conducted for economic market values (MV) in power (US$/$kW_{year}$) as well as energy terms (US$/MWh). Conversion is performed with the product of discharge duration (DD) and annual cycles (Cyc_{pa}) of the respective application.

$$MV_{energy} = \frac{MV_{power} * 10^3}{(DD * Cyc_{pa})} \tag{29}$$

In an alternative approach, economic market values are not sampled from the explicit literature values identified, but randomly chosen between 25th and 75th percentiles of those values. This is performed to test the robustness of the analysis.

3.4.2 Profitability of modelled applications

Economic market values for discharge duration and frequency of the 12 core applications are calculated in each Monte Carlo trial (Appendix D.3). The values are assessed against the result of the lifetime cost Monte-Carlo simulation with highest probability of lowest LCOS or ACC (Chapter 3.3.4) to compute the profitability probability for electricity storage in each one of the modelled core applications from 2015-2050.

Mean LCOS and ACC of the most cost-efficient technologies in each year are assessed against mean economic market values across the entire duration-frequency spectrum to compute the profitability of electricity storage in 2015-2050 for applications with any possible discharge duration and frequency requirement combination and year.

3.4.3 System Value

The value of electricity storage in enabling low-carbon power systems is investigated in a meta-analysis by reviewing 10 academic, industry and government studies conducted within the last 5 years that model the future evolvement of Great Britain's (GB) power system.

The value electricity storage offers to power systems is a function of three study dimensions: the power system set-up (e.g., renewable, nuclear, flexibility capacity), model type (e.g., temporal and spatial resolution, technology detail), and input assumptions (e.g., technology cost, carbon and fuel prices). An additional study would likely be limiting to one viewpoint on all of these aspects and could not present a consensus view. Instead, considering all openly available studies in a meta-study approach allows heterogeneity across all study dimensions and enables identification of trends and a consensus view (if one exists).

The GB system is suitable for assessing the system value of electricity storage due to:

- High data availability from multiple studies by various institutions
- Ambitious targets for decarbonisation of the power system[7]
- Increasing penetration of low-carbon electricity (25 to 53% from 2009 to 2018[15])
- Limited interconnection to neighbouring countries (4 GW in 2018[243])

The chosen studies employ power system models and optimise for lowest cost under carbon emission and technology penetration constraints. The study by Edmunds et al. (Table 2.6) is not considered, because installed electricity storage capacities do not reflect requirements for system adequacy but the specific potential of two newly proposed pumped hydro storage sites[190].

All scenarios in the reviewed studies are assessed for installed capacity and generation of all electricity technologies (i.e., coal, gas, wind, solar, hydro, nuclear, biomass, geothermal, waste, wave, electricity storage, DSR, interconnection, OCGT, oil, diesel) and peak demand.

Electricity technologies are grouped into three categories:

1. Generation capacity: Coal, gas CCGT, wind, solar, nuclear, biomass, geothermal, waste, wave
2. Flexibility capacity: Electricity storage, DSR, interconnection, OCGT, oil, diesel, hydro
3. Dispatchable capacity: all except wind and solar

Missing information were inquired directly from the authors of the studies. If CCGTs are modelled with less than 100 full load hours per year, they are categorised as flexibility and not generation capacity. Respective values for the existing GB power system in 2017 for comparison are taken from the Digest of UK energy statistics report[244].

The resulting data is assessed for modelled electricity storage, flexibility and total capacity relative to the share of wind, solar and nuclear power capacity and energy generation. These three low-carbon technologies are chosen as dependencies because of their intermittent (i.e., solar, wind) or relatively inflexible (i.e., nuclear) generation pattern, creating the need for flexibility capacity such as electricity storage (Chapter 1.2).

To account for varying assumptions of peak demand, electricity storage, flexibility and total capacity requirements are normalised for this factor. The modelled dispatchable capacity relative to peak demand is also assessed.

In addition, the impact on electricity storage or flexibility requirements of the following aspects were tested: nuclear penetration, electricity storage discharge duration, the ratio of wind to solar.

The analysis of global flexibility capacity requirements is based on projections for the power sector of the Integrated Assessment Modelling Consortium (IAMC) to 2100 used for the

IPCC 1.5°C report in scenarios with a 50% likelihood to limit average global surface temperature increase to below 2°C[1,245,246].

Global noncoincident peak demand in each year is determined by dividing total global annual electricity demand by 8,760 hours to compute average demand and multiply that with 1.8, the ratio between average and peak demand. The ratio of 1.8 is identified by comparing average demand in 2005 to 80% of total generation capacity. In 2005, wind and solar capacity were only 1% of total generation capacity. It is implied that only 80% of the generation capacity is supposed to meet peak demand, yielding a common system margin of 20% (Appendix D.5). The ratio between average (440 GW) and noncoincident peak demand (770 GW) in the US is also 1.8[247]. The implicit assumption is that hourly demand profiles remain unchanged compared to 2005. Although some studies model an increase of 20-25% between average and peak demand by 2050 in selected countries[248], the high uncertainty around this development justifies the constant ratio in this study. In contrast, technologies like demand-side response are likely to reduce this ratio, but it is reasonable not to model this impact upfront since their potential as flexibility capacity is assessed here.

Projections for hydro and oil-based generation capacity are considered as flexibility capacity, in addition to 2015 installation levels[11] of electricity storage (153 GW), interconnection (177 GW) and demand-side response (40 GW) since these are not projected into the future.

The results are compared to the flexibility capacity modelled in the study by Jacobson et al. for a 100% wind, water and sunlight based energy system in 2050[249].

4. Projecting Future Investment Cost

This chapter conducts a comparative appraisal of experience curves for promising electrical energy storage (EES) technologies, followed by the projection of future prices based on increased cumulative capacity and a feasibility test against possible cost floors set by material and manufacturing cost. Using market growth models, feasible timescales for realising these prices and the required investments in deployment are determined. Finally, key implications of this analysis are discussed with two stylised examples to show how the derived experience rates (ERs) can be used to assess uncertainty around future competitiveness of storage.

Although many studies refer to cost reduction potentials along experience curves of single storage technologies[23,98,142,215,231,250], there is no holistic overview covering multiple technologies within a consistent scope and methodology. Such an overview, as presented in this chapter, helps to identify overarching trends in cost reduction, compare investment levels required to achieve competitive price levels[121] and evaluate the technology-specific value added to renewable power systems[25]. The experience curve dataset and respective analyses are publicly available in an Online Data Repository[251].

4.1 Experience Curves for Electricity Storage Technologies

Prices for storage technologies differ by scope, application and size[36]. The results for EES experience curves are differentiated along two main dimensions, application category and technology scope. Application category covers portable (consumer electronics), transport (hybrid electric vehicle - HEV, and electric vehicle - EV) and stationary (residential, utility); technology scope covers cell, battery, module, pack, ex-works system and system. Please note that electrolyser and fuel cell stacks are also referred to as ‘packs’ for simplicity (Chapter 3.1.1).

Figure 4.1 shows decreasing product prices per unit of energy capacity with increasing cumulative installed nominal energy capacity for most EES technologies. Pumped hydro (system), lead acid (module), alkaline electrolysis (pack) and lithium ion for consumer electronics (battery) and electric vehicles (pack) exhibit current prices below 300 US$/kWh above 100 GWh installed. The relatively low ERs (ERs) below 5% of the first two are contrasted by 17% for electrolysis (pack) and 30% and 21% for lithium-ion batteries and packs respectively. Technologies with between 1 and 100 GWh cumulative installed capacity, such as nickel-metal hydride (pack), utility-scale lithium ion (system) or sodium sulphur (system) show current prices between 300 and 800 US$/kWh and ERs of 11% and 16%. Those below 1 GWh like residential lithium ion (system), lead acid (system), redox flow (system) and fuel cells (pack) cost more than 800 US$/kWh with ERs between 13% and 16%. Possible drivers for the negative ER of pumped hydro are explored in Appendix A.6 by analysing hydropower plant price developments. It should also be noted that product prices for electrolysers and fuel cells in US$/kWh are from price data in $/kW (Figure 4.2). The $/kW value is divided by 10 based on the assumption that a hydrogen storage tank with a capacity large enough to provide a fuel cell with hydrogen for 10 hours at nominal power is used.

ER uncertainty is determined using the 95% standard error-based confidence interval (CI). This is relatively small (<±5%) for most emerging and maturing technologies, however most mature technologies (pumped hydro, lead-acid modules, alkaline electrolysis) exhibit higher ER uncertainty (>±5%) and are not significantly different from zero (p>0.05).

EES technologies for which there is not enough data are excluded, but these may still hold promise in the future. For sodium sulphur, no feasible ER could be determined from the compiled data (displayed in Fig. 4.1. for reference).

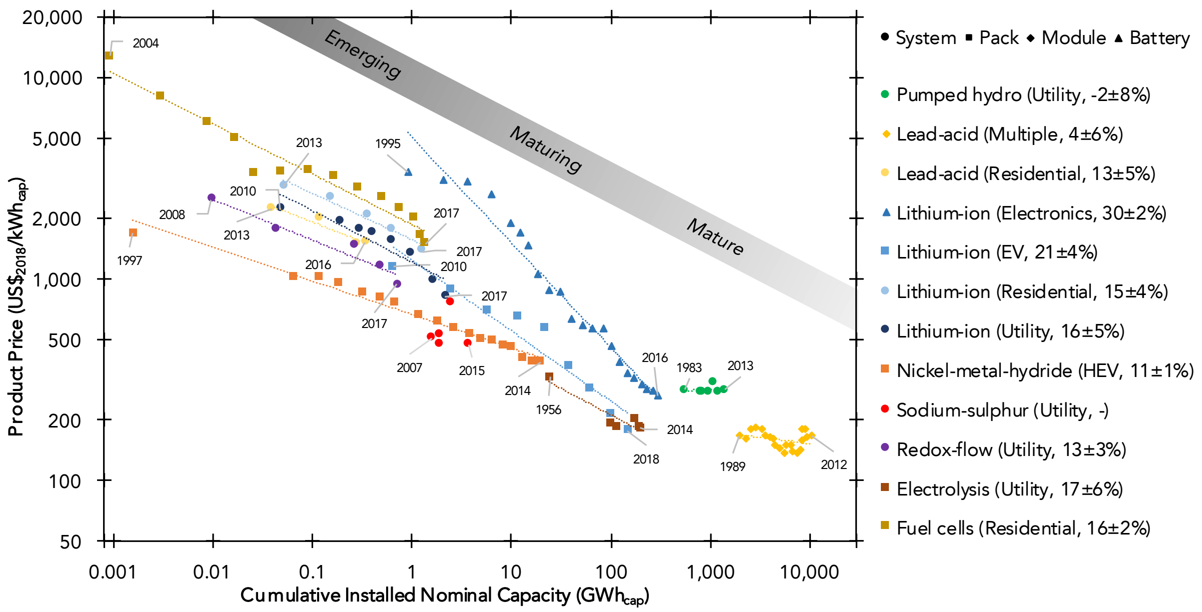


Figure 4.1 – Experience curves for EES technologies (energy terms). Results shown for product prices per nominal energy capacity. Dotted lines represent the resulting experience curves based on linear regression of the data. Top legend indicates technology scope and bottom legend denotes technology (including application and ER with uncertainty). ER uncertainty is quantified as its 95% standard error confidence interval. Grey bars indicate overarching trend in cost reduction for EES relative to technology maturity. Maturity level assessments in the literature[24,66] are used to categorise the technologies relative to their cumulative installed capacity as: Emerging (<1 GWh), Maturing (<100 GWh) and Mature (>100 GWh). According to this simplified categorisation, emerging technologies cost above 600 US$/kWh, maturing ones between 300 and 3,000 US$/kWh and mature technologies below 500 US$/kWh. Fuel cell and electrolysis must be considered in combination to form an EES technology (electrolysis converts electricity to storable hydrogen gas; fuel cells reconvert hydrogen to electricity). Data for lead acid (module) refer to multiple applications, including uninterruptable power supply or heavy-duty transportation. kWh_{cap} - nominal energy storage capacity.

Figure 4.2. displays experience curves of EES technologies in power terms (i.e., US$/kW) against GW of power capacity installed. These were determined by applying the average power-to-energy ratio (i.e., maximum discharge rate relative to maximum energy capacity) to product price and cumulative installed capacity. These are fixed for each technology, therefore ERs stay the same as in Figure 4.1. However, it can be observed that the range of prices is much wider, clearly differentiated along the power-to-energy ratio of the different technologies. Nickel-metal hydride battery packs used in HEVs with a ratio of 15 cost 20 US$/kW, lithium-ion packs with a rate of 4 cost 50 US$/kW and all other technologies with ratios below 0.5 cost more than 550 US$/kW for transportable batteries, modules or above 1,500 US$/kW for stationary systems. This indicates that up to the pack level, energy capacity is the cost defining criterion for electrochemical storage technologies and they can be cost-optimally designed for power requirements of the target application. For comparison, the ERs of solar PV modules and inverters are displayed, indicating that ERs of EES technologies are within the same range.

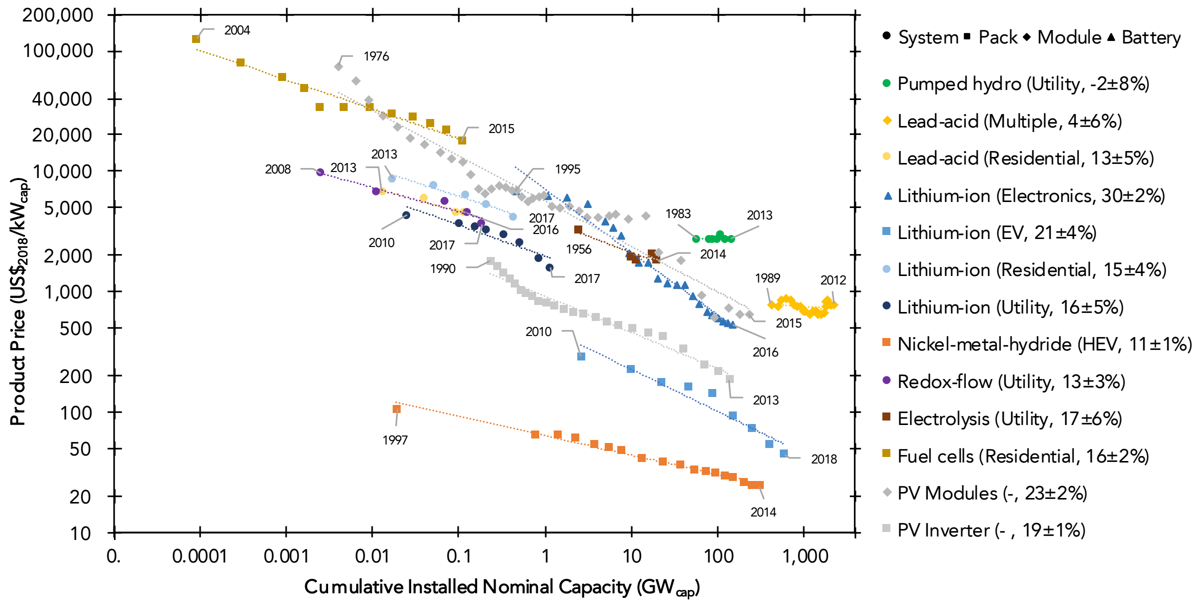


Figure 4.2 – Experience curves for EES technologies (power terms). Results are shown for product prices per nominal power capacity. Top legend indicates technology scope and bottom legend denotes technology (including application and ER with uncertainty). Indicative power-to-energy ratios (Appendix A.1) are used to convert prices and capacity from energy to power terms and vice versa. Solar PV module[252] and PV inverter[253] experience curves in grey are shown for reference.

In addition, it can be observed that ERs for lithium-ion technologies decrease with increasing technology scope (Figure 4.3.). Higher ERs for cells and batteries than for packs and systems imply that cost reductions are likely driven by experience in cell manufacturing rather than other components required in packs and systems. Stronger cost reduction for consumer electronics batteries compared to 18650 cells could reflect the ongoing shift from cylindrical 18650 to more cost-competitive prismatic and laminate cells used for consumer electronics batteries[254]. Strong cost reduction for 18650 cells in 2013, 2014 and 2015 might be the result of increased demand in EV packs, partly driven by Tesla[254].

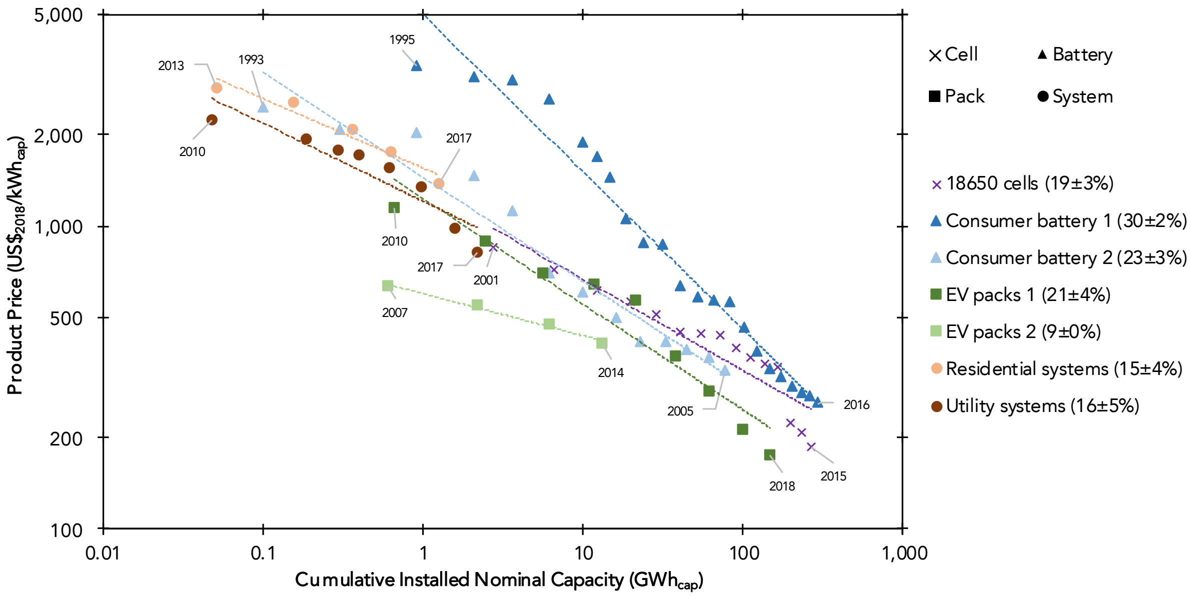


Figure 4.3 – Experience curves for lithium-ion technologies (energy terms). Results shown for product prices per nominal energy capacity. Dotted lines represent the resulting experience curves based on linear regression of the data. Top legend indicates technology scope and bottom legend denotes technology (including ER with uncertainty). ER uncertainty is quantified as its 95% standard error confidence interval. Data Sources: 18650 cell[93], Consumer battery 1[254–256], Consumer battery 2[257], EV packs 1[96,258], EV packs 2[23], Residential systems[224,226], Utility systems[259,260].

4.2 Future Investment Cost

Using the derived ERs, future prices for EES based on increased cumulative capacity are projected (Fig. 4.4.) and the feasibility of these projections is tested against indicative cost floors defined by raw material and production cost.

When projecting the experience curves forwards to 1 TWh cumulative capacity, the categorisation of EES technologies along product prices and cumulative installed capacities can be refined into cost reduction trajectories for the three application categories. Prices for stationary systems reduce to a narrow range between 200 and 450 US$/kWh, and for battery packs to between 110 and 200 US$/kWh, regardless of technology. This implies that the one technology that manages to bring most capacity to market is likely to be the most cost competitive. This novel insight can be derived, because this thesis, for the first time, produces ERs for multiple electricity storage technologies and uses them to derive future cost estimates. Prices for portable batteries reduce to 140 US$/kWh.

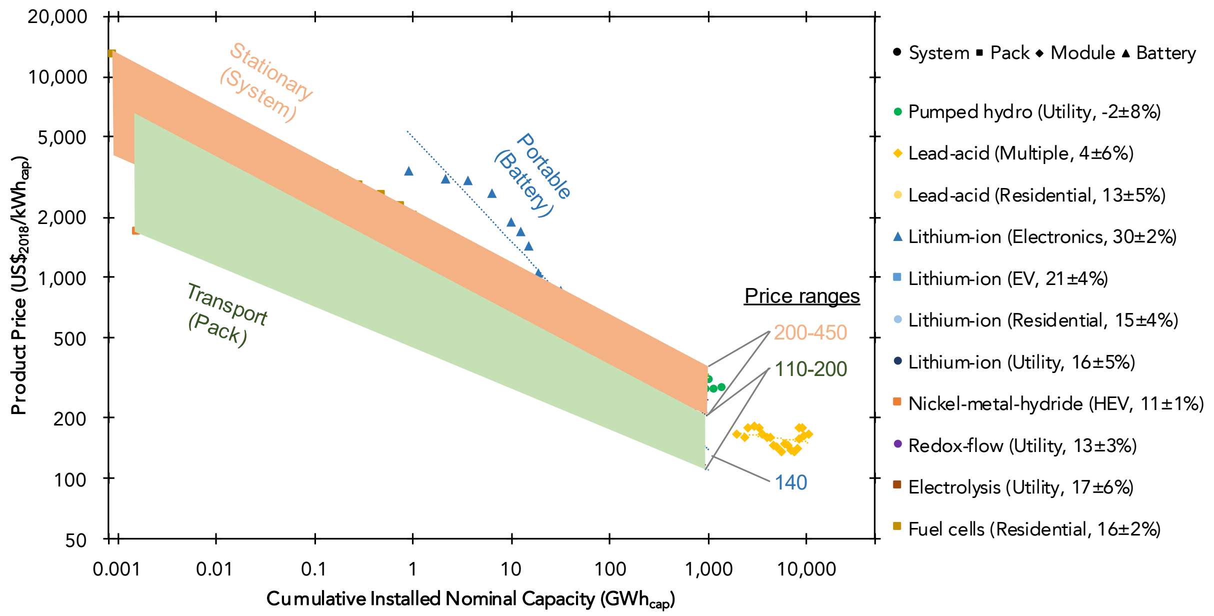


Figure 4.4 – Future cost of EES technologies at 1 TWh cumulative capacity. Experience curves (dotted lines) are projected forwards to analyse product prices at future amounts of cumulative capacity. Top legend indicates technology scope and bottom legend denotes technology (including application and ER with uncertainty). Shaded regions are visual guides indicating the cost reduction trajectory for each application category (at a particular technology scope). These narrow to the price ranges given on the right of the figure; Systems used for stationary applications: 200-450 US$/kWh; Packs used for transport applications: 110-200 US$/kWh; Batteries used for portable applications: 140 US$/kWh. For fuel cells and electrolysers prices are only reported on pack-level. The combination that could be used for stationary storage would cost 450 US$/kWh at pack-level (electrolysis: 115 US$/kWh, fuel cell: 335 US$/kWh), setting the upper bound of the range for stationary system. However, at system-level this combination would cost more, implying a higher upper bound. Pumped hydro systems and lead-acid modules are beyond 1 TWh cumulative installed capacity but cost 280 US$/kWh (pumped hydro) and 180 US$/kWh respectively, which is well within the ranges identified for stationary storage systems and transport packs. kWh_{cap} - nominal energy storage capacity.

Due to the empirical rather than analytical nature of experience curves, extrapolations are subject to uncertainty of the derived ERs and uncertainty associated with unforeseeable future changes (technology breakthroughs, knowledge spill-overs, commodity price shifts)[120,125]. When accounting for uncertainty of the underlying price and capacity data, the resulting price range at 1 TWh is 123 – 614 US$/kWh (systems), 94 – 217 US$/kWh (packs) and 131 – 145 US$/kWh (batteries) (Table 4.1).

Table 4.1 – Impact of ER uncertainty on cost projections for 1 TWh cumulative installed capacity. Central rate numbers refer to the experience-curve-based price projections in Figure 4.4. Low and high rate numbers are based on the lowest and highest ER of the 95% standard error confidence intervals respectively. Cumulative installed nominal energy capacity for pumped hydro (system) and lead acid (module) is already above 1 TWh. Therefore, projected prices at 1 TWh refer to historic investment cost (pumped hydro: 2000, lead-acid: pre-1989). The price range is then a result of back-casting at the respective ERs.

	Central rate		*Low rate*		*High rate*	
Technology	ER **(central)**	Price **(US$/kWh)**	ER **(low)**	Price **(US$/kWh)**	ER **(high)**	Price **(US$/kWh)**
Pumped hydro (Utility, System)	-1.5%	282	-10%	272	6%	293
Lead-acid (Multiple, Module)	4.3%	175	-1%	144	10%	213
Lead-acid (Residential, System)	12.6%	316	8%	614	17%	163
Lithium-ion (Electronics, Battery)	30.3%	138	28%	145	32%	131
Lithium-ion (EV, Pack)	21.4%	111	17%	131	25%	94
Lithium-ion (Residential, System)	14.7%	319	11%	477	18%	213
Lithium-ion (Utility, System)	16.3%	204	11%	340	21%	123
Nickel-metal hydride (HEV, Pack)	10.9%	207	10%	217	12%	197
Redox-flow (Utility, System)	13.0%	245	10%	367	16%	164
Electrolysis (Utility, Pack)	16.7%	115	10%	136	23%	96
Fuel cells (Residential, Pack)	15.9%	333	13%	436	18%	265

Experience curve studies should include cost floors in extrapolated forecasts to avoid excessively low cost estimates[120,125]. Raw material cost for each technology are calculated by multiplying material inventories from the literature with commodity prices of the past 10 years (Figure 4.5., Appendix A.3 and A.7). The average raw material cost across all technologies is significantly below their high ER projection (Table 4.1.). Production and other cost are typically below 20%[217,218] of final system price for electrochemical, or between 50 and 80%[219] for mechanical storage technologies, that are technologically mature. This confirms that the identified cost reduction potentials to 110-450 US$/kWh are feasible.

However, it should be acknowledged that despite using price ranges of the past ten years, there is still high uncertainty on the development of commodity prices. On the one hand, there could be raw material and other input bottlenecks as storage takes off, increasing commodity prices, whilst on the other, the take-off potentially attracts new producers of raw materials and other inputs, depressing commodity prices.

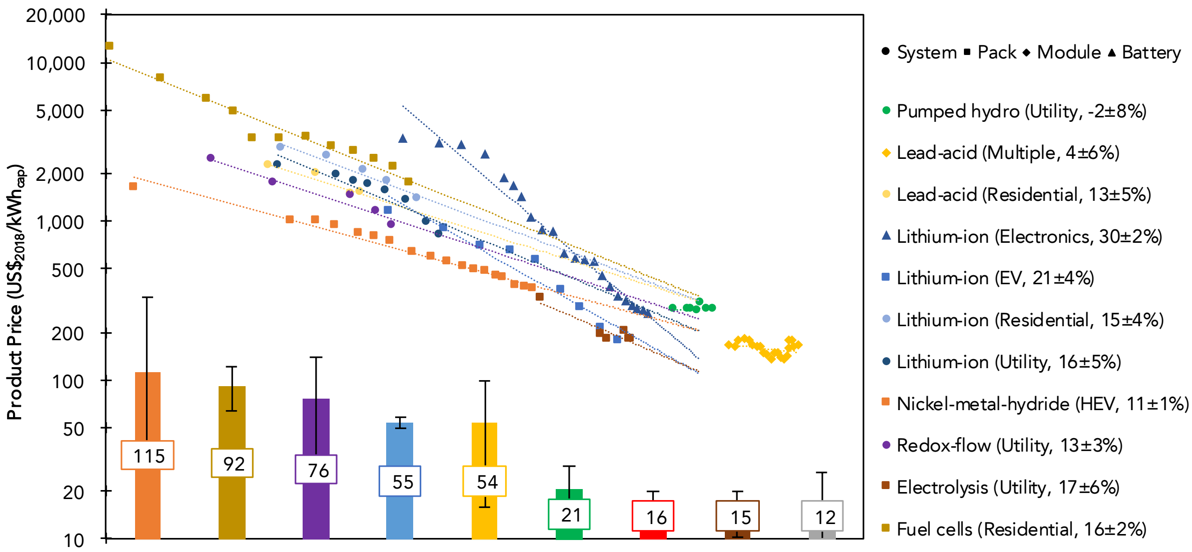


Figure 4.5 – Raw material cost for each technology compared to price projections. Raw material cost are calculated by multiplying material inventories from the literature (Appendix A.7) with commodity prices of the past 10 years (Appendix A.3). The bars show raw material cost of EES technologies in the respective experience curve colour code. The cost are per system for pumped hydro and per pack for all other technologies. Error bars account for variations in each technology's material inventory and commodity prices over the past 10 years.

Nickel-based batteries exhibit relatively high raw material cost and are subject to high commodity price sensitivity, with cost of 340 US$/kWh in the worst case for nickel-metal hydride. The material cost of other electrochemical storage technologies are also driven by their active materials like platinum, vanadium, lithium and lead and lie between 15 and 90 US$/kWh. The raw material cost for a stainless steel tank to store hydrogen is around 12 US$/kWh and should be added to the 15 US$/kWh for an alkaline electrolyser and 92 US$/kWh for a PEM fuel cell to obtain the full raw material cost of a hydrogen-based electricity storage system[261,262]. It should be noted that lithium ion is a family of technologies with different options for materials used in the cathode. Raw material cost of the different lithium-ion battery types range from 42 to 62 US$/kWh (Appendix A.7). Mechanical storage technologies have the lowest material cost below 20 US$/kWh due to the low-cost materials employed. Higher average material cost can be attributed to technologies designed for high power applications for which no experience curves are derived. These require expensive materials to withstand extreme conditions: high electric charge for supercapacitors; low temperatures for superconducting magnetic energy storage (SMES); or high velocities for flywheels (Appendix A.7).

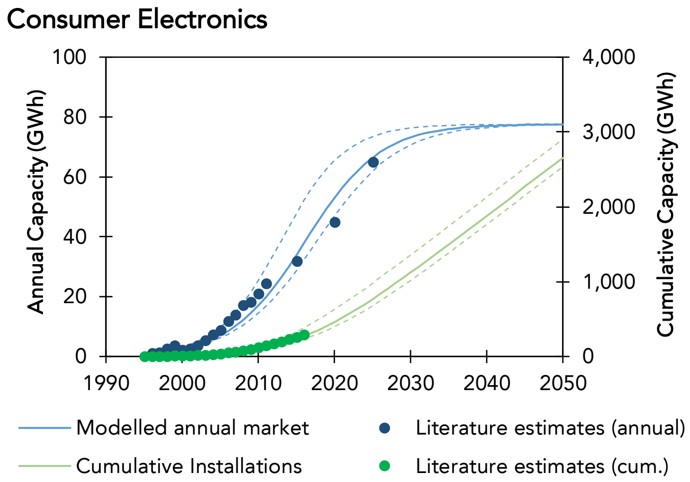
Resource availability is a key concern for the future deployment potential of certain electricity storage technologies. However, it is found that all active materials of the investigated EES technologies have a reserve base sufficient for the production of beyond 10 TWh storage capacity with current technology[263]. Resource availability is therefore unlikely to affect the price ranges identified in Figure 4.2 and will not become a limiting factor for technology deployment before 2035 according to market growth projections (Table 4.2).

While ERs can be useful to project future investment cost, a high-level comparison of EES technologies can only be made based on application-specific levelised cost[89]. This would account for additional technical and economic parameters, for example technology lifetime, which are not reflected in this analysis, but considered in Chapter 6.

4.3 Timeframe of Potential Cost Reduction

To map future cost reductions to time, the market diffusion process of EES technologies is modelled with the archetypal sigmoid function (i.e., S-curve) that has been observed for the deployment of several technologies[264] using annual market deployment and saturation forecasts from the literature (Chapter 0). The resulting market growth projections are displayed in Table 4.2.

Table 4.2 – Growth projections for various electricity storage applications.



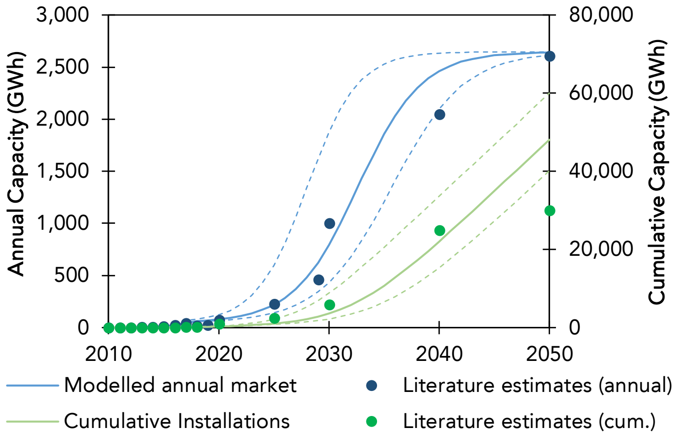
Key parameters:
- Growth rate: 0.204
- Standard error: 0.004

- Min growth rate = 0.190
- Max growth rate = 0.241

Assumptions:
- Initial capacity: 1.0 GWh p.a. (1995[255])
- Saturation: 80 GWh p.a. (2050)
- Literature estimates[254,255]

Comment: Li-ion battery market for portable devices to double by 2025

Electric Vehicles



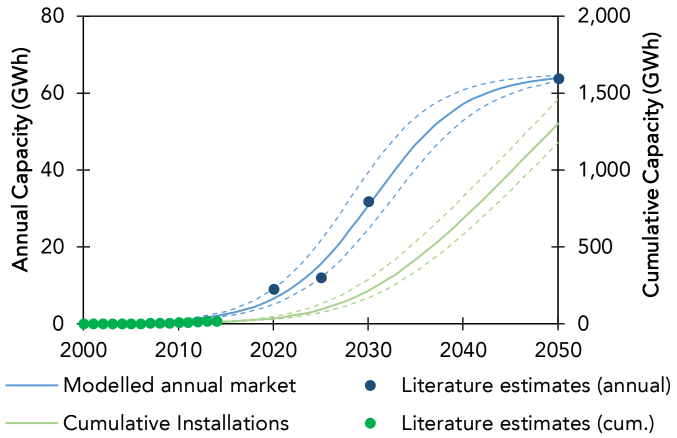
Key parameters:
- Growth rate: 0.348
- Standard error: 0.008

- Min growth rate = 0.306
- Max growth rate = 0.436

Assumptions:
- Initial capacity: 1.0 GWh p.a. (2011[250])
- Saturation: 2,600 GWh p.a. (2050[265])
- Literature estimates[250,265–267]

Comment: EV sales up from 0.46mn (2015) to 15mn (2030) and 41mn (2040)[266]

Hybrid Electric Vehicles



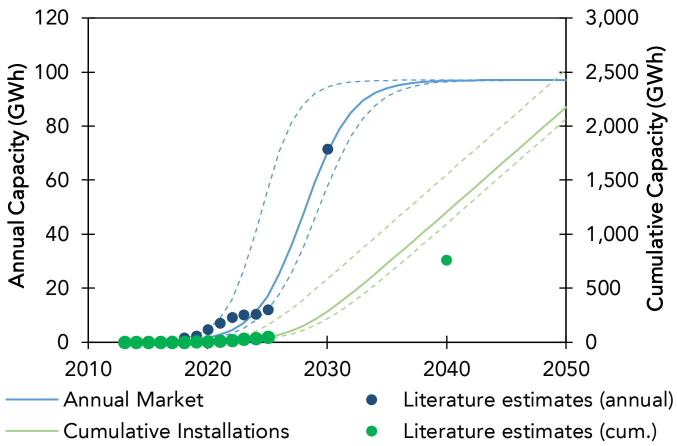
Key parameters:
- Growth rate: 0.208
- Standard error: 0.004

- Min growth rate = 0.197
- Max growth rate = 0.225

Assumptions:
- Initial capacity: 0.06 GWh p.a. (1998[268])
- Saturation: 65 GWh p.a. (2050[265])
- Literature estimates[254,265,268]

Comment: HEV sales up from 5mn (2015) to 25mn (2030) and 50mn (2050)[265]

Residential Storage



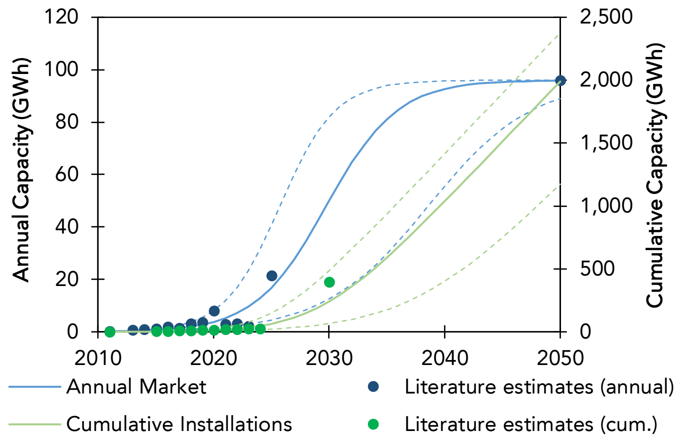
Key parameters:
- Growth rate: 0.500
- Standard error: 0.007

- Min growth rate = 0.466
- Max growth rate = 0.656

Assumptions:
- Initial capacity: 0.05 GWh p.a. (2013)
- Saturation: 97 GWh p.a. (2050[24])
- Literature estimates[169,269–271]

Comment: 4 GW (~12 GWh) of residential systems installed annually by 2025[269]

Utility-scale Storage:



Key parameters:

- Growth rate: 0.326
- Standard error: 0.013

- Min growth rate = 0.222
- Max growth rate = 0.425

Assumptions:

- Initial capacity: 0.21 GWh p.a. (2011[260])
- Saturation: 96 GWh p.a. (2050[24])
- Literature estimates[24,169,260,267,272]

Comment: 30 GWh cumulative installed storage in grid applications by 2025[169]

It is found that 1 TWh cumulative capacity could be installed for most new technology types within 5 to 20 years (Figure 4.6). That means by 2030, stationary systems cost between 280 and 430 US$/kWh with pumped hydro and residential lithium ion as minimum and maximum values respectively. When accounting for ER uncertainty, the price range expands to 200 – 710 US$/kWh (min: utility-scale lithium-ion, max: residential lead-acid). The price range for transport applications in 2030 is 70 – 270 US$/kWh. Lithium-ion EV pack prices reduce to 70 US$/kWh by 2030 due to the high ER of 21% combined with the high demand if 15m EVs are sold annually by 2030[266]. This equals more than 700 GWh annual capacity, compared to 50 GWh for utility storage. Lower demand projections combined with a lower ER for nickel-metal hydride HEV battery packs, means prices reduce only to 270 US$/kWh. Lithium-ion batteries for consumer electronics would be at 130 US$/kWh by 2030. Note that Figure 4.6 shows the impact of ER uncertainty on future cost projections as shaded area. Appendix A.8 depicts this impact separately for each EES technology as well as the additional impact of market growth uncertainty.

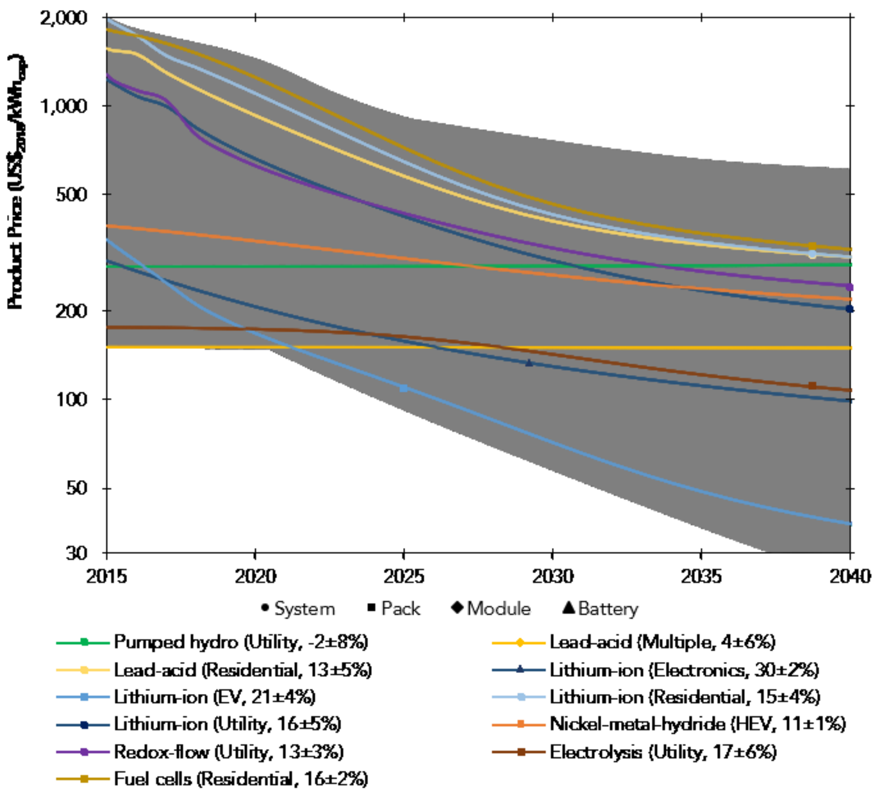


Figure 4.6 – Future cost of EES technologies relative to time. Cost projections are based on ERs and S-curve type market growth assumptions for consumer electronics, hybrid electric vehicles, electric vehicles, residential storage and utility-scale storage. Market growth in different applications is mutually exclusive, but technology penetration is not (i.e., 100% market share assumed for each technology). Symbols indicate when 1 TWh cumulative installed capacity could be achieved for each technology under this condition. No symbol means 1 TWh cumulative capacity is not achieved within the given timeframe (pumped hydro: 2000, lead-acid - modules: pre-1989, NiMH: 2046). Shaded area marks impact of ER uncertainty. See Appendix 8 for the impact of ER and additional market growth uncertainty on each EES technology separately. Legend denotes technology (including application and ER with uncertainty). Fuel cell and electrolysis must be considered in combination to form an EES technology. kWh_{cap} - nominal storage capacity.

The identified price range of 280 – 430 US$/kWh for stationary systems by 2030 lies within other projections (140 – 620 US$/kWh, Table 4.3). However, individual products like the lithium ion based *Tesla Powerwall 2* were at an estimated retail price of 500 US$/kWh already by 2017[273]. A possible explanation could be synergistic learning effects for an EES technology across applications due to shared components, cross-over techniques or knowledge spill-overs, leading to cost reductions not considered in this analysis[131]. In contrast, the cost projections in this study assume 100% market share for each technology in their respective application, which yields optimistic trajectories, and would support the projections at the upper end of the literature.

The range of 70 – 270 US$/kWh for transport packs is at the lower end of similar projections (70 – 750 US$/kWh, Table 4.3), but supported by recent industry announcements of lithium-ion cells reaching 100 US$/kWh as early as 2022[94]. Since higher estimates come from expert interviews versus lower from ER projections, the difference could be based on the latter placing more emphasis on future capacity additions, which would be significant if transportation is electrified. Conversely, increasingly competitive markets have driven strong price reductions since 2014, which could overestimate the underlying production cost reductions and distort the ERs derived in this thesis[124].

It should also be noted that the price projection for lithium-ion battery packs beyond 2030 approaches the raw material cost floors identified in Chapter 4.2. Therefore, if these projections materialise, significant reductions in commodity prices, improvements in energy density, or changes in commodity composition of lithium-ion batteries have to be achieved. The latter two developments are currently displayed on that timeline in lithium-ion innovation roadmaps[258,274].

Table 4.3 – Comparison of experience-curve-based cost projections to the literature. Projections from the experience curve analysis are shown in the '2030' and '2040' columns (central ER). They can be compared to the findings from the literature in the 'Literature' column, qualified through respective comments in the 'Method/Comment' column.

Technology	2030 ($\$_{2018}$/kWh)	2040 ($\$_{2018}$/kWh)	Literature ($\$_{2018}$/kWh)	Method/Comment
Pumped hydro (Utility, System)	285	287	148 - 244	Long-term estimate for 90% renewables system[88]
Lead acid (Multiple, Module)	150	151	206 - 260 127 - 180	Bottom-up engineering model for 'Future State Price'[92] Long-term estimate for 90% renewables system[88]
Lead acid (Residential, System)	407	307	206 - 260	Bottom-up engineering model for 'Future State Price'[92]
Lithium ion (Electronics, Battery)	130	99	105 105	Experience curve analysis for 2020[95] GM forecast for 2022 for pack-grade cells[94]
Lithium ion (EV battery, Pack)	71	38	169 - 318 224 - 483 180 - 333 219 - 328 215 – 754 62	Literature Review for 2030[23]; Bottom-up Engineering Model for 2030[97]; Bottom-up Engineering Model for 2030[97]; Literature Review for 2030[98]; Expert Elicitation for 2030[99]; Experience curve analysis for 2030[96]
Lithium ion (Residential, System)	429	308	-	-
Lithium ion (Utility, System)	298	204	196 - 217 255 - 337 261 - 648 470 - 575 309 - 526 227 - 390	Bottom-up engineering model for high manufacturing[101] Bottom-up engineering model for 'Future State Price'[92] Analyst projections for 2030[102]; Experience Curve Analysis for 2030[102] Experience Curve Analysis for 2030[100] Experience Curve Analysis for 2040[100]
Nickel-metal hydride (HEV, Pack)	271	225	-	
Redox flow (Utility, System)	326	243	157 - 275 191 - 265 185 - 196	Bottom-up engineering model for 'Future State Price'[92] Bottom-up engineering model for 2GWh demand p.a.[104] Bottom-up engineering model for high manufacturing[101]
Electrolysis (Utility, Pack)	143	109	52 – 111	Expert Elicitation for 2030[56]
Fuel Cell (Residential, Pack)	455	318	404 - 563	Consultancy report for mass-market production[106] (> 10,000 units cum production per company)

4.4 Cumulative Investment for Cost Reductions

The cumulative investment required to deploy EES is of interest to academics, industry and policy[24,167]. By linking product prices to cumulative capacity, experience curves offer the possibility to quantify this[120,125,275].

Global investment in renewable power generation and network infrastructure were at US$300bn each in 2017[276,277]. Investment in electricity storage technologies was around US$10bn, 3% relative to network investments.[277,278] Figure 4.7 shows that investments worth US$120bn (lithium ion, pack) to US$630bn (electrolysis & fuel cells, pack) would be required for the deployment of each EES technology to reach the identified price range at 1 TWh cumulative installed capacity. This means 4 to 19% of network or renewables investments must be spent on each storage technology if this price range were to be reached by 2030. Accounting for ER uncertainty, the investment range could be US$115-460bn in the high ER or US$130-690bn in the low ER case (Appendix A.9).

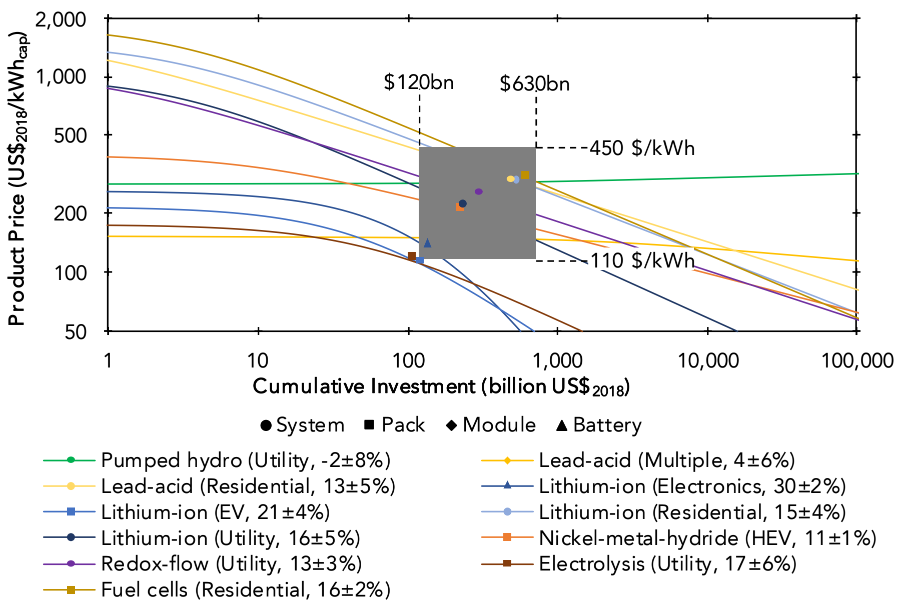


Figure 4.7 – Impact of cumulative investment in EES deployment on future cost of EES. Graph shows investment in storage deployment required to "pull" technologies along individual experience curves. This investment could be consumer capital, industry capital, government subsidy or a mix of all. Shaded rectangle indicates investment required to reach prices of 110 – 450 US$/kWh. Symbols mark the amount of investment required to deploy 1 TWh cumulative capacity for each technology. No symbol means 1 TWh cumulative capacity is already deployed (pumped hydro, lead-acid modules). Legend denotes technology (including application and ER with uncertainty). Fuel cell and electrolysis must be considered in combination to form an EES technology and represents highest investment requirement (i.e., US$ 630bn to achieve 450 US$/kWh). kWh_{cap} - nominal storage capacity. Symbols: circle – system, square – pack, diamond – module, triangle – battery.

If end-users were willing to pay 320 US$/kWh for residential lithium-ion systems already today, then US$90bn of the US$410bn total investment would be required to subsidise deployment until this price level is reached.

This insight can inform policymakers and industry on appropriate deployment policies and investment requirements. In light of the largest country-specific investments in renewable energy capacity ranging from US$10bn (Germany) to US$126bn (China) in 2017[276], global cumulative investment of US$120 to US$630bn for individual EES technologies by 2030 appear reasonable.

4.5 Discussion

This analysis comes with three key implications for industry, policy-makers and academics, among them the possibility to assess future competitiveness of electricity storage.

4.5.1 Implications

First, the common cost trajectory identified for EES technologies enables practitioners to assess proposed technologies against existing ones; with cost trajectories lying above or below signalling that the technology may remain uncompetitive or become disruptive. But, such conclusions are limited to investment cost, and a complete assessment of competitiveness must include additional factors (such as lifetime and efficiency) that affect application-specific levelised costs[89] (Chapter 6).

Second, the future projections made for EES technology prices enable simple assessment of price targets and investment requirements established for the competitiveness of EES. For example, it is suggested that benefit-stacking, the provision of multiple services simultaneously, can make EES competitive at 650 US$/kWh[167]. The present analysis indicates this price threshold could be achieved once 7 GWh of redox-flow or 11 GWh of utility-scale lithium-ion systems have been deployed (central ER), which according to market growth assumptions for utility-scale storage could be achieved by 2021 if all future deployments were one of these technologies. This would correspond to US$5 – 7 billion invested in the deployment of the respective technology. Such quantification enables an informed discussion about the scale of, and split between, private and public sector investments[167]. Note that such analyses are incomplete without considering alternatives to EES, such as network expansion, demand-side management and flexible low-carbon generation. Also, some manufacturers already propose installed system prices below 500 $/kWh[273]. If these prices prove sustainable, this represents a step-change in cost improvement which is not captured in this experience curve analysis.

The third and main implication of this analysis is that the provision of the experience curve dataset can remove a significant barrier to analysing the future competitiveness of EES in distinct applications, and its associated uncertainty. Figure 4.8 shows two stylised examples for EV transportation and residential storage, which are deliberately simplified to showcase the potential insights that can be gained from such data. The myriad of applications, technologies and location-specific contexts that are absent from this cursory analysis can now be more readily explored in future studies.

4.5.2 Competitiveness analyses

A recent study suggested EVs are suitable to replace the majority of vehicles in the US based on daily driving requirements[223]. To assess the economic competitiveness, ER analysis can be used to project cost of ownership (in US$ per mile travelled) for the energy inputs and storage components of EVs and conventional cars (Appendix A.5). In this simplified example (Figure 4.8a), EVs become competitive at lithium-ion pack costs of 150 US$/kWh, which has also been found in similar studies[23,279]. In addition, the combined uncertainty in ER and growth rates could alter the date at which EVs become competitive by up to 4 years (2020 to 2024). The required cumulative production lies between 400 and 650 GWh of battery packs or 8mn and 13mn EVs (at 50 kWh per pack; average between Nissan Leaf[280] and Tesla Model S[281]). Note that this is a simplified example, neglecting any differences in vehicle performance or the price of other vehicle components, but this impact of ER uncertainty would carry through into more detailed analyses.

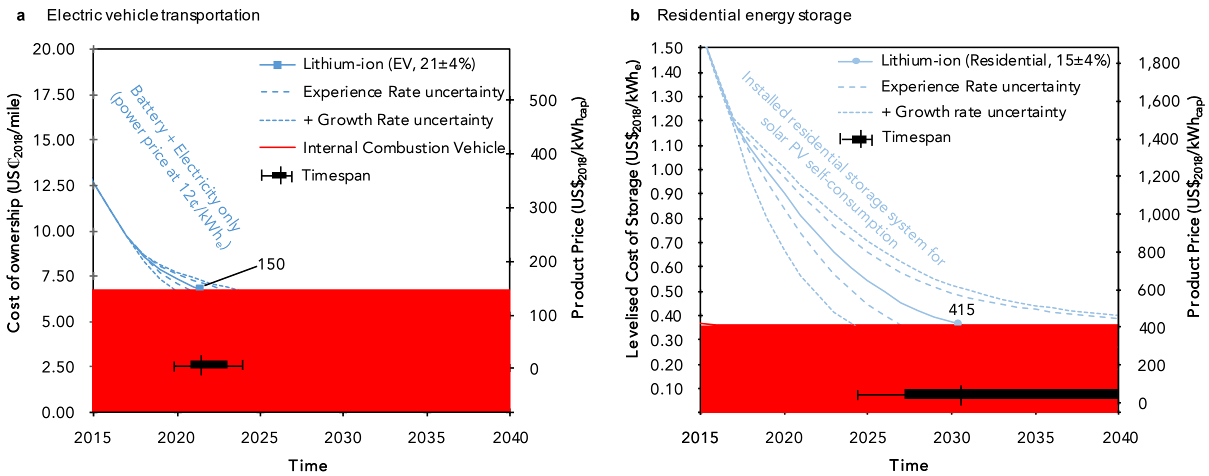


Figure 4.8 – Applicability of experience-curve-based cost projections to application-specific levelised cost analyses. Experience-curve-based investment cost projections are included in levelised cost calculations for two stylised examples. (a): Cost of ownership for personal transport in the US, comparing lithium-ion battery pack plus cost of electricity (blue) and a fuel tank plus cost of gasoline at US$50 per barrel oil price (red). (b): Levelised cost of storage (LCOS) in Germany for solar PV coupled residential lithium-ion system (blue) compared to retail power price (red). Retail price assumed fix at 2016 levels. Dashed and dotted lines in both panels represent impact of ER uncertainty alone and combined with market growth uncertainty, respectively. Black bars indicate possible timespan for costs to equalise with the conventional technology based on these uncertainties (vertical line: equalisation at central ER; thick bar: equalisation timespan when accounting for ER uncertainty; thin bar: equalisation timespan when accounting for ER and growth rate uncertainty). Numbers in figure specify EES product price. kWh_e - unit of electricity, kWh_{cap} - nominal energy storage capacity. Symbols: circle – system, square – pack. All parameters relevant to the levelised cost calculations can be found in Appendix A.5.

Integrated solar photovoltaic (PV) and storage systems are considered an effective means for reducing the intermittency of the generated electricity and could increase its consumption by residential generators themselves in light of decreasing feed-in tariffs[282]. In the second stylised example (Fig. 4.8b) the levelised cost of storage (LCOS) of such a system in Germany in comparison to the retail power price is modelled (Appendix A.5). There appears to be much greater uncertainty regarding the future competitiveness than in the previous example. Already the spread between central ER projection and high ER combined with high growth rate projection is 7 years (2024 to 2031), translating into required cumulative capacities of 100 and 300 GWh respectively. Regardless of simplifications, this highlights the emerging state of the residential storage market. The rate at which experience is gained through the early phase will be a significant determinant of whether lithium-ion systems will become competitive in this application before 2040 at all.

4.5.3 Uncertainty and limitations

Uncertainty affecting all data stems from the use of product prices (i.e., investment cost) instead of production cost. The theory of learning[122] applies to production cost and experience curves can only be used as proxy to mirror their development. Any cost projections considering additional cost factors reflected in the product price (e.g., raw material cost, cost of sales) are subject to these additional cost factors remaining unchanged[125]. In practice, however, experience curves are widely used to project future product prices and have proven useful for multiple technologies[252,253].

An additional uncertainty regarding the use of product prices as proxy for production cost development relates to early stage markets, in which these quantities might deviate in particular[124,125]. Only four out of the eleven datasets cover the recommended two orders of magnitude in data length (i.e., cumulative installed capacity) to avoid this shortcoming[138]. These are the datasets for consumer electronics and electric vehicle lithium-ion batteries, nickel-metal hydride batteries and fuel cells.

Multiple studies identified ERs for energy technologies in the last 35 years[129,132,283,284]. These range from -11% (wind farms, CCGT) up to 47% (solar PV) with nearly two thirds of observations between 10% and 25%. The ERs identified in this study for electricity storage technologies, including their uncertainty, are well within these extrema (Figure 4.9).

Mirroring the distribution of ER observations for energy technologies, 8 of the 11 rates (i.e., around two thirds) are also within 10% and 25%.

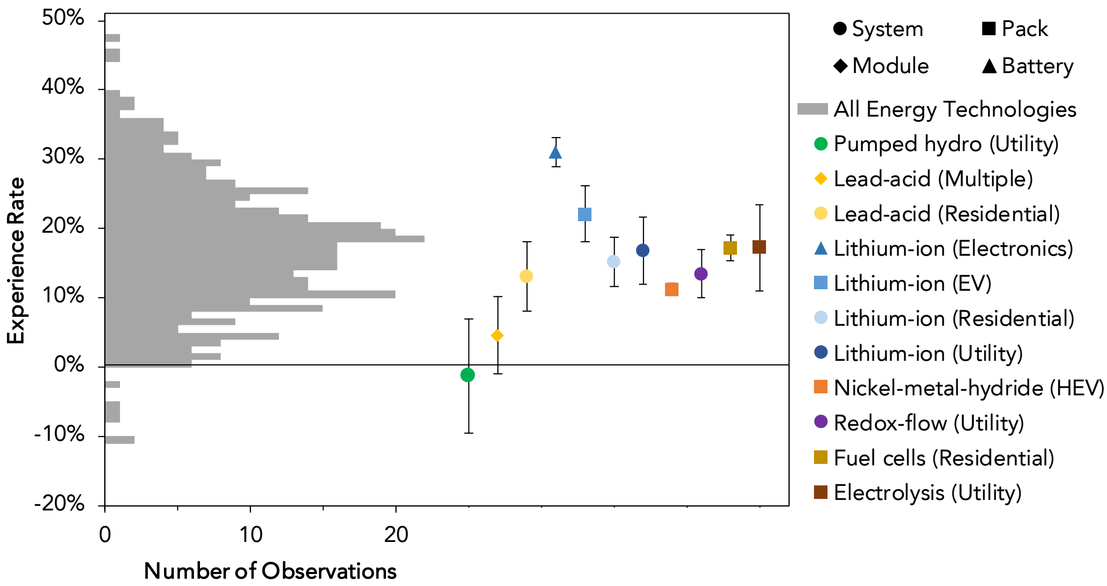


Figure 4.9 – Comparison of EES ERs to rates observed for other energy technologies in the last 35 years[129,132,283,284]. Grey bars refer to observations of distinct ER for energy technologies. Coloured shapes indicate ERs identified for electricity storage technologies in this study (Figure 4.1). Error bars reflect their associated uncertainty.

Finally, experience or learning rates are ideally derived for specific components of industry goods[125,133]. By reporting prices on pack- or system-level, there is uncertainty due to aggregation of potentially different ERs of individual components (e.g., cells, housing, power electronics, inverters) and due to inclusion of non-manufacturing related cost (e.g., installation, commissioning), which might follow cost dynamics not captured with the ERs derived in this thesis.

5. Analysing Cost Reduction Drivers

This chapter presents the results of expert elicitations on the future cost and performance parameters for two key energy storage technologies, water electrolysers and lithium-ion batteries. Electrolysers represent the gateway technology to transform electricity into hydrogen and thereby enable seasonal storage using existing natural gas infrastructure as well as decarbonisation of other energy sectors like heat and transport, and the industrial sector[33,54]. Lithium ion experiences significant cost reductions driven by large-scale markets in consumer electronics and electric vehicles and is likely to be cost-competitive for stationary grid-scale applications (Chapter 4, Chapter 6). Expert elicitations are used to better understand underlying cost reduction drivers for these two technologies and to compare elicited cost projections to projections based on experience curves.

5.1 Future Investment Cost based on Expert Elicitations

Figure 5.1 shows cost estimates across all experts for all three water electrolyser types in 2020 and 2030. Investment cost for AEC systems by 2020 at current R&D funding and without production scale-up (◆R&D, 1x) lie between 1,100 and 1,900 US$/kW$_{el}$ (all 50th percentile estimates) but could range from 600 to 2,000 US$/kW$_{el}$ (lowest 10th, highest 90th), when accounting for increased R&D funding and manufacturing scale-up. This is the most mature electrolysis technology, which is a possible explanation for its relative cost advantage and limited cost reduction potential. For PEMEC, the respective range is 1,500 to 1,900 US$/kW$_{el}$ (all 50th in ◆R&D, 1x) and 800-2,200 US$/kW$_{el}$ (lowest 10th, highest 90th), representing a strong improvement compared to the 2016 reference value and reduction of the gap to AEC system cost. Its more recent commercialisation as well as potentially transferrable innovations for the related PEM fuel cells lead to a higher research and product development focus for this technology. SOEC electrolysers are estimated to be most expensive at 4,000-7,000 US$/kW$_{el}$ (all 50th) with a significantly higher uncertainty range of 1,500-11,500 US$/kW$_{el}$ (lowest 10th, highest 90th). This technology is in its early commercialisation phase, explaining the wide range of future cost estimates.

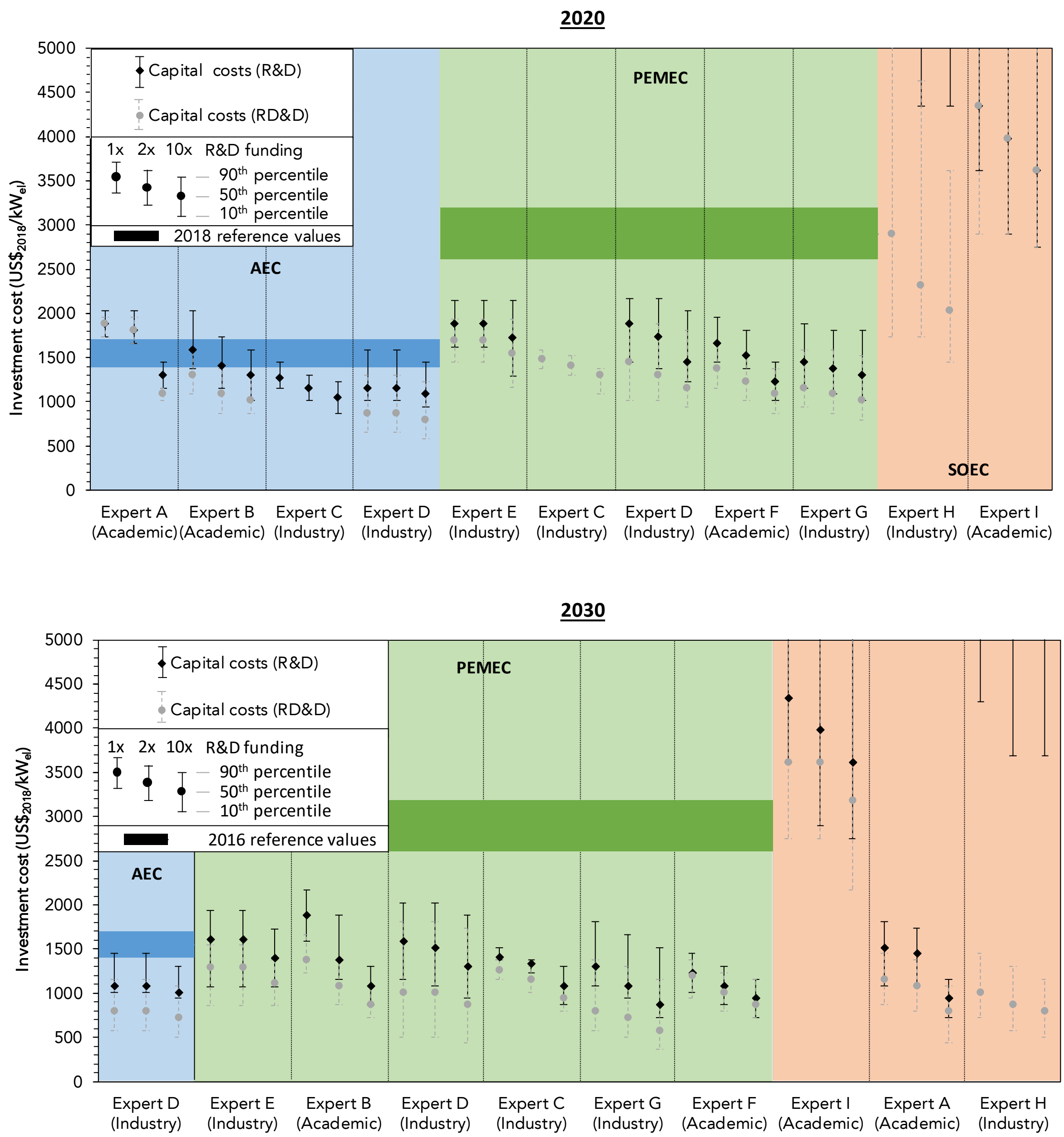


Figure 5.1 – Elicited expert estimates for 2020 and 2030 investment cost without (◆ R&D) and with production scale-up (● RD&D) as a function of R&D funding (1x, 2x, 10x) . Data points indicate 50th, uncertainty bars 90th and 10th percentile estimates. Expert C made 2020 estimates for AEC (R&D) or PEMEC (RD&D). Expert D made all estimates for AEC and PEMEC. Results are sorted by technology and in descending order for 50th percentiles without production scale-up. 2016 reference values based on Table 2.2. No 2016 reference values for SOEC as this technology is not yet widely commercialised. All values in tabular form can be found in Appendix B.1.

For 2030, most estimates are given for PEMEC and SOEC, because the majority of experts believe these technologies will be dominant by 2030. AEC electrolyser cost at current funding and without production scale-up (◆ R&D, 1x) are estimated slightly lower than in 2020 at 1,050 US$/kW$_{el}$ (50th), potentially ranging from 500 to 1,500 US$/kW$_{el}$ (lowest 10th, highest 90th). Similarly, the respective PEMEC estimates are slightly below 2020 figures, ranging from 1,200 to 1,600 US$/kW$_{el}$ (all 50th in ◆ R&D, 1x) or 400-2,200 US$/kW$_{el}$ (lowest

10^{th}, highest 90^{th}). SOEC systems could experience the strongest relative cost reduction by 2030 in this scenario with cost ranges of 1,500-6,000 US$/kW$_{el}$ (all 50^{th} in ◆R&D, 1x), however still highly uncertain at 400-10,000 US$/kW$_{el}$ (lowest 10^{th}, highest 90^{th}). Experts A and H suggest SOEC investment cost similar to AEC and PEMEC by 2030 with production scale-up (● RD&D).

Figure 5.2. shows cost estimates across all experts for lithium-ion battery packs used in stationary off-grid systems in 2020 and 2030. Investment cost by 2020 at current R&D funding and without production scale-up (◆R&D, 1x) lie between 230 and 350 US$/kWh$_{cap}$ (all 50^{th} percentile estimates) but could range from 160 to 530 US$/kWh (lowest 10^{th}, highest 90^{th}), when accounting for increased R&D funding and manufacturing scale-up, according to the academic experts interviewed. Industry experts are more conservative with respective cost ranges at 180 to 650 US$/kWh$_{cap}$ (all 50^{th} in ◆R&D, 1x) and 90-700 US$/kWh$_{cap}$ (lowest 10^{th}, highest 90^{th}). That's also because industry experts appeared more sceptical than academics towards recently announced price points for EV battery packs. Interestingly, most cost estimates without production scale-up lie above the median 2014 reference value of 300 US$/kWh$_{cap}$[23]. Please note that the interview process started in 2015, which is why 2014 reference values are used. Estimates accounting for production scale-up indicate only a slight improvement compared to 2014 cost for the majority of experts interviewed.

For 2030, cost estimates by academic experts range from 130 to 270 US$/kWh$_{cap}$ without production scale-up (all 50^{th} in ◆R&D, 1x), but could be 50-320 US$/kWh$_{cap}$ (lowest 10^{th}, highest 90^{th}). Again, industry experts are more conservative with the respective ranges at 100-460 US$/kWh$_{cap}$ (all 50^{th} in ◆R&D, 1x) and 20-540 US$/kWh$_{cap}$ (lowest 10^{th}, highest 90^{th}). Even in 2030 with production scale-up (●RD&D) and 10x increase in R&D funding, only 4 experts believe it is likely (i.e., 50^{th} percentile estimates), that battery pack cost are below the 2014 confidence interval. Many experts believe the majority of battery pack prices that led to the development of the 2014 confidence interval[23] were priced below cost, making future reductions difficult to achieve.

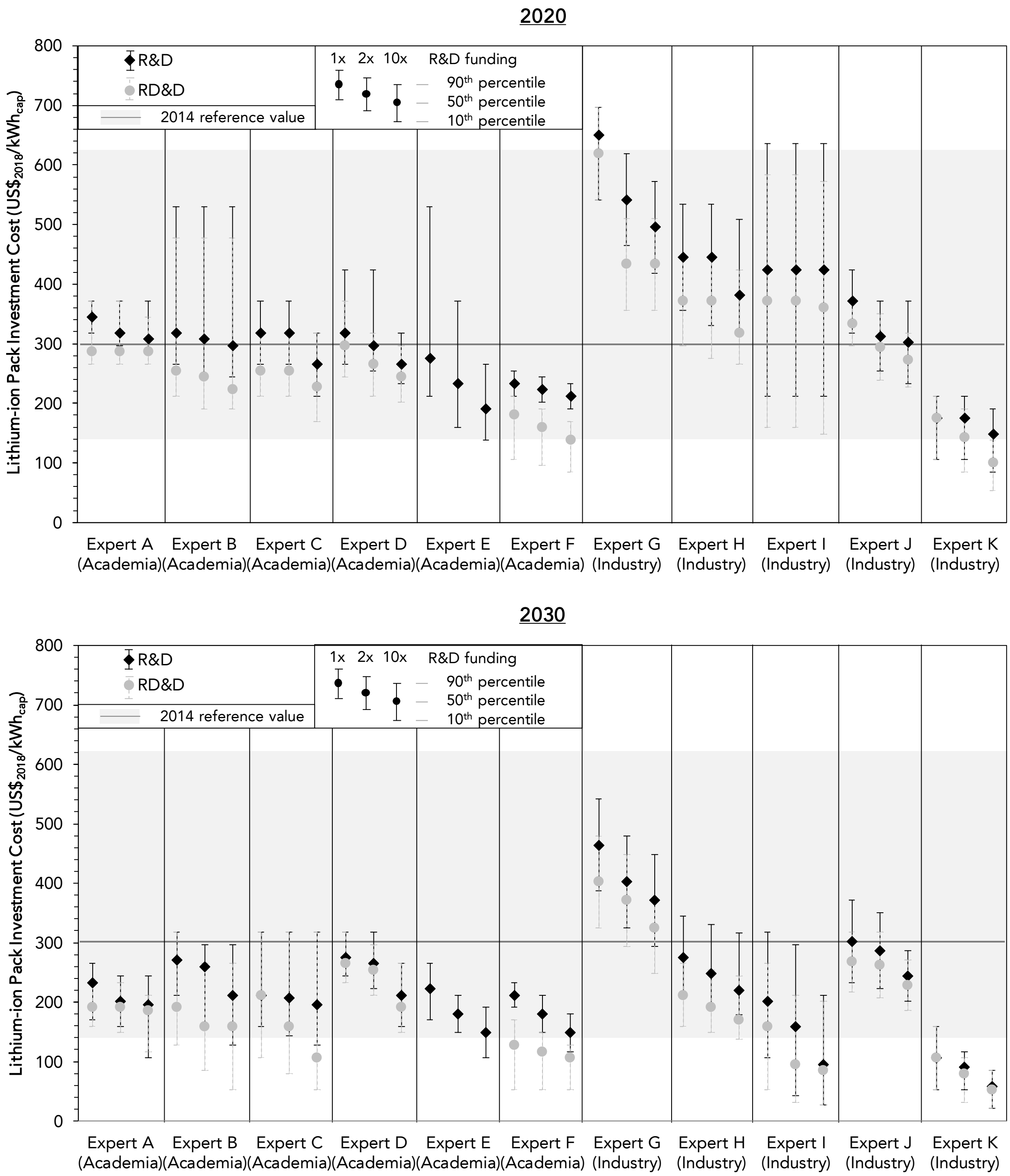


Figure 5.2 – Elicited expert estimates for 2020 and 2030 investment cost without (◆ R&D) and with production scale-up (●RD&D) as a function of R&D funding (1x, 2x, 10x). Data points indicate 50th, uncertainty bars 90th and 10th percentile estimates. Results are sorted by technology and in descending order for 50th percentiles without production scale-up. 2014 reference values represent 95% confidence interval of cost data for market leaders in 2014[23]. Expert E did not estimate cost for the production scale-up situation. All values in tabular form can be found in Appendix B.1.

5.2 Impact of R&D and Manufacturing Scale-Up

Figure 5.3 explicitly depicts the relative impacts of increased R&D funding and production scale-up for water electrolysers based on the median percentage reductions of the experts' 50th percentile estimates. The cost impact of production scale-up at current funding (RD&D, 1x) ranges from 17-30% by 2020 and 23-27% by 2030 across the three electrolysis technologies and is higher than increasing R&D funding only (R&D, 2x and 10x): 6-18% by 2020 and 0-24% by 2030. This novel quantification aligns with previous studies which find that cost reductions for solar PV modules are mainly attributed to economies of scale as opposed to technology advances[152]. Other studies, however, discuss the importance of R&D funding and production scale-up at different development stages and find that R&D funding has a stronger cost reducing impact in all of them when comparing a two-fold increase in cumulative R&D spending to a two-fold increase in cumulative production[130].

The particularly high cost reduction potential for SOEC systems of 30-40% by 2020 (RD&D) in this study indicates that production scale-up is most significant for technologies that are not yet commercialised. It would mean that learning in production in the early development stage of SOEC has a larger marginal effect on cost reduction than for the commercial AEC and PEMEC systems, for which improvements in production have been partially exploited already. This argument would follow the learning curve theory[122], where each doubling of cumulative produced capacity leads to a constant relative cost reduction. The same absolute increase in production then leads to higher cost reductions for early stage technologies than for mature ones. In terms of the other technologies, higher cost reduction potentials are expected for PEMEC by 2030 than for AEC based on increased R&D funding alone (8-24% vs. 0-7%). This could reflect the lower technological maturity of PEMEC, where more potential for innovation from R&D remains unexploited.

The figures also show the diminishing returns of increasing R&D funding as observed in previous studies[152]. While a doubling of R&D funding in the absence of production scale-up leads to 6-8% cost reduction, a ten-fold increase has an impact of 7-24% across all technologies. Thus, the three-fold additional cost reduction potential (8% to 24%) is lower than the five-fold funding increase (2x to 10x).

Compared to other energy technologies, the cost reducing impact of doubling R&D funding by 2020 without production scale-up for AEC (0-7%) is comparable to other mature technologies (e.g., supercritical coal: 6.03%[130], hydropower: 2.63%[130]; data from POLES energy systems model[130]), and for PEMEC and SOEC (6-8%) just above other emerging technologies (e.g., offshore wind: 4.9%[130], solar thermal: 5.3%[130]).

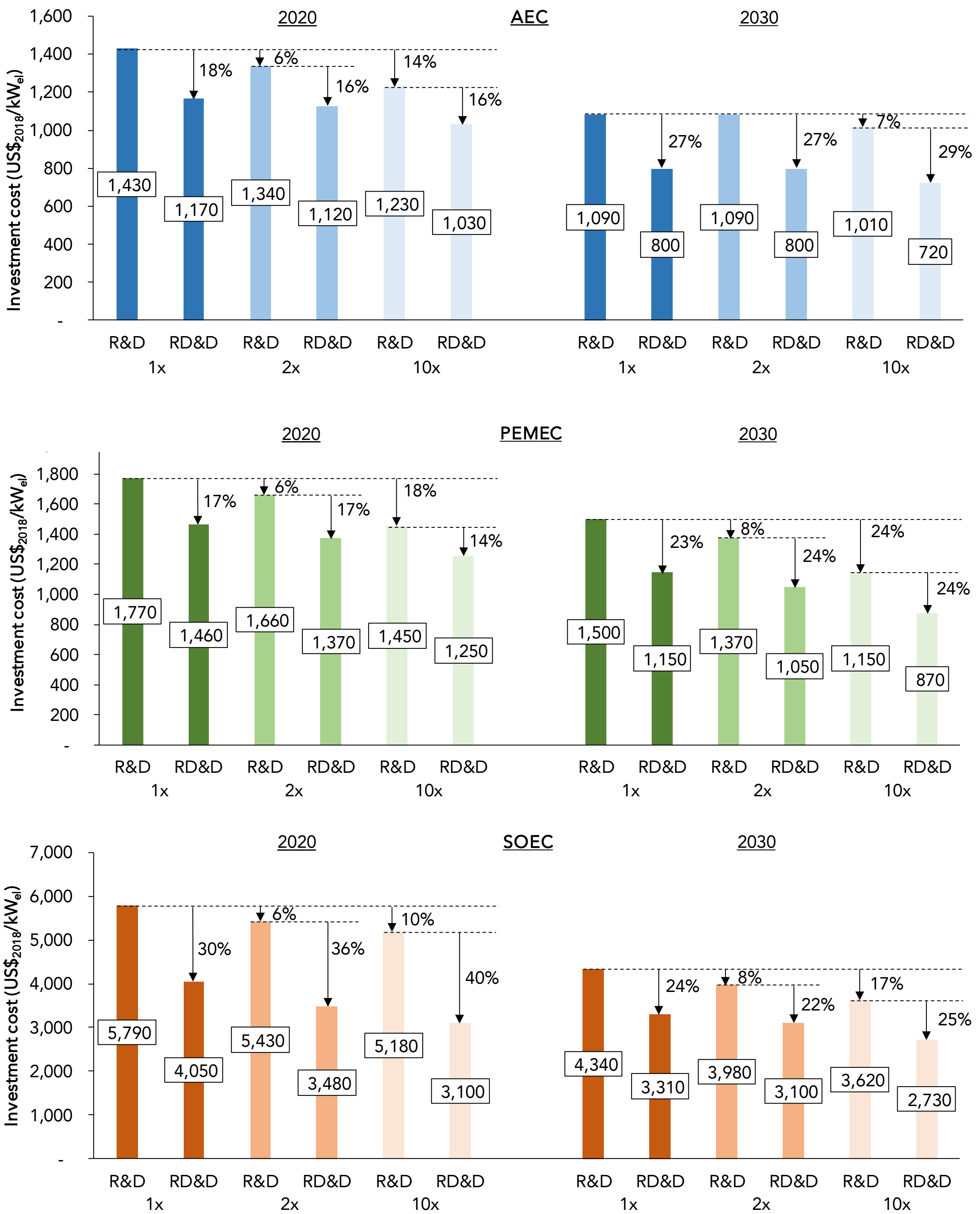


Figure 5.3 – Relative impact of R&D funding (1x, 2x, 10x) and production scale-up (R&D, RD&D) on water electrolyser investment cost. Expert responses: AEC, 2020 = 4 (R&D) and 3 (RD&D); AEC, 2030 = 1; PEM, 2020 = 3 (R&D) and 4 (RD&D), PEM, 2030 = 6; SOEC, 2020 = 2; SOEC, 2030 = 3. First bar in 2020 and 2030 represents median of experts' 50th percentile cost estimates. All other investment cost figures are based on median percentage reduction of experts' 50th percentile estimates (percentage numbers). Displayed investment cost values are rounded to the nearest ten.

Figure 5.4 depicts the relative impacts of increased R&D funding and production scale-up on investment cost for lithium-ion battery packs. Similar to water electrolysers, cost reductions achieved through production scale-up (12%-17%) have a larger impact than doubling of R&D funding (5-13%). However, a ten-fold increase in R&D funding can match (15%, 2020) or exceed (22%, 2030) cost reductions through production scale-up.

Experts expect manufacturing advances and supply chain optimisation through production scale-up to have a larger impact on cost than R&D breakthroughs. A ten-fold increase in R&D funding may have a comparable effect, because it makes the achievement of clearly identified innovation potentials leading to higher energy density and lower cost more likely[258]. However, experts indicated that some research processes cannot be accelerated through more funding, a possible explanation for the higher relative cost reduction by 2030. Also, if research does go well, high R&D funding could have the most significant impact on cost, shown by the median 90th percentile estimate for 2030 of 120 US$/kWh$_{cap}$, which is 38% below the median 90th percentile estimate for 2030 at current R&D funding.

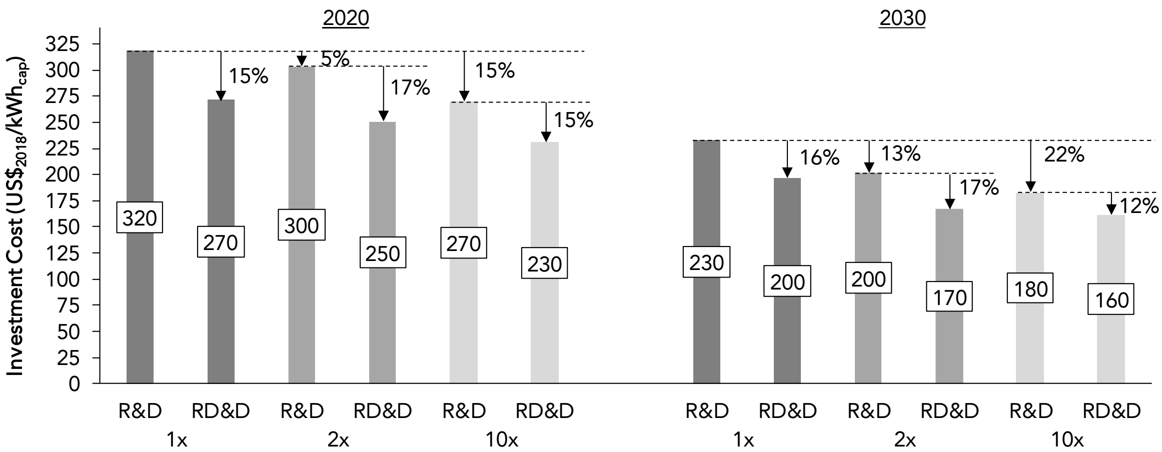


Figure 5.4 – Relative impact of R&D funding (1x, 2x, 10x) and production scale-up (R&D, RD&D) on lithium-ion battery pack investment cost. Expert responses: R&D scenario = 11, RD&D scenario = 10. First bar in 2020 and 2030 represents median of experts' 50th percentile cost estimates. All other investment cost figures are based on median percentage reduction of experts' 50th percentile estimates (percentage numbers). Displayed investment cost values are rounded to the nearest ten.

5.3 Performance Projections and R&D Impact

Investment cost is a key parameter to consider when deploying electricity storage technologies. However, there are also other cost and performance parameters that determine lifetime cost in a specific application. Eventually, the optimal combination of all those parameters determines competitiveness. Therefore, the key performance parameters lifetime and efficiency are also explored in this thesis with regards to their future development potential and underlying innovations.

5.3.1 Lifetime

Figure 5.5 shows that at current R&D funding (1x), AEC lifetime by 2020 is estimated to be likely within the range of 41,000 to 90,000 hours (all 50th; equivalent to 5-10 years at continuous operation). When accounting for uncertainty, the range expands slightly to 40,000-110,000 hours (lowest 10th, highest 90th). The uncertainty ranges of experts A and C remain constant across funding scenarios (2x, 10x), following the rationale that currently achievable lifetimes of up to 90,000 hours are sufficient for the given case study (i.e., at intermittent operation 90,000 hours means about 20 years) and technological advances are more likely to be directed towards investment cost reductions. Expert C specifically referred to warranted lifetimes of commercial products, acknowledging that actual lifetimes can be higher.

The respective lifetime ranges for PEMEC systems are 41,000-60,000 hours (all 50th; equivalent to 7-10 years at continuous operation) and 40,000 – 85,000 (lowest 10th, highest 90th), which is slightly lower than for AEC. The estimates of expert C show that from a commercial perspective, lifetime warranties for PEMEC are equal to AEC systems.

For SOEC systems, there is a significant difference in academic and industry perspective for 2020 lifetime estimates. The academic expert suggests a range of 6,000-15,000 (lowest 10th, highest 90th; equivalent to 0.7-1.7 years at continuous operation), while industry expert deems 50,000-100,000 hours possible (lowest 10th, highest 90th). This is indicative of the current research efforts to increase SOEC lifetime and varying views regarding its success probability.

Expert J made estimates for a potential development of AECs, a zero-gap configuration where porous electrodes are directly attached to the membrane, similar to PEMEC and SOEC (compare Figure 2.15), thereby reducing the inter-electrode gap to minimise internal resistance and increase cell efficiency[285,286]. The lifetime of such systems is estimated at 10,000-40,000 hours (lowest 10th, highest 90th), below traditional AEC systems but with potential for improvement due to increased R&D funding.

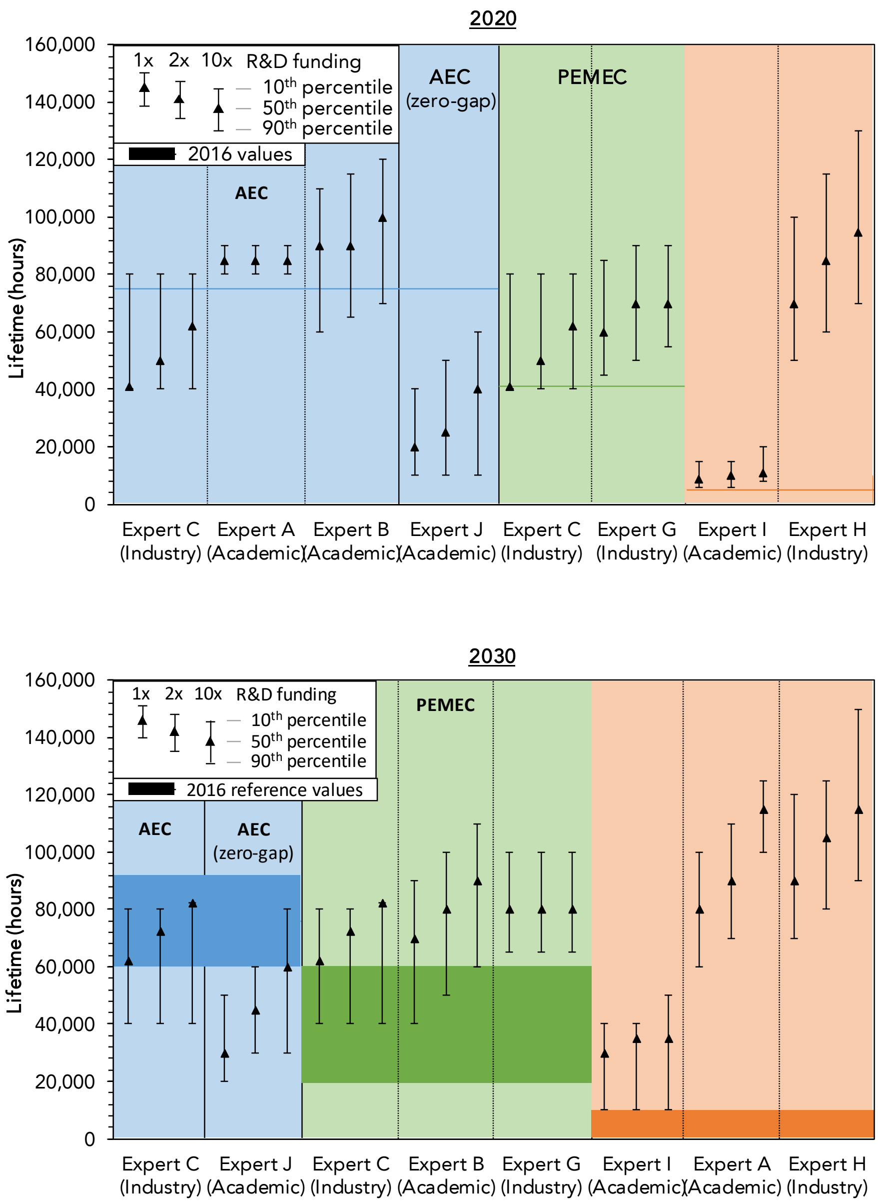


Figure 5.5 – Elicited water electrolyser expert estimates for 2020 and 2030 lifetime (in hours) as a function of R&D funding (1x, 2x, 10x). Data points indicate 50th, uncertainty bars 90th and 10th percentile estimates. Alphabetic order of experts is consistent with Figure 5.1. Expert C made estimates for AEC and PEMEC. Expert J made estimates for AEC zero-gap configurations. Results are sorted by technology and in ascending order for 50th percentile estimates. 2016 reference values based on Table 2.2. All values in tabular form can be found in Appendix B.2.

By 2030 little improvement is expected for traditional AEC systems, based on the belief that longer lifetime is not required, while zero-gap AEC and PEMEC systems could match the lifetime of AEC systems, the former in particular with increased R&D funding. The lifetime of SOEC systems is expected to match that of AEC and PEMEC systems, even with the potential to surpass it under increased R&D funding. For context, PEM and solid oxide fuel cell lifetimes have increased ten-fold since the early 2000s to around 40,000–80,000 hours for residential systems[287]. But there remains strong disagreement whether these improvement potentials for SOEC systems can be realised, with 50th percentile estimates ranging from 30,000 up to 90,000 hours.

The impact of increased R&D funding (2x, 10x) appears to have a smaller effect on traditional AEC (0-33%) compared to PEMEC (14-34%) and SOEC (16-29%) lifetime, reflecting their relative immaturity (Figure 5.6). Again, the diminishing returns of increased R&D funding can be observed. At most, the additional improvement potential by a five-fold increase in additional funding (2x to 10x) is two-fold. The current SOEC research focus on lifetime is reflected in the expected two-fold increase from 2020 to 2030.

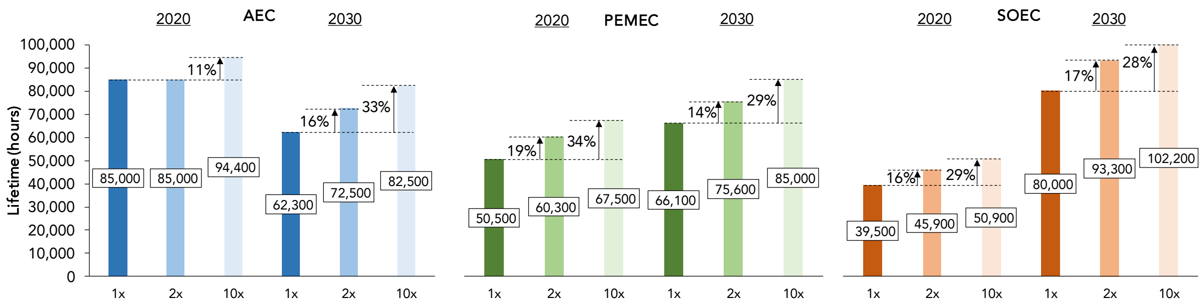


Figure 5.6 – Relative impact of R&D funding (1x, 2x, 10x) on water electrolyser lifetime. Expert responses: AEC, 2020 = 3; AEC, 2030 = 1; PEM, 2020 = 2, PEM, 2030 = 3; SOEC, 2020 = 2; SOEC, 2030 = 3. First bar in 2020 and 2030 estimates shows median of experts' 50th percentile estimates. All other lifetime numbers are based on median percentage reduction of experts' 50th percentile estimates (percentage numbers). Responses for AEC zero-gap technology not displayed. Reduction of AEC lifetime to 2030 is result of reduced number of expert responses whereby optimistic experts give estimates for alternative technologies.

For lithium-ion battery packs, cycle life in 2020 at current R&D funding (1x) and 80% depth-of-discharge is estimated between 1,500 and 15,000 (all 50th), but could range from 1,000 to 20,000 with a ten-fold increase in R&D funding (lowest 90th, highest 10th). Similar to investment cost, industry experts are more conservative than academics (50th median, 1x R&D: 2,600 vs 4,500). The wide range of estimates could be a projection of the existing cycle life variations based on different cathode chemistries, cell and pack quality, and use cases[65,74,288]. Lithium-ion packs with a lithium-titanate (LTO) anode can last for up to 15,000 cycles, however, no expert explicitly referred to this technology. Some indicated systems with a lithium-iron-phosphate (LFP) cathode would be most feasible for the case study and that non-LTO technology options could achieve these cycle life levels by 2020.

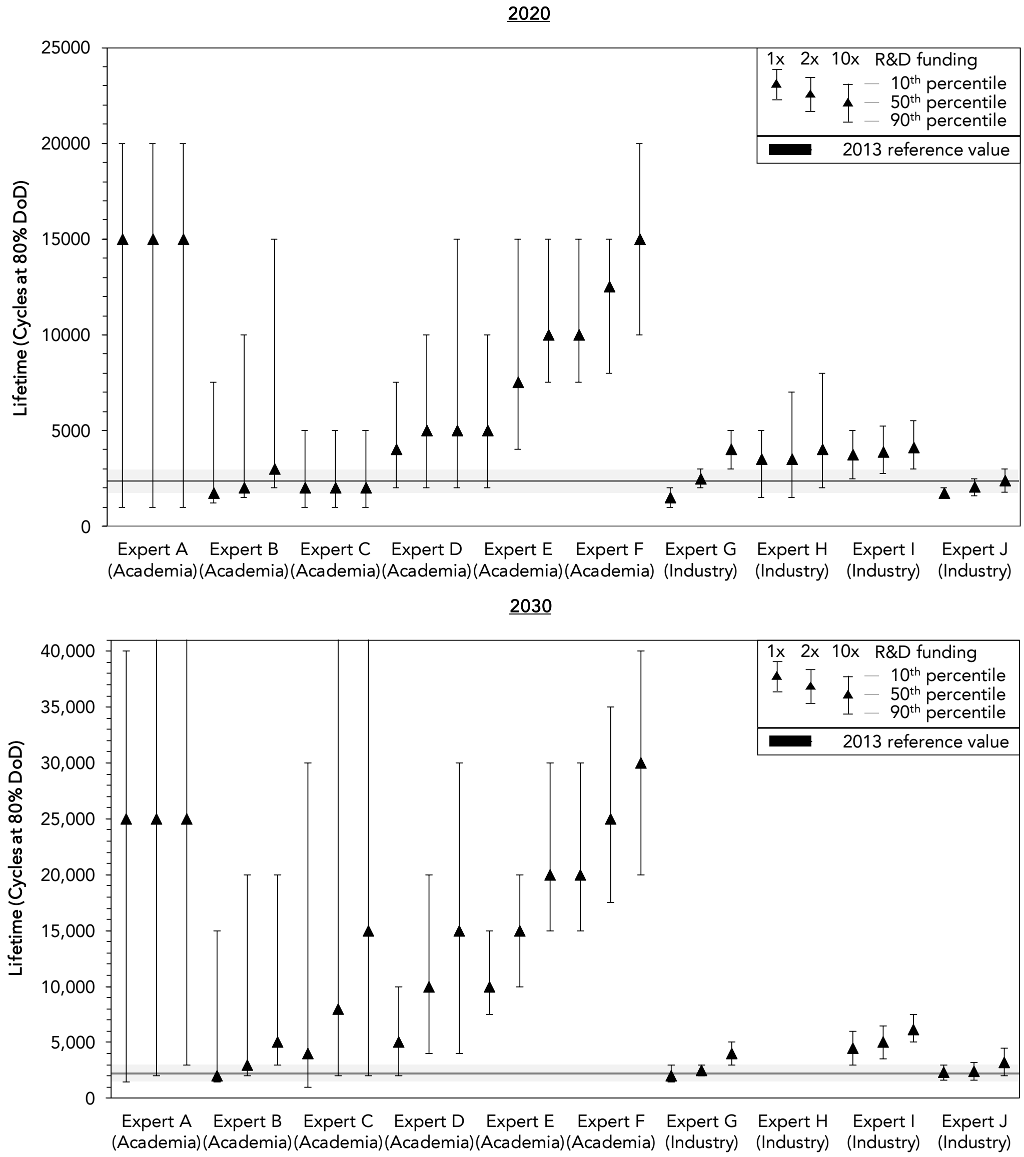


Figure 5.7 – Elicited lithium-ion pack expert estimates for 2020 and 2030 lifetime as a function of R&D funding (1x, 2x, 10x). Data points indicate 50th, uncertainty bars 90th and 10th percentile estimates. Alphabetic order of experts is consistent with Figure 5.2. Expert H made no estimates for 2030. Expert K did not make any estimates and is not displayed. 2013 reference values based on lithium-ion storage systems for utility and distributed applications with 365 annual cycles and pack replacement intervals of 5 and 8 years[65]. All values in tabular form can be found in Appendix B.2.

By 2030, the range is even wider at 2,000 to 20,000 cycles (1x R&D, all 50th), or 1,500 – 100,000 (lowest 90th, highest 10th). Again, industry experts are more conservative than academics (50th median, 1x R&D: 2,300 vs 7,500). The reduction of the median estimate by industry experts compared to 2020 stems from the missing values of expert H who expressed a lack of confidence to quantify 2030 improvements. It should also be noted that expert K did not estimate cycle life, arguing that this parameter will be engineered to meet application and cost requirements. This challenge in separating cost and cycle life parameters could also be an explanation for the wide range of elicited values in general. Finally, a smaller uncertainty range for individual industry expert estimates by 2030 compared to 2020 can be noticed. This reflects the perception of a higher likelihood to achieve distinct R&D-based improvement targets in the long-term.

The impact of increased R&D funding (2x, 10x) is reasonable on cycle life, increasing median 50th percentile values by 16-31% (2020) and 25-100% (2030) (Figure 5.8). The effect of diminishing returns of increased R&D funding can also be observed for cycle life. This effect is less pronounced by 2030 than 2020, supporting the view epressed by some experts that certain R&D processes cannot be accelerated with more funding alone.

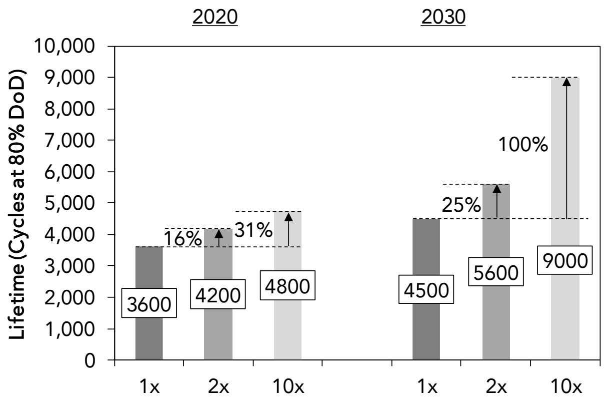


Figure 5.8 – Relative impact of R&D funding (1x, 2x, 10x) on lithium-ion pack lifetime. Expert responses: 10 for 2020, 9 for 2030. First bar in 2020 and 2030 estimates shows median of experts' 50th percentile estimates. All other lifetime numbers are based on median percentage increase of experts' 50th percentile estimates (percentage numbers).

5.3.2 Efficiency

Six of the ten interviewed experts indicated that improvements in efficiency of water electrolysers are possible but not prioritised for two reasons. First, relatively low electricity cost and non-continuous operation in the given case study mean that operating cost are small, so that reduction of investment cost has priority. Second, efficiencies are maximised at low current density, but to reduce cost, research is focussed on increasing current density. Experts also highlight that system efficiency alone is not the most important factor, but rather the efficiency including hydrogen purification and pressurisation for its final application[105].

Four experts, however, indicated which efficiency improvements are conceivable for AEC, zero-gap AEC and PEMEC (Figure 5.9). For AEC, current R&D funding could improve system efficiencies beyond the boundaries given in Table 2.2 by 2020, while for PEMEC this would only be the case by 2030. Zero-gap AEC systems could become more efficient than AEC or PEMEC then. For SOEC systems, experts highlight that feasible thermodynamic limits can already be achieved at the cell level. Improvements are focussed on fully translating these efficiencies to the system level.

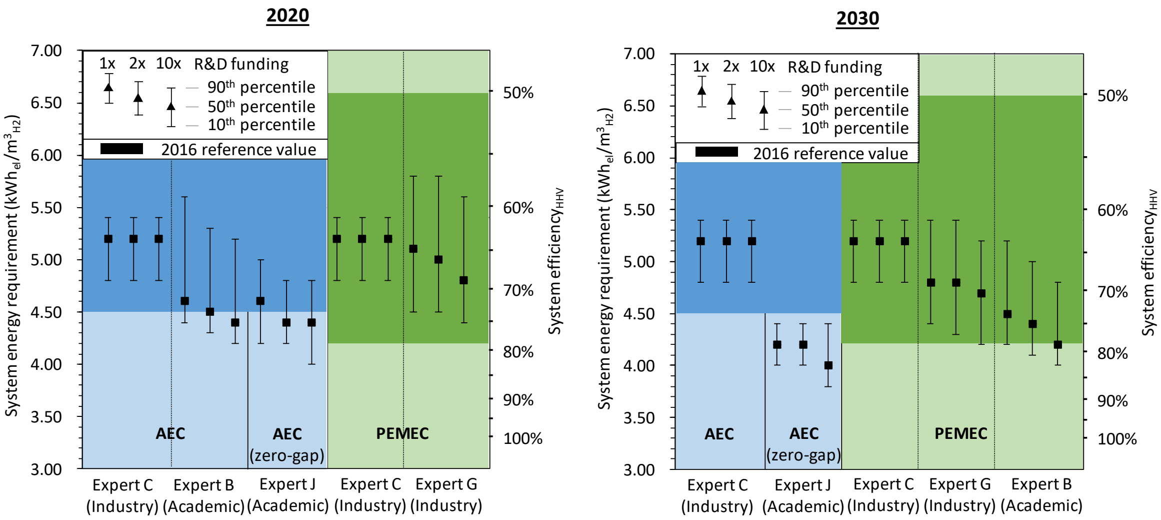


Figure 5.9 – Elicited expert estimates for 2020 and 2030 electrolysis system energy requirements (in kWh_{el}/m^3_{H2} – refers to norm cubic meter of hydrogen at standard conditions). Data points indicate 50th, uncertainty bars 90th and 10th percentile estimates. Secondary y-axis shows thermodynamic system efficiency relative to the higher heating value of hydrogen (HHV). Expert C made estimates for AEC and PEMEC. Expert J made estimates for AEC zero-gap configuration. Results are sorted by technology and in ascending order for 50th percentiles. 2016 reference values based on Table 2.2.

For stationary lithium-ion systems, round-trip efficiencies are at around 80%[74] already and experts unequivocally argued that any improvement would not be an R&D priority, refusing to make estimates for future values.

5.3.3 Environmental Impact

The environmental impact of water electrolyser manufacturing and operation was not a core knowledge area for many of the experts, in particular with respect to lifecycle carbon dioxide emissions. Three main themes emerged when discussing the environmental impact of electrolysis coupled with renewable generators:

1. When low-carbon generators provide the power input, carbon dioxide emissions are insignificant compared to alternative hydrogen production technologies (e.g., steam methane reformation)[289,290]. More significantly, several experts believe that the potential to store renewable electricity or decarbonise other energy sectors like heat or transport outweighs any emissions or toxicity impact associated with electrolyser manufacturing.

2. Experts believe it is likely that electrolysis-based energy storage would outperform other electrochemical energy storage technologies in terms of lifecycle carbon dioxide emissions if the natural gas network is used as an existing storage facility, or if composite storage tanks are developed.

3. The majority of experts mentioned catalyst mining as the key source of environmental impact in electrolysis manufacturing. In addition to the associated energy consumption, health and contamination issues related to Nickel and Platinum usage were highlighted. PEMEC is most prone to these issues, also due to the use of fluorinated membrane materials, and AEC to a limited extent due to the use of Nickel. This shows a potential environmental advantage for SOEC since none of these materials are used.

These views closely mirror the findings from life cycle assessments for the analogous fuel cell types[291–293].

Similar to water electrolysis, the environmental impact of lithium-ion battery pack manufacturing and operation, such as the energy stored on invested[294,295] or lifecycle carbon dioxide emissions[211,296], were outside the expertise of interviewees. On a qualitative note, the majority of experts acknowledge that lithium-ion recycling must become standard, but will likely be more energy-intense and expensive than lead-acid battery recycling due to higher device complexity[297].

The lack of knowledge on the environmental impacts of water electrolyser and lithium-ion battery manufacturing and the lack of established end-of-life procedures are an important finding to focus future research activities.

5.4 Drivers of Cost and Performance Improvements

When eliciting cost and performance estimates, experts also noted the particular technical and value chain innovations upon which their estimates are based.

Figure 5.10 depicts the relative share of identified innovations for water electrolysis along the dimensions: technology, impact, innovation area; as well as the absolute count of innovations mentioned by experts along the innovation areas and their sub-groups. Appendix B.3 lists the specific innovations.

The novel insight is that regardless of technology, the key areas for innovation are catalysts, electrodes and membranes at the cell level, optimised system set-up and balance-of-plant components at the system level and automation, methods and scale effects in manufacturing. Supply chain improvements refer to increased bargaining power due to higher purchase volumes and more supplier competition and were only mentioned by industry experts.

Manufacturing automation, new electrode coating methods and increased production rates are perceived as key drivers for AEC cost reductions. At the cell level, experts envision increased current densities up to 0.6 A/cm^2 through better mixed metal oxide catalysts and more stable electrodes and electrolytes for potential high temperature operation by 2030[298,299], and perhaps, more radically, a move to zero-gap configurations[285,286].

For PEMECs, a significant investment cost reduction driver seems to be component standardisation, which, combined with production scale-up, enables the shift to high volume production methods like laser cutting, plastic injection moulding or 3D printing[300]. In addition, further increased current density (>3A/cm^2) is investigated through better electrode design, catalyst coatings and thinner membranes[301]. In parallel, the reduction of catalyst loading and replacement of titanium in bipolar plates with high-conductivity coatings on low-cost substrates like steel would reduce cost[302,303]. Finally, more operational experience would enable the de-risking of system design to optimise and combine system components for better system integration and operation at optimised set points.

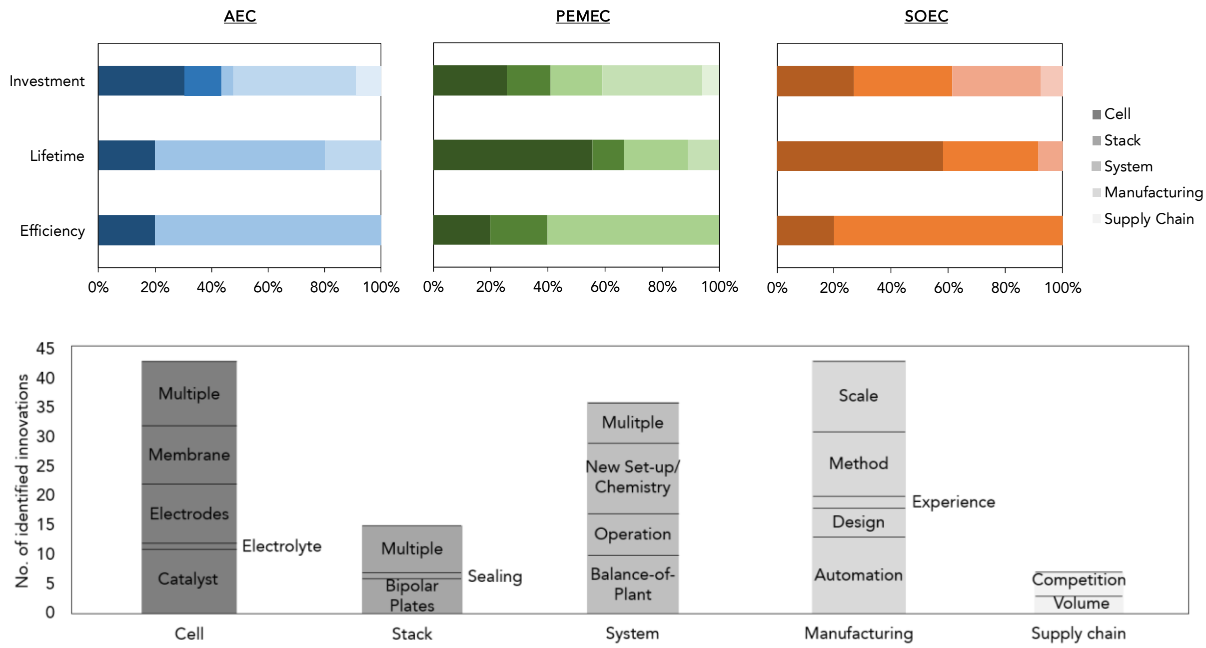


Figure 5.10 – Relative share and absolute number of innovations for water electrolysis along technology, impact and innovation area. Top: Relative share of identified innovations along technology (AEC, PEMEC, SOEC), impact (Investment cost, Lifetime, Efficiency) and innovation area (From darkest to lightest: Cell, Stack, System, Manufacturing, Supply Chain). No innovation mentioned on stack level for SOEC. Bottom: Absolute number of mentioned innovations along innovation areas and sub-groups. Includes double-counting of same innovation if mentioned by different experts. Please refer to the Appendix B.3 for a detailed breakdown of innovations for each technology and impact group.

For SOEC systems, investment cost reductions would be based on reducing the electrode polarisation resistance to enable lower operating temperatures (~450°C) that then allow the use of lower cost component materials like stainless steel[304]. Similar to PEMEC, increased field experience could allow leaner system engineering and improved system integration. The mentioned manufacturing (high volume methods, reduced overhead cost) and supply chain improvements (higher volumes, more suppliers) apply to SOEC systems as well.

Increasing lifetime is at the heart of current research efforts for SOECs. High operating temperatures lead to fast degradation of active materials and balance-of-system components. Therefore, again the reduction in operating temperature was mentioned in parallel with more robust materials[305,306]. For PEMEC, membranes with higher impurity tolerances are a key area of innovation alongside structural improvements of electrode and catalyst coatings to reduce the movement or deactivation of active catalyst particles[307].

For all three technologies, efficiency improvements can be achieved through innovations on the system level like feed water and hydrogen purification as well as optimised system integration due to increased operational experience. On the cell level, zero-gap design for AECs[285,286] or thinner membranes for PEMECs[308] could improve efficiency, while the focus for

SOECs appears to be on improved material-microstructure integration for better oxygen conductivity[59].

Figure 5.11 depicts the relative share of identified innovations for lithium-ion batteries along the dimensions: impact and innovation area; as well as the absolute count of innovations mentioned by experts along the innovation areas and their sub-groups. Appendix B.4 lists the specific innovations.

The key areas for innovation are electrode and electrolyte materials on the cell level, optimised battery and thermal management systems on the module level and increased experience, faster and more efficient techniques, and battery component standardisation for manufacturing.

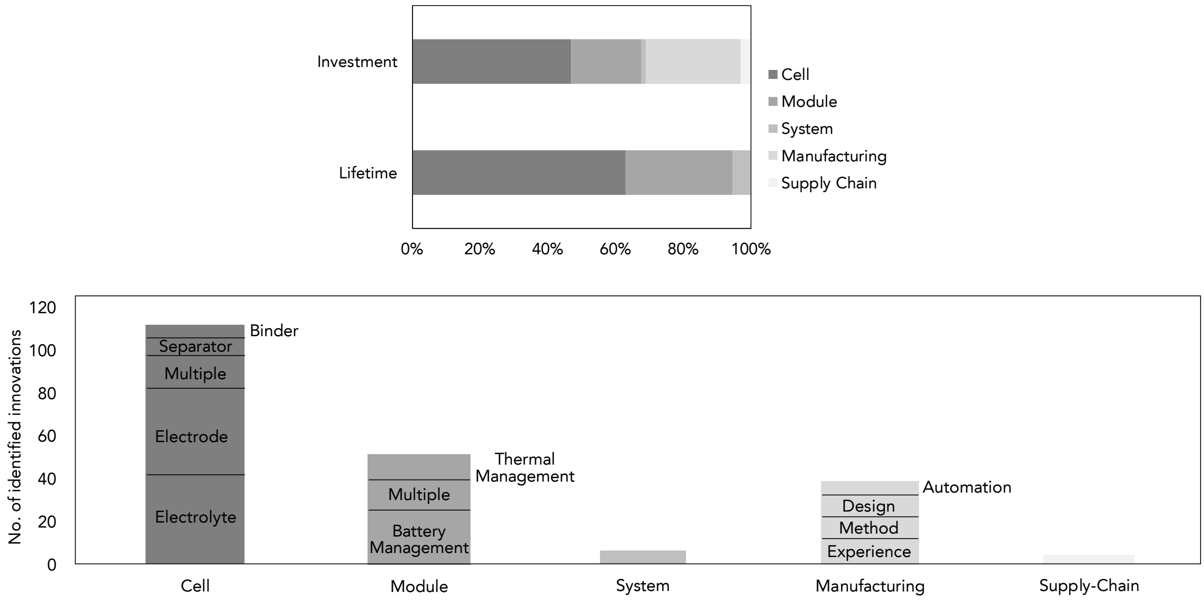


Figure 5.11 – Relative share and absolute number of innovations for lithium ion along impact and innovation area. Top: Relative share of identified innovations along impact (Investment cost, Lifetime) and innovation area (From darkest to lightest: Cell, Module, System, Manufacturing, Supply Chain). Bottom: Absolute number of mentioned innovations along innovation areas and sub-groups. Includes double-counting of same innovation if mentioned by different experts. Please refer to the Appendix B.4 for a detailed breakdown of innovations.

All innovations on the cell level mentioned by the experts aim to either reduce material cost or increase energy density. For example, experts mentioned the reduction of expensive cobalt in the cathode to reduce material cost in the short-term. Its replacement with Nickel enables higher discharge voltages for the cathode, increasing energy density. Equally, the insertion of silicon in the graphite anode leads to higher energy density. Electrolyte improvements are required in parallel to resist high voltage operation. A solid made from polymer or ceramic would be most effective. However, most experts expect only incremental changes to battery chemistry by 2020, which was 5 years away during the interview process, due to timescales associated with translating research insights to commercial products.

Standardisation of the battery management system and improvements in battery module packaging could leverage engineering-based cost reductions on the module level. Some experts stressed that larger format cells are less susceptible to mechanical stress arising from the volume changes during battery charge and discharge. The battery management system can also have a positive impact on lifetime through optimised operation patterns that maximise usable energy capacity while minimising degradation, based on an improved understanding of usage patterns causing degradation. More effective thermal management, for example liquid cooling, could also contribute to longer lifetimes.

In terms of manufacturing, standardisation of cell chemistry and geometry, new methods such as spray coating of electrodes, incremental efficiency improvements through learning-by-doing, and increased automation are the largest levers to reduce future investment cost.

This explicit account of innovations underlying the elicited cost and performance improvements adds a qualitative dimension to the quantitative results and enables targeted investment and policy recommendations[151,156,161].

It reveals that the strongest improvement potentials for water electrolysis can be realised through investment in production methods and product standardisation to automate manufacturing and produce higher quality components (e.g., electrode and bipolar plate coatings). The operation of pilot plants is key to gaining operational experience and optimise system design. Laboratory research should be focussed on reducing the operating temperature for SOECs and developing new system designs like zero-gap AECs or PEMEC stacks for higher pressure or differential pressure operation.

For lithium-ion batteries, large potential for cost and lifetime innovation is in high stability electrode and electrolyte materials that enable higher operating voltages, new cell formats, component standardisation and battery and thermal management systems that optimise energy capacity usage. Product standardisation, automation and increased manufacturing experience can deliver further investment cost reductions along the value chain.

5.5 Discussion

To discuss elicited investment cost estimates, they are compared to investment cost projections based on experience rates (ERs). This comparison enables the analysis of expert estimates in the context of historic cost developments and in relation to a fundamentally different method for projecting future investment cost[152].

For AEC systems, an ER of 17±6% is identified in Chapter 4 as the rate at which AEC system investment cost have reduced between 1956 and 2014 relative to increased cumulative produced capacity. Due to the lack of published ERs for PEMEC and SOEC systems, the rates of the related fuel cell technologies are used as a proxy. These are 16±2% for PEMFC (Chapter 4) and 28±16% for SOFC systems[235].

Figure 5.12 displays the comparison of expert estimates with the ER based projection for water electrolysis. For AEC systems the 2016 reference value for investment cost (Table 2.2) is well within the uncertainty range given by the ER. The projection of the experience curve beyond 2016 also accounts for production scale-up uncertainty. A constant annual electrolysis market means no production scale-up (R&D) and annual market growth by a factor of 3 by 2020 and 7 by 2030[56] (Chapter 3.2.5) translates to the respective production scale-up (RD&D). In both cases, experts estimate future investment cost at the lower end of the uncertainty range given by the ER projection for 2020 and below the range by 2030. This means, experts expect stronger cost reductions for AEC systems in the future than observations from the past indicate.

Regarding PEMEC, experts are also more optimistic in their cost estimates for 2020 than an ER of 16±2% would suggest given the underlying capacity additions. Only the 2030 estimate in the RD&D scenario matches the experience curve projection with production scale-up. This could suggest that experts tend to underestimate the detrimental impact of limited market size on technology cost reductions. It should be noted, however, that the ER applies to PEM fuel cells and is only used as a proxy in this analysis.

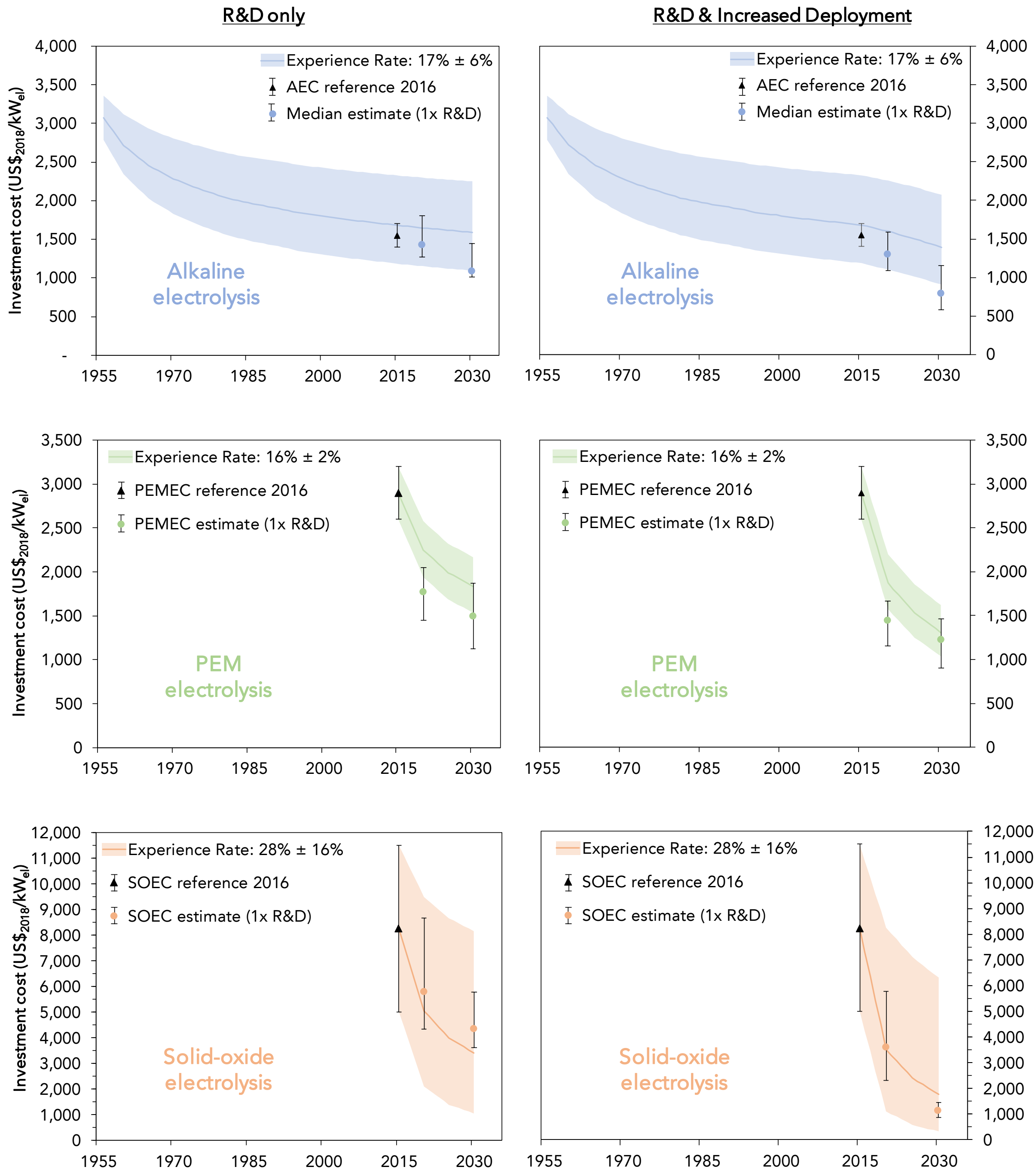


Figure 5.12 – Comparison of expert estimates and ERs for investment cost projection of water electrolysis. Median expert estimates are compared to projections based on ERs for AEC, PEMEC and SOEC at current R&D funding (1x) without (left) and with production scale-up (right). Left: Constant production capacity from 2016 onwards based on continued historic deployment rates; annual market 0.36 GW_{el}. Right: Production scale-up from 2016 onwards as a result of increased deployment, annual market of 1 GW_{el} by 2020 and 2.5GW_{el} by 2030[56] (Chapter 3.2.5). Error bars represent range of reference values or median 90th and 10th percentile of expert estimates. AEC ER is based on investment cost development and capacity deployment between 1956 and 2014 (Chapter 4). ER investment cost projections for PEMEC and SOEC are speculative, based on proxy ERs from related fuel cell technologies[109,235] and assumptions on global cumulative capacity for PEMEC and SOEC in 2016. Due to limited capacity deployment for these technologies before 2016, the investment cost reference value (Table 2.2) is chosen as starting point for the ER uncertainty range.

In line with these findings, a study based on stakeholder expectations rather than analyses of historic cost reductions also found cost ranges for 2020 and 2030 below the range indicated by the ERs[56]. Similarly, a recent expert elicitation study on future wind energy cost found that expert estimates were more optimistic than preceding cost developments indicated[151]. This could show that expert elicitations tend to yield overly optimisitic projections due to the limited ability of experts to take into account historic trends and the possible relation to cumulative produced capacity. On the other hand, it could show that experts can factor-in potential step-change innovations, which cannot be captured by experience curves. A retrospective analysis could reveal the applicability of each hypothesis.

For SOEC, 2020 estimates are broadly in line with an ER of 28%. 2030 estimates are above or below this rate in the no production scale-up (R&D) and production scale-up (RD&D) scenario respectively, however still within the 28±16% uncertainty range. Again, this ER originally refers to solid oxide fuel cells, so must be used with caution in this analysis.

The comparison between expert estimates and ER projections for lithium-ion battery packs also allows an assessment of the performance of both methods, in particular due to detailed cost information that have become available in recent years.

Figure 5.13 shows the expert estimates for 2020 and 2030 (1x R&D) for both deployment scenarios, R&D only and RD&D. The blue shaded area shows the projections based on the identified ER and the different deployment scenarios. The ER is based on price data from 2010 to 2015 to reflect information at the time of expert interviews. Similarly, the grey shaded area displays an identified price range for lithium-ion battery packs for 2005 to 2014 from a different study (95% confidence interval, whole industry)[23].

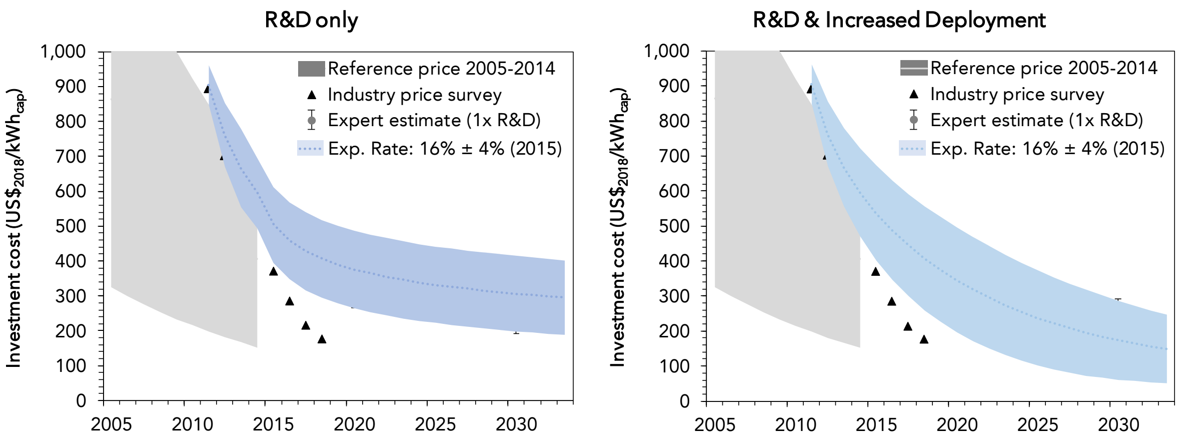


Figure 5.13 – Comparison of expert estimates and ERs for investment cost projection of lithium-ion battery packs. Median expert estimates (grey circles) for 2020 and 2030 investment cost at 1x R&D funding without (left) and with production scale-up (right) are compared to projections based on ERs (blue trajectory). Left: Constant production capacity from 2014 onwards at 12 GWh_{cap} per year. Right: Production scale-up from 2014 onwards as a result of increased deployment (Table 4.2). Error bars represent median 90th and 10th percentile of expert estimates. Price survey data are displayed for information (black triangles)[96]. The ER is based on price survey data from 2010 to 2015 only to reflect the information status when expert estimates were elicited. Grey shaded area shows price range for lithium-ion battery packs of various manufacturers for 2005 to 2014[23].The blue shaded area accounts for ER uncertainty as well as market size uncertainty.

Comparing expert estimates and experience curve projection, both methods identify similar price ranges for 2020 and 2030. While expert estimates are slightly lower than experience curve projections for 2020, for 2030 they are lower with R&D only, but higher with increased deployment. This confirms the previous hypothesis that experience curves are more sensitive to future technology deployment than experts' estimates. With respect to the reference price range for lithium-ion battery packs for 2005 to 2014 (grey shaded area), both projections appear reasonable, in particular for the increased deployment scenario.

However, when accounting for recent price survey data for 2016 to 2018, which became available after the interview process in 2015, it is obvious that both methods perform badly in projecting future prices. There was an increase in annual capacity deployment, so the assessment should be focussed on the increased deployment scenario (right panel in Figure 5.13). Still, the median 50th percentile estimate of experts for 2030 was realised in 2018. The same is true for the 16% ER projection (dotted line). One could argue that experts elicited values for battery packs used in stationary applications, while industry price survey data refers to EV packs. However, the higher prices for stationary packs due to the lower volume orders (2018: 227 vs. 176 US$/kWh)[96,309] are still below the uncertainty range of the ER projection.

The main reasons for the sharp decline in pack prices between 2015 and 2018 are economies of scale, chemistry changes and engineering improvements to cells and packs[96,309]. The increase in average manufacturing plant size to above 5 GWh/year unlocked cost savings from economies of scale. Chemistry changes in the cathode towards nickel-based chemistries (e.g., from LFP to NMC), as well as the increase of nickel content within nickel-based chemistries (e.g., from NMC111 to NMC622) led to an increase in energy density, reducing cost per kWh given raw material prices in recent years. Finally, engineering improvements to cell size (e.g., 21700 vs 18650 cylindrical cells), pack design (e.g., less inactive material, fewer chips in battery management system) and size (e.g., cost of pack components distributed over more kWh) reduced prices.

From expert responses to underlying innovations for future estimates (Figure 5.11 and Appendix B.4), it appears that experts highlighted improvements in cell chemistry for higher energy density but underestimated the impact of economies of scale and engineering improvements. It could therefore be argued that experts may be subject to a conservatism bias for technologies that are about to be widely deployed, because they underestimate cost efficiency potentials when moving from small-scale to mass manufacturing. This could be related to the higher complexity of this change compared to a specific scientific or technical advance. Similar observations have been made for the projection of solar PV penetration in total electricity generation, which experts systematically underestimated for more than 20 years[310]. This insight could be used to inform background material and elicitation protocols for future expert elicitations.

The poor performance of experience curves is related to the few historic data points that were available in 2015 spanning only one third of a magnitude in cumulative deployment data (1 GWh_{cap} to 30 GWh_{cap}). This is a common risk associated with experience curves for novel technologies, which is discussed in detail in Chapters 2.3.1 and 4.5.3. The majority of experience curves derived in Chapter 4 span at least two orders of magnitude in cumulative deployment data or are just below that threshold.

6. Projecting Future Levelised Cost of Storage

The literature review (Chapter 2) highlights that adequate cost assessments for electricity storage solutions are challenging due to the diversity of technologies possessing different cost and performance characteristics and the varying requirements of storage applications. Recent studies as well as Chapter 4 and 5 of this thesis focus on future investment cost of storage technologies. However, only the levelised cost of storage (LCOS) computes the discounted cost per unit of discharged electricity for a specific storage technology and application and therefore accounts for all technical and economic parameters affecting the lifetime cost of an electricity storage technology. It is the appropriate tool for cost comparison of electricity storage technologies and the assessment of their competitiveness in distinct applications.

This chapter presents a first-of-its-kind overview of LCOS for 9 electricity storage technologies in 12 stationary applications from 2015 to 2050. These results enable to determine the likelihood of each technology to offer the lowest LCOS in a distinct application and to derive patterns of technology dominance along distinct application requirements.

The full input parameters and output results from this work are made available (Online Data Repository[311]). An interactive version of the LCOS model is available online at www.EnergyStorage.ninja. By increasing transparency on lifetime cost of multiple storage technologies and their competitiveness in diverse applications, this study can help reduce uncertainty around the future role of electricity storage.

6.1 Electricity Storage Technologies and Applications

Electricity storage technologies can be used in numerous applications covering the entire electricity supply chain[24,27,65,73,166,312]. Different technical requirements of these applications determine the suitability of distinct technologies and affect the LCOS of suitable ones. Therefore, LCOS comparisons should always be application-specific[89,112].

Figure 6.1 describes 12 core applications for stationary storage within the electricity value chain. They amalgamate 25 identified unique-purpose applications based on similar technical requirements and represent a mutually exclusive and collectively exhaustive set of storage applications on that basis (Table 3.7 and Table 3.8). Figure 6.1 also shows the technical suitability of the 9 most commonly deployed stationary electricity storage technologies for these applications. Technical suitability is determined based on technology characteristics and application requirements (Chapter 3.3.2).

Table 6.1 – Qualitative description of electricity storage applications and technology suitability. Applications are grouped by role within the electricity value chain. Selection and description of applications based on review of common electricity storage services[24,27,65,73,89,164,166,167,312]. See Appendix C.3 and Table 3.7 for amalgamation of 25 unique-purpose to 12 core applications and their quantitative requirements. Selection of storage technologies represents most widely deployed stationary systems by power capacity[64]. Suitability assessment is based on technology characteristics in terms of system size, discharge duration and response time. See Table 3.8 for quantitative technology characteristics. T&D – Transmission and Distribution, PHES – Pumped hydro energy storage, CAES – Compressed air energy storage (underground), VRFB – Vanadium redox-flow battery. Hydrogen storage refers to a system with electrolyser, storage tank and fuel cell.

Role	Application	Description	PHES	CAES	Flywheel	Lithium ion	Sodium sul.	Lead acid	VRFB	Hydrogen	Supercap.
	1. Energy arbitrage	Purchase power in low-price and sell in high-price periods on wholesale or retail market	✓	✓		✓	✓	✓	✓	✓	
System operation	2. Primary response	Correct continuous and sudden frequency and voltage changes across the network			✓	✓	✓	✓	✓	✓	✓
	3. Secondary response	Correct anticipated and unexpected imbalances between load and generation	✓	✓	✓	✓	✓	✓	✓	✓	✓
	4. Tertiary response	Replace primary and secondary response during prolonged system stress	✓	✓		✓	✓	✓	✓	✓	
	5. Peaker replacement	Ensure availability of sufficient generation capacity during peak demand periods	✓	✓		✓	✓	✓	✓	✓	
	6. Black start	Restore power plant operations after network outage without external power supply	✓	✓	✓	✓	✓	✓	✓	✓	✓
	7. Seasonal storage	Compensate long-term supply disruption or seasonal variability in supply and demand	✓	✓					✓	✓	
Network operation	8. T&D investment deferral	Defer network infrastructure upgrades caused by peak power flow exceeding existing capacity	✓	✓		✓	✓	✓	✓	✓	
	9. Congestion management	Avoid re-dispatch and local price differences due to risk of overloading existing infrastructure	✓	✓		✓	✓	✓	✓	✓	
Consumption	10. Bill management	Optimise power purchase, minimise demand charges and maximise PV self-consumption				✓	✓	✓	✓	✓	
	11. Power quality	Protect on-site load against short-duration power loss or variations in voltage or frequency			✓	✓	✓	✓	✓	✓	✓
	12. Power reliability	Cover temporal lack of variable supply and provide power during blackouts				✓	✓	✓	✓	✓	

Pumped hydro and underground compressed air energy storage are characterised by relatively slow response times (>10 seconds) and large minimum system sizes (>5 MW)[65,68,73]. Therefore, they are ill-suited for fast response applications like primary response and power quality and small-scale consumption applications. Flywheels and supercapacitors are characterised by short discharge durations (<1 hour)[68,86], and are not suitable for applications requiring longer-term power provision. Seasonal storage requires power provision for months, a requirement that can only be met by technologies where energy storage capacity can be designed fully independent of power capacity.

Note that this analysis considers common application requirements and technology characteristics. Market-specific implementation of these applications can result in a higher number of services and requirements outside the ranges considered in Table 3.7 (see multiple primary response services in the UK for example[313]). Similarly, technology characteristics can be engineered outside of the ranges given in Table 3.8 to meet certain application requirements. However, such deviations are not representative for the majority of existing electricity storage systems.

The key parameters that affect the LCOS of each technology, but are set by respective applications, are nominal power capacity, discharge duration, annual cycles and electricity price. While the first two affect investment, O&M and end-of-life cost, annual cycles affect project life and total discharged electricity. In combination with each technology's efficiency, the electricity price affects charging cost. Electricity prices captured during charging will vary between applications, regions and over short and long timescales[314]. This study assumes two generic values that are broadly representative of wholesale and retail prices. This is intended to give a price difference that is applicable globally and relevant for network or system applications, and behind-the-meter consumer applications respectively (Chapter 3.3.2). A graphical overview of the assumed requirements for the 12 core applications considered in this study is given in Figure 6.1. Readers may test the impact of alternative electricity prices, applications or technology definitions via the interactive online version of this model.

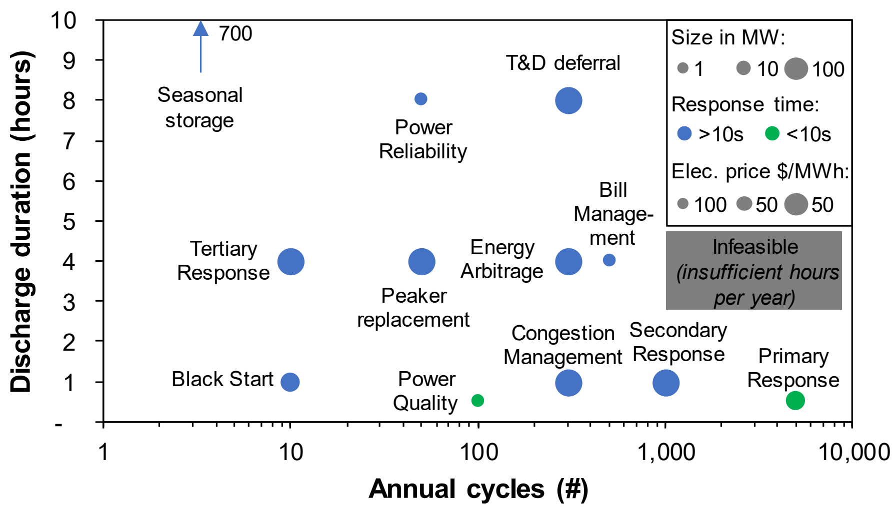


Figure 6.1 – The 12 core applications with modelled requirements. The distinct annual cycle and discharge duration requirements for each application are chosen from within the ranges in Table 3.7 and such that the entire spectrum for these parameter combinations is represented among all 12 applications. Annual cycles or discharge frequency refers to full equivalent charge-discharge cycles.

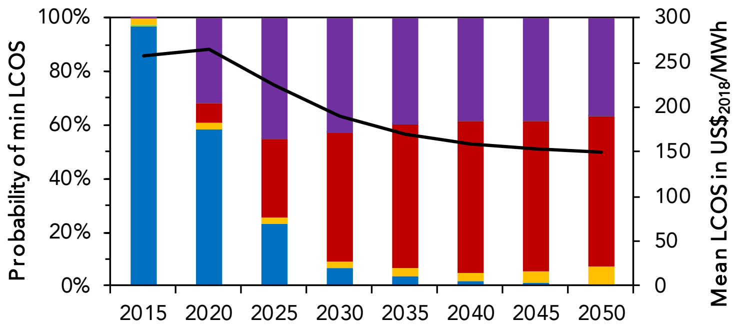
6.2 Projecting Levelised Cost of Storage

LCOS for the 9 technologies and 12 applications in Table 6.1 are projected from 2015 to 2050. Technology cost and performance data and application requirements are based on a review of industry and academic publications and were verified with industry experts (Table 2.3 and Figure 6.1). Variation and uncertainty in the technology data are accounted for in a Monte-Carlo simulation of the LCOS calculation.

Figure 6.2 shows the results for *secondary response*. It describes application requirements, projected LCOS for the four most competitive technologies, their probability to be most cost-efficient and the mean LCOS of the technology with the highest probability to be most cost-efficient. Probability reflects the frequency with which each technology offers the minimum LCOS accounting for the uncertainty ranges (Chapter 3.3.4).

3 **Secondary Response**

Power capacity	100 MW
Discharge duration	1 hour
Annual cycles	1,000
Response time	>10 seconds
Electricity price	50 $/MWh$_{el}$



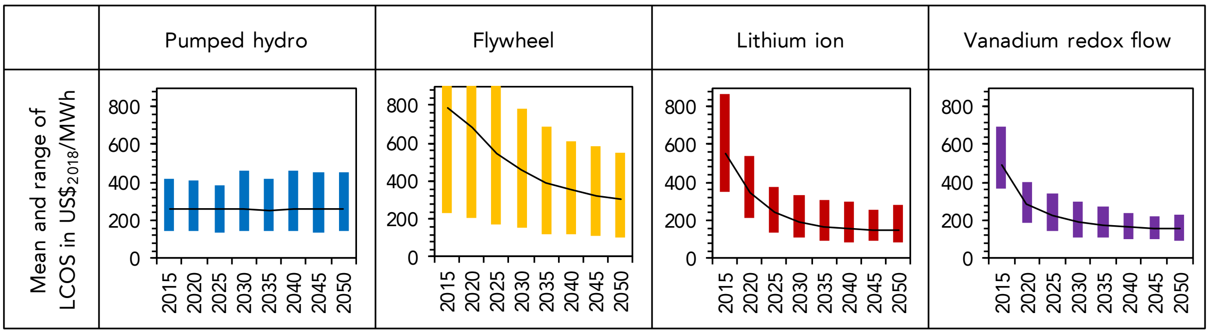


Figure 6.2 – LCOS projections for secondary response. Application requirements (top-left), probability of exhibiting lowest LCOS (top-right) and explicit LCOS projections for four most competitive technologies, including uncertainty ranges based on Monte-Carlo simulation of LCOS calculation (bottom). The simulation conducts 500 LCOS calculations per technology and year with random technology input parameter values from an 80% confidence interval of parameter's attributed normal distribution, corresponding to 1.285 standard deviations from the mean. Top-right chart includes mean LCOS of technology with highest probability to be most cost-efficient (black line). Probability reflects the frequency with which each technology offers the minimum LCOS accounting for the uncertainty ranges. See Figure 6.3 for probability charts of other applications. Projected LCOS of all 9 technologies and 12 applications can be reproduced in the online webtool of the model at www.EnergyStorage.ninja.

Secondary response is characterised by short discharge duration and frequent cycles. It can be large-scale and does not require fast response, which makes it suitable for pumped hydro with favourable geographic conditions. Pumped hydro exhibits the lowest LCOS in 2015

(150-400 US$/MWh) due to lifetimes beyond 30 years at 1,000 annual cycles, and despite relatively high power-specific investment cost. Mean LCOS for flywheel storage is much higher than for pumped hydro, however large investment cost uncertainty translates to a small probability for minimum LCOS. The strong anticipated investment cost reductions for battery technologies mean that by 2030 vanadium redox flow and lithium ion are likely to be most cost-efficient for this application, despite operating life of only 8 and 13 years respectively (Table 2.3, Appendix C.1 and Appendix C.2).

The mean LCOS of the most cost-efficient technology reduces from 250 US$/MWh in 2015 to 190 and 150 US$/MWh in 2030 and 2050 respectively. Investment cost make up the largest proportion of LCOS across the four technologies, between 65 and 90% in 2015. Reduced investment cost for the two battery technologies mean this share falls from 80% (2015) to 55% (2030) and 40% (2050). Charging cost represents the second largest contributor for the four technologies at 7 to 25% due to the high annual cycle requirement. Projected LCOS of all 9 technologies and 12 applications and cost breakdowns can be reproduced in the online webtool of the model at www.EnergyStorage.ninja. Note that these LCOS projections are solely based on future investment cost reductions, disregarding potential performance improvements.

Figure 6.3 shows an overview of all technologies' probabilities to exhibit lowest LCOS, and the mean LCOS of the most cost-efficient technology for all 12 investigated electricity storage applications. In 2015, pumped hydro and compressed air dominate most applications apart from consumption services and *primary response*, where size and response time requirements make these technologies unsuitable. In consumption service applications, battery systems such as lead acid, sodium sulphur, lithium ion and vanadium redox flow compete for least-cost, while *primary response* is dominated by flywheels.

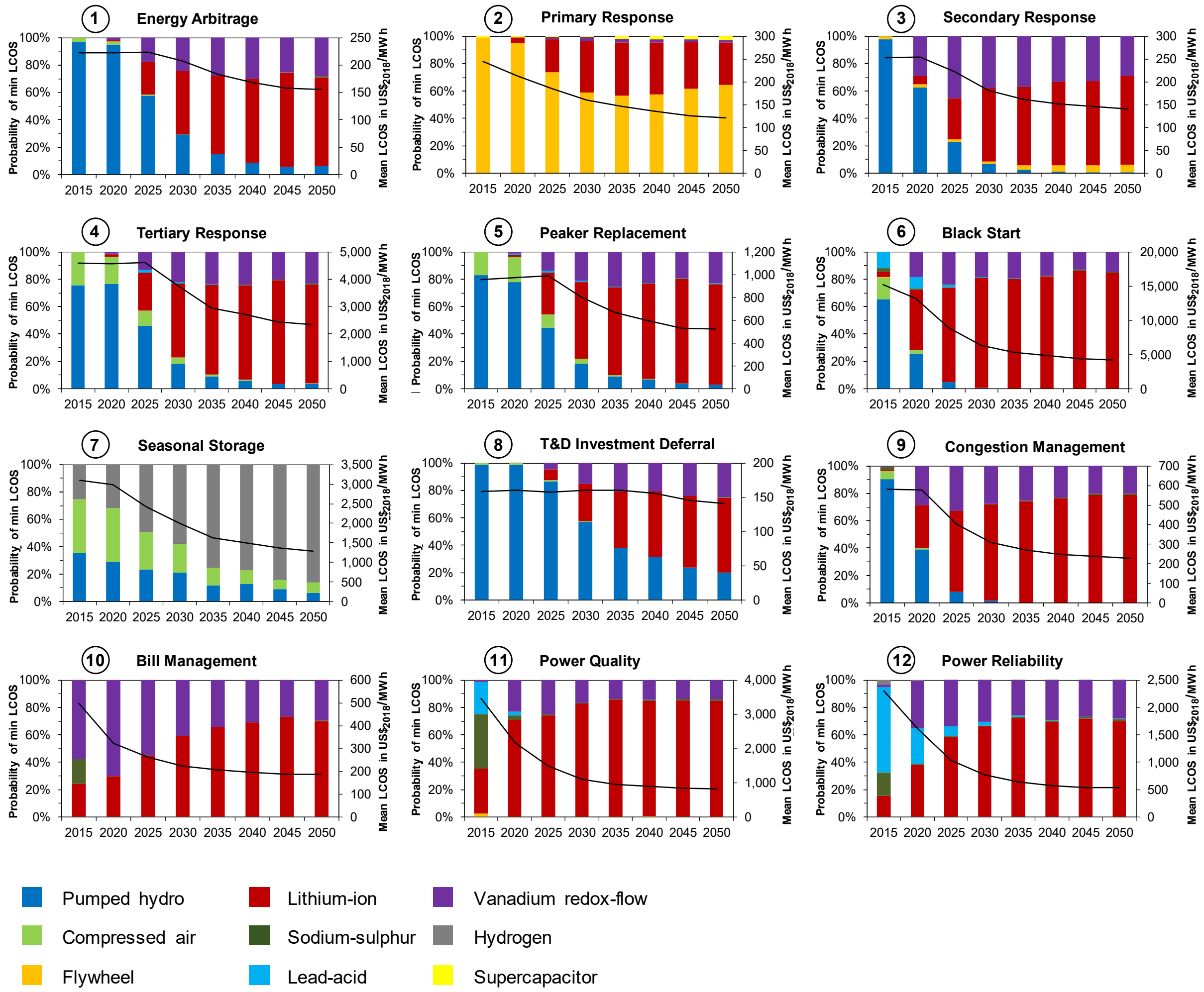


Figure 6.3 – Lowest LCOS probabilities for 9 electricity storage technologies in 12 applications from 2015 to 2050. Left axis displays probability that a technology will exhibit lowest LCOS in a specific application. Right axis displays mean LCOS of technology with highest probability for lowest LCOS. Note there are different scales between panels. Probabilities reflect the frequency with which each technology offers the minimum LCOS accounting for the uncertainty ranges identified with the Monte-Carlo simulation of the LCOS calculation. Circled numbers in panel titles correspond to applications in Table 6.1. Note that applications like primary response or power quality are usually reimbursed for provision of power capacity, not energy output. Please refer to Figure 6.4 for probability analysis and projection of LCOS in power terms (i.e., annuitised capacity cost in $US\$_{2018}/kW_{year}$). Application requirements are displayed in Figure 6.1. Discount rate is 8%. All technology input parameters can be found in Table 2.3 and Appendix C.

Projected cost reductions for battery technologies limit the competitiveness of pumped hydro and compressed air. Battery technologies exhibit the highest probability of lowest LCOS in most applications beyond 2025. By 2030 lithium ion appears to be cheapest in most applications, in particular with <4 hours discharge and <300 annual cycles like *power quality* and *black start*. For applications with higher duration and cycle requirements, vanadium redox flow stays competitive, albeit never being the most likely to offer minimum LCOS. These applications are *power reliability* (>4 hours) or *secondary response* and *bill management* (>300 cycles). For *seasonal storage* with more than 700 hours discharge, hydrogen storage is likely to become most cost-efficient. *Primary response* with 5,000 full charge-discharge cycles sees the dominance of flywheels contested by lithium ion.

On average, mean LCOS of technologies with highest probability to be most cost-efficient reduce 36% and 53% by 2030 and 2050 relative to 2015 respectively across the modelled applications. For applications ≥300 annual cycles, LCOS reduce from 150-600 US$/MWh (2015) to 130-200 US$/MWh (2050), for between 50 and 100 annual cycles from 1,000-3,500 (2015) to 500-900 US$/MWh (2050), and applications with ≤10 annual cycles never cost below 1,500 US$/MWh. The annual cycle requirement is so important, because it affects energy throughput per unit of installed capacity. The higher the energy throughput per unit capacity deployed, the lower the LCOS. This observation is a result of the high share of investment cost in the LCOS.

Another LCOS driver appears to be discharge duration. Applications with longer discharge requirements exhibit lower LCOS than applications with similar cycle and shorter discharge requirements. Examples are minimum LCOS for *T&D investment deferral* (150 US$/MWh, 8 hours) or the relatively low LCOS for s*easonal storage* (1,500-3,000 US$/MWh, 700 hours) compared to applications with more cycles but lower discharge duration like *black start* and *tertiary response*. This is the result of the energy-discharge focussed metric US$/MWh. Any increase in discharge duration for a technology entails a similar increase in modelled energy discharge, but a lower relative increase in total investment cost because only energy-related and no power-related cost is affected.

Figure 6.4 displays lifetime cost in US$/kW$_{year}$, also called annuitised capacity cost (ACC). This metric matters for applications valued for power provision like *primary response* or *power quality*. It reflects the cost at which a technology can provide a unit of power capacity for an entire year or the annual reimbursement it should receive per kW for a net present value of zero. Here, technologies with low round-trip efficiencies like compressed air can be more cost-efficient and applications with short discharge and few annual cycles like *black start* or *power quality* exhibit lowest cost. This highlights the importance of choosing the appropriate metric, energy- or power-focussed, when determining application-specific lifetime cost for economic investment decisions in electricity storage technologies.

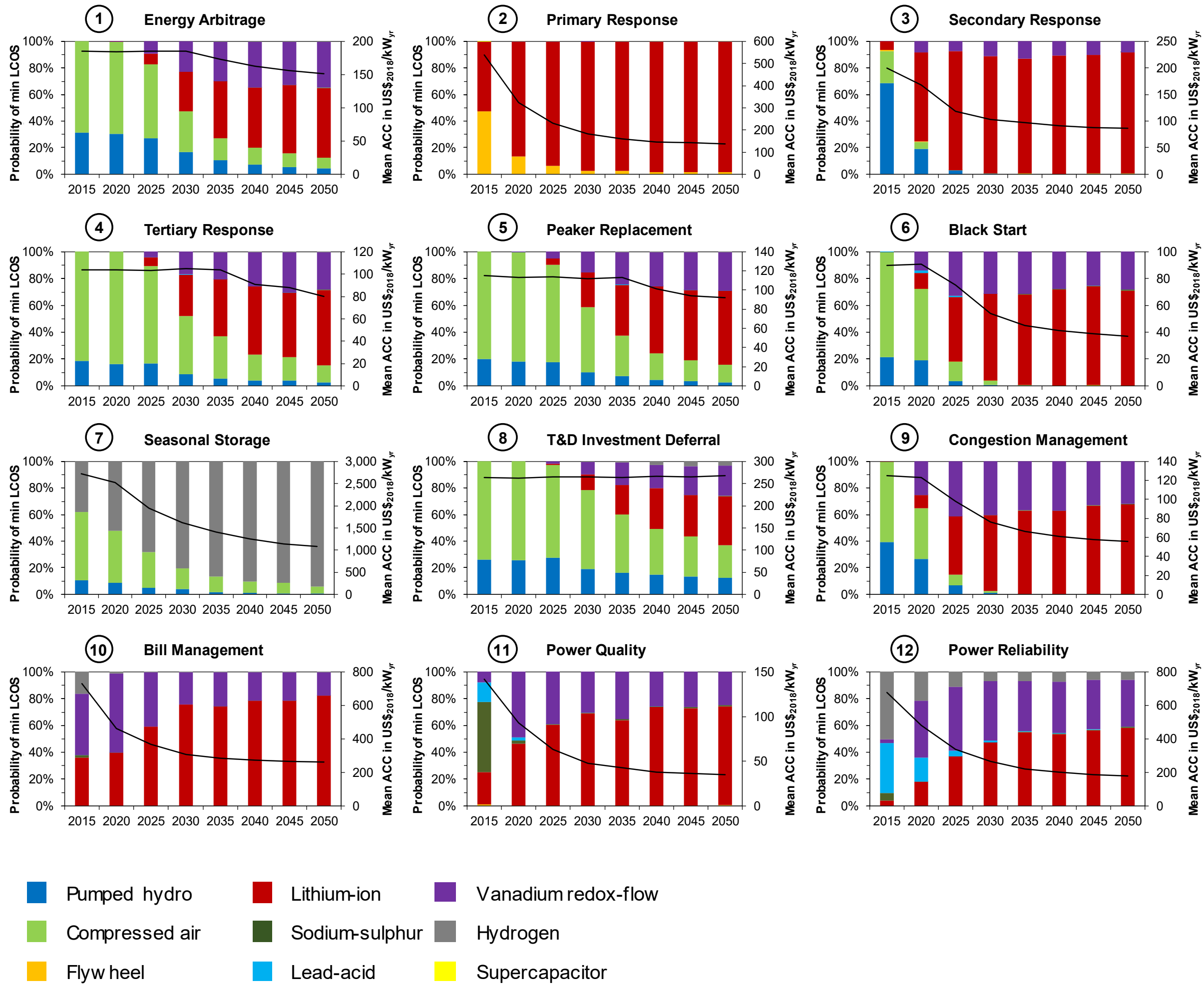


Figure 6.4 – Lowest ACC probabilities for 9 electricity storage technologies in 12 applications from 2015 to 2050. Left axis displays probability that a technology will exhibit lowest ACC in a specific application. Right axis displays mean ACC of technology with highest probability for lowest ACC. Note there are different scales between panels. Probabilities reflect the frequency with which each technology offers minimum ACC accounting for the uncertainty ranges identified with the Monte-Carlo simulation of the ACC calculation. Circled numbers in panel titles correspond to applications in Table 6.1. Application requirements are displayed in Figure 6.1. Discount rate is 8%. All technology input parameters can be found in Table 2.3 and Appendix C.

6.3 Sensitivity to Application Requirements

Figure 6.5 explores the sensitivity of technologies to be most cost-efficient relative to discharge duration and annual cycles. The right-hand panel excludes pumped hydro and compressed air, as they have limited geographic suitability.

It is found that pumped hydro, compressed air and flywheel energy storage were the most competitive technologies across the entire spectrum of modelled discharge and frequency combinations in 2015. Pumped hydro dominates due to good cycle life combined with low energy- and moderate power-specific investment cost. Compressed air is more competitive above 45 hours discharge due to significantly lower energy-specific investment cost. Flywheels are more competitive above 5,000 annual cycles and below 0.5 hours discharge due to better cycle life and lower power-specific cost.

Projecting future LCOS based on investment cost reductions, indicates that lithium-ion batteries become cost-competitive for low discharge duration applications by 2020, competing with vanadium redox flow and flywheels at high frequencies due to their better cycle life. However, in terms of power-focussed ACC (Figure 6.6) there is a strong cost advantage for lithium ion also at high frequency combinations, relevant for primary response applications, due to considerable cycle life improvement when operating below 100% depth-of-discharge. This finding is supported by the recent uptake of lithium-ion systems for primary response applications[86].

With continued investment cost reduction, lithium ion could outcompete vanadium redox flow at high frequencies and displace pumped hydro at long discharge durations to become the most cost-efficient technology for most modelled applications by 2030. At the same time, hydrogen storage becomes more cost-efficient than compressed air for long discharge applications.

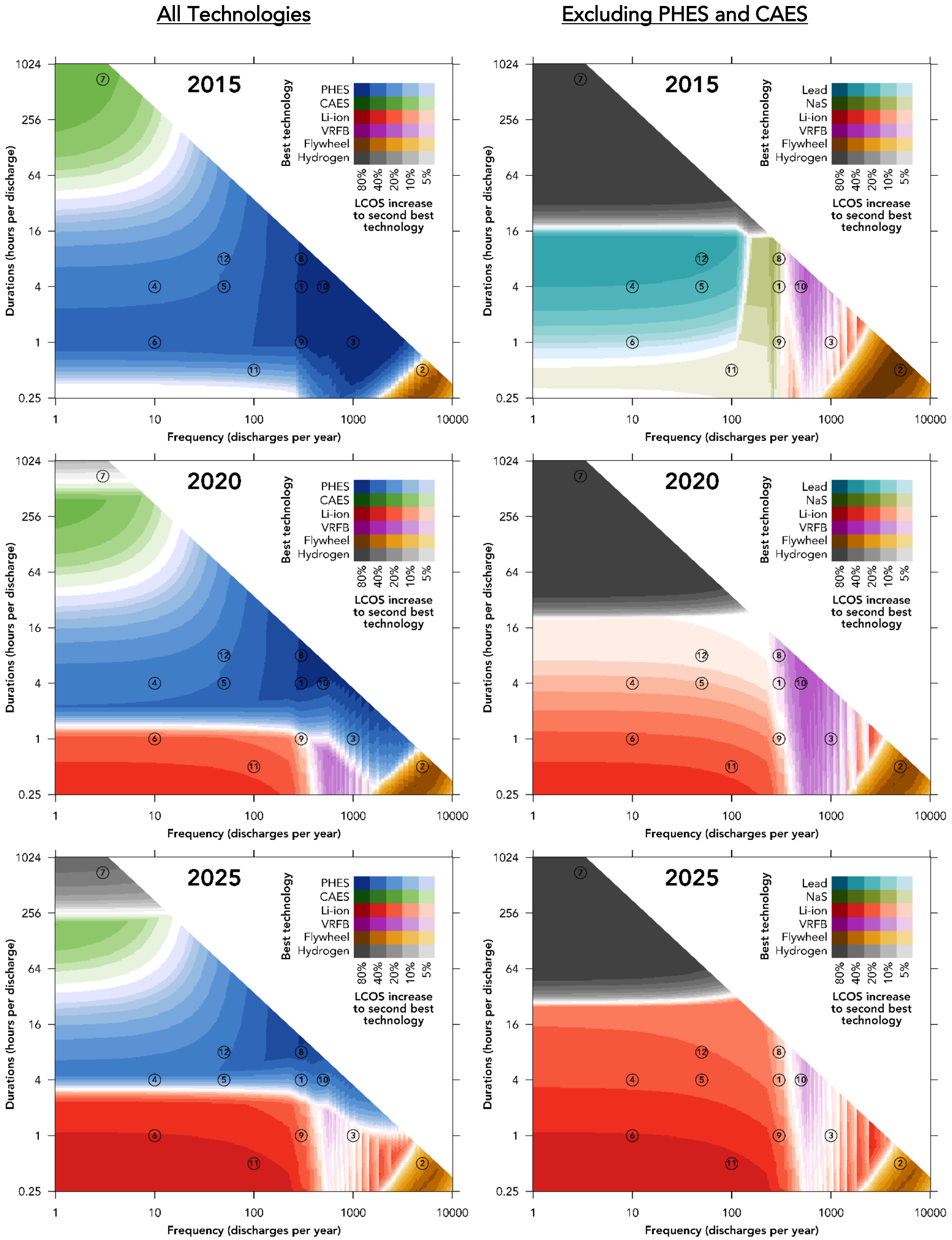
Excluding pumped hydro and compressed air reveals that hydrogen storage is already most cost-efficient in 2015 for discharge durations beyond one day, and a wider ecosystem of cost-efficient technologies emerges. Sodium sulphur and lead acid dominate applications up to 300 and lithium ion, vanadium redox flow and flywheels above 300 cycles per year. Projecting future LCOS confirms that lithium ion becomes cost competitive for most discharge and frequency combinations below 8 hours discharge, with a particularly strong cost advantage at frequencies below 300 and above 1,000. The initial increase and subsequent decrease in cost efficiency of vanadium redox flow between 300 and 1,000 cycles shows its possible cost reduction dynamic compared to lithium ion. As a relatively immature technology, flow batteries could realise more significant cost reductions in the near-term at comparable deployment levels[109] (Appendix C.4). The experience curve analysis still reveals stronger cost reductions for lithium ion in the long-term due to a higher experience rate (ER, Chapter 4). Lithium ion is thereby likely to replace all other battery technologies by 2030 and dominate all discharge and frequency combinations together with flywheels and hydrogen storage.

Figure 6.6 displays most cost-efficient technologies along the discharge duration and annual discharge frequency spectrum for ACC or LCOS in power terms.

The dominance of compressed air and pumped hydro in 2015 is also challenged by lithium ion, which becomes highly competitive at high cycle frequency and short discharge duration applications. By 2025, lithium ion is most cost-competitive for all applications requiring less than one-hour discharge duration, and by 2035 for all applications requiring less than four-hours.

Excluding compressed air and pumped hydro again reveals a much wider ecosystem of cost-efficient storage technologies in 2015, namely lead acid for applications below 100 cycles per year, sodium sulphur between 100 and 300 cycles, lithium ion above 300 cycles, and hydrogen at above six-hours discharge duration. While vanadium redox flow becomes most cost-efficient for applications below 300 annual cycles and 6-hours discharge duration in the early 2020s, by 2030 this spectrum is also dominated by lithium ion. Lithium ion even pushes out hydrogen's cost-effectiveness to beyond 16 hours discharge duration applications.

Figure 6.5 and Figure 6.6 thereby present first-of-their-kind ´maps´ that can be used to identify most cost-efficient technologies for applications at any discharge duration or frequency requirement.


All Technologies
Excluding PHES and CAES
2015
2020
2025
Best technology
PHES
CAES
Li-ion
VRFB
Flywheel
Hydrogen
Lead
NaS
80%
40%
20%
10%
5%
LCOS increase to second best technology
Durations (hours per discharge)
Frequency (discharges per year)
1024
256
64
16
4
1
0.25
1
10
100
1000
10000

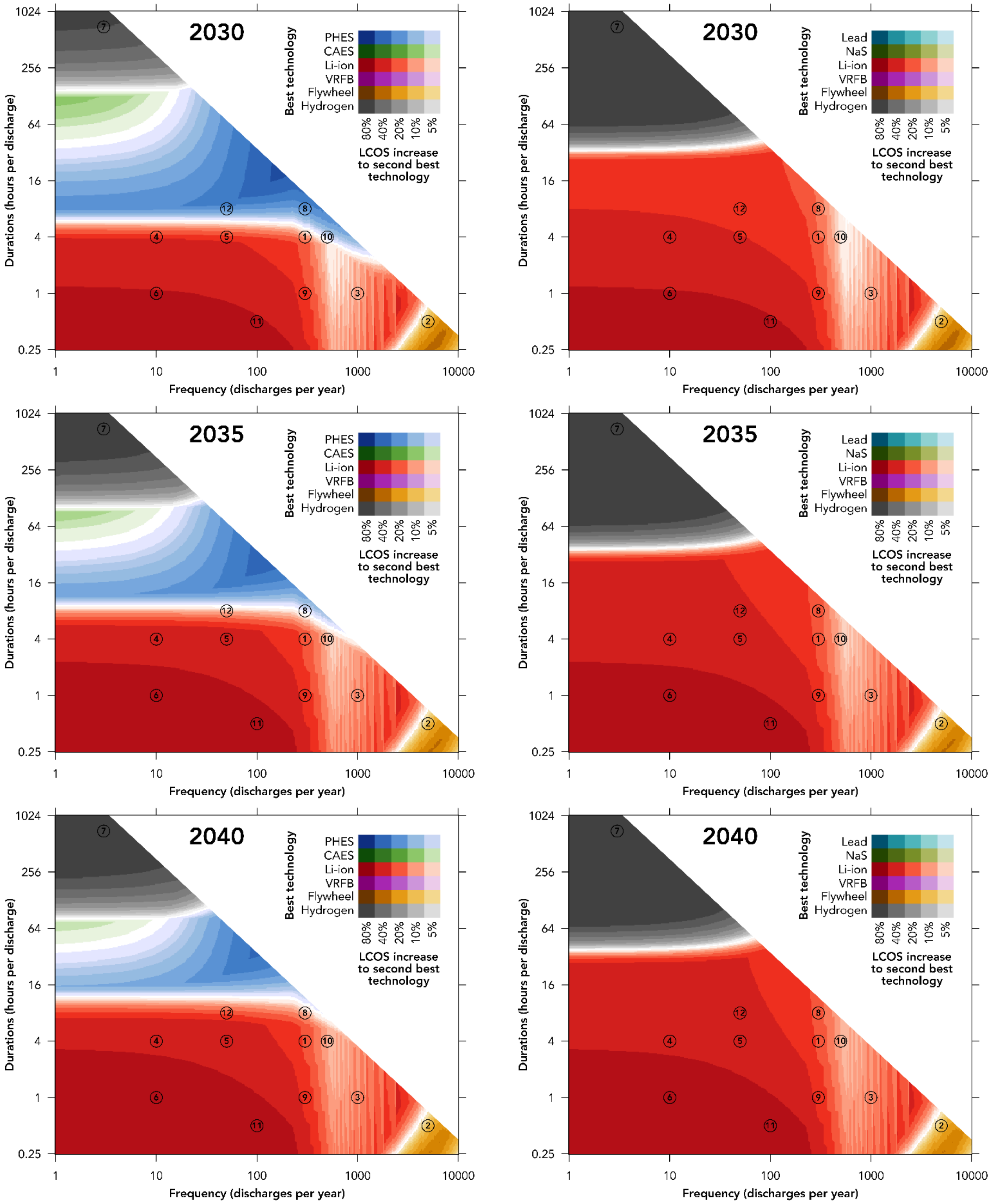
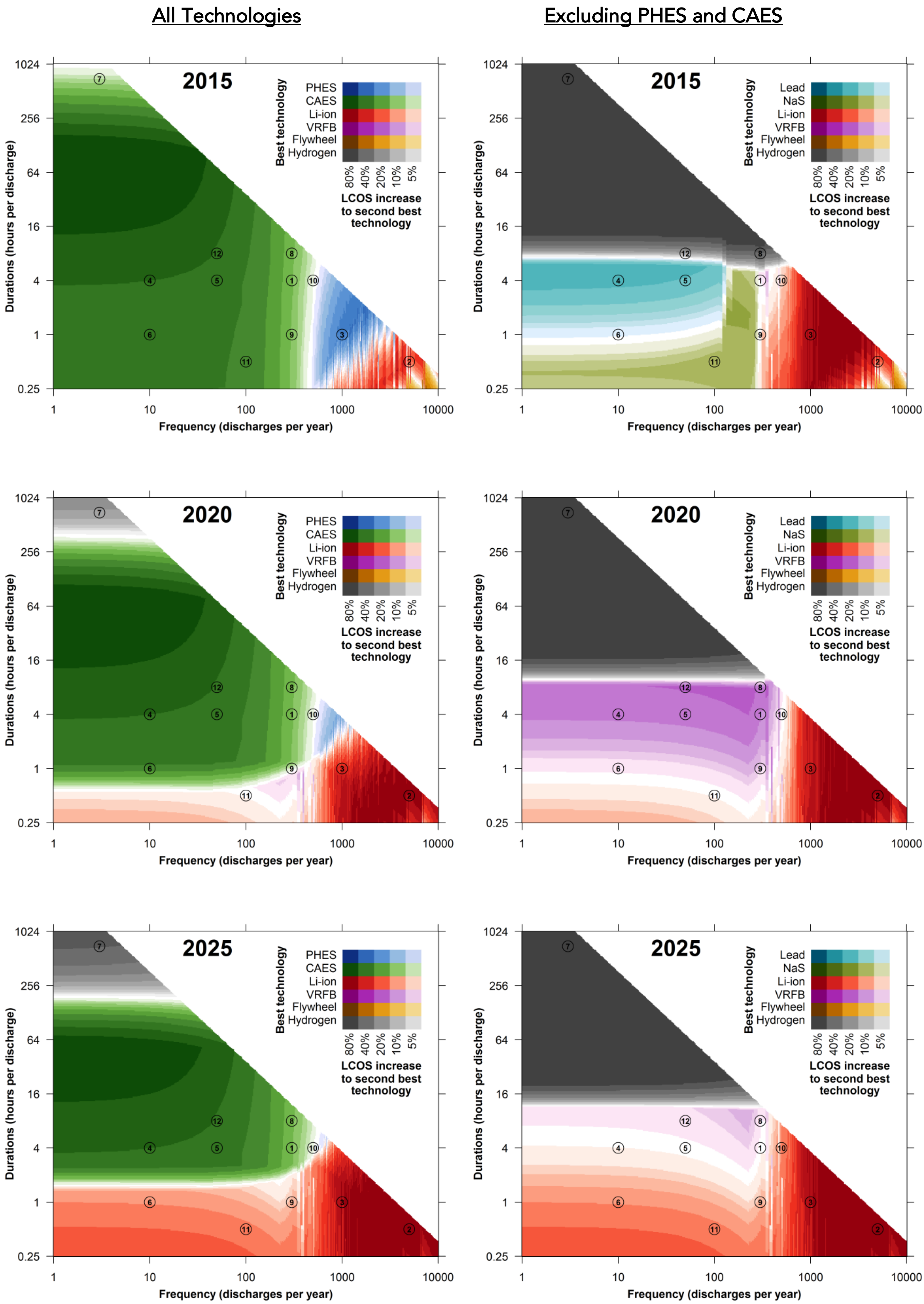


Figure 6.5 – LCOS discharge duration and annual cycle sensitivity – most cost-efficient technologies. Chart displays technologies with lowest LCOS relative to discharge duration and annual cycle requirements for all modelled technologies (left) and excluding pumped hydro and underground compressed air (right). Circled numbers represent the requirements of the 12 core applications introduced in Table 6.1: 1-Energy Arbitrage, 2-Primary Response, 3-Secondary Response, 4-Tertiary Response, 5-Peaker Replacement, 6-Black Start, 7-Seasonal Storage, 8-T&D Investment Deferral, 9-Congestion Management, 10-Bill Management, 11-Power Quality, 12-Power Reliability. Colours represent technologies with lowest LCOS. Shading indicates how much higher the LCOS of the second most cost-efficient technology is; meaning lighter areas are contested between at least two technologies, while darker areas indicate a strong cost advantage of the prevalent technology. White spaces mean LCOS of at least two technologies differ by less than 5%. The sawtooth pattern above 1,000 cycles reflects the marked lifetime reductions at more frequent discharges that affect competitiveness of individual technologies. The modelled electricity price is 50 US$/MWh. Discount rate is 8%. See these videos for animated versions of both charts: Video S1-All_Tech, Video S2-Excl_PHES_CAES. All technology input parameters can be found in Table 2.3 and Appendix C. Refer to Figure 6.6 for a similar overview of most cost-efficient technologies based on ACC (US$/$kW_{year}$).


All Technologies
Excluding PHES and CAES
2015
2020
2025
Best technology
PHES
CAES
Lead
NaS
Li-ion
VRFB
Flywheel
Hydrogen
80% 40% 20% 10% 5%
LCOS increase to second best technology
Durations (hours per discharge)
1024
256
64
16
4
1
0.25
Frequency (discharges per year)
1
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10000
1 2 3 4 5 6 7 8 9 10 11 12

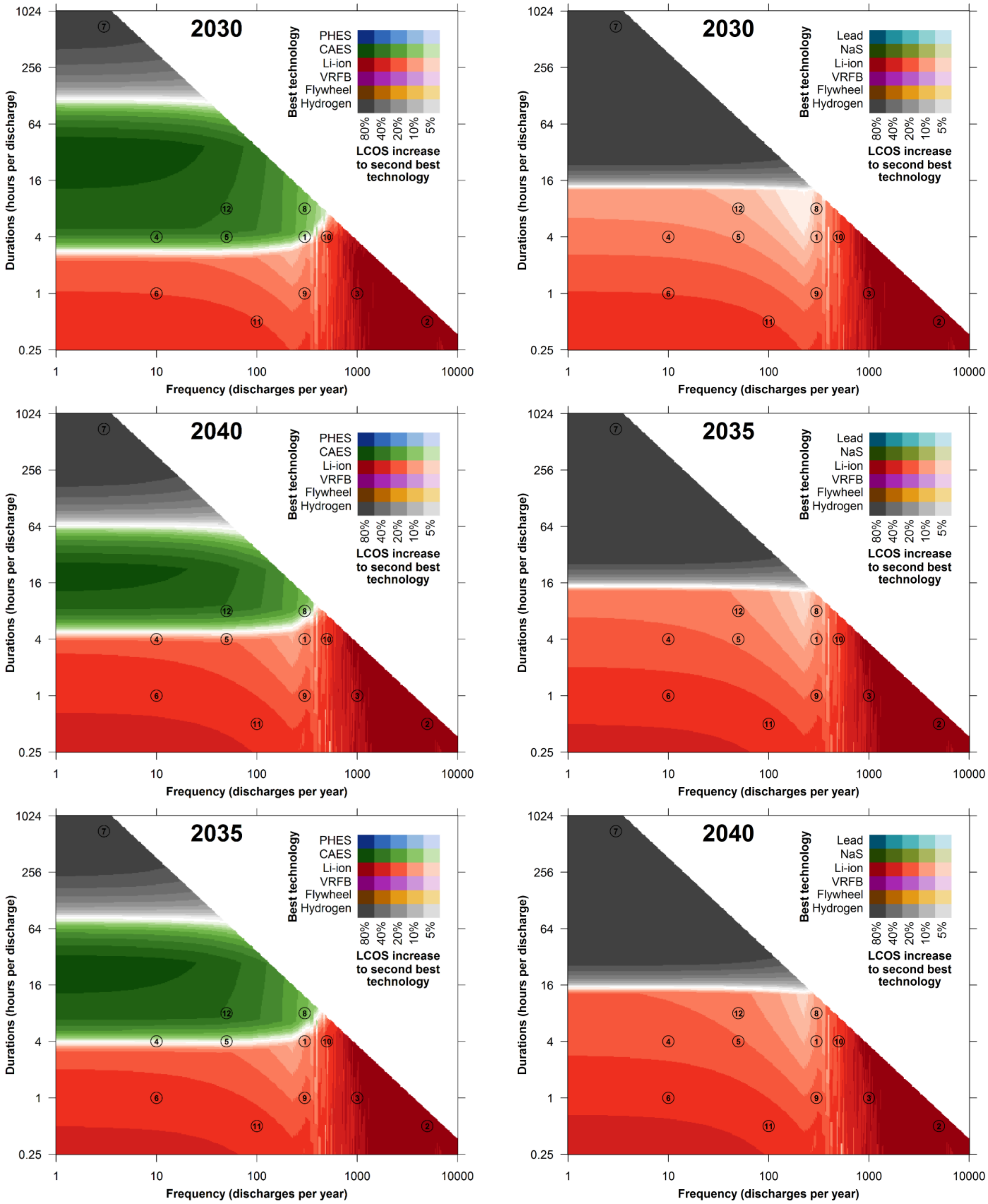

Figure 6.6 – ACC discharge duration and annual cycle sensitivity – most cost-efficient technologies. Chart displays technologies with lowest ACC relative to discharge duration and annual cycle requirements for all modelled technologies (left) and excluding pumped hydro and underground compressed air (right). Circled numbers represent the requirements of the 12 core applications introduced in Table 6.1: 1-Energy Arbitrage, 2-Primary Response, 3-Secondary Response, 4-Tertiary Response, 5-Peaker Replacement, 6-Black Start, 7-Seasonal Storage, 8-T&D Investment Deferral, 9-Congestion Management, 10-Bill Management, 11-Power Quality, 12-Power Reliability. Colours represent technologies with lowest LCOS. Shading indicates how much higher the LCOS of the second most cost-efficient technology is; meaning lighter areas are contested between at least two technologies, while darker areas indicate a strong cost advantage of the prevalent technology. White spaces mean LCOS of at least two technologies differ by less than 5%. The modelled electricity price is 50 US$/MWh. Discount rate is 8%. All technology input parameters can be found in Table 2.3 and Appendix C.

The LCOS of the most cost-efficient technology for all discharge and frequency combinations is displayed in Figure 6.7. Lowest LCOS are achieved by pumped hydro for moderate discharge (~4 hours) and frequency (~1,000) combinations. The LCOS range of 100 to 150 US$/MWh in 2015 corresponds to cost of new pumped hydro facilities[87]. LCOS increase is proportional to the reduction of annual cycles and discharge duration as these determine lifetime energy discharged, the denominator of the energy-focussed LCOS metric. The projection of LCOS translates into LCOS reduction across the entire discharge and frequency spectrum without changes in this proportional pattern, despite the changing technologies that achieve these LCOS (Figure 6.5).

For ACC, the pattern is reverse (Figure 6.8). Lowest ACC are achieved for short discharge duration and few annual cycle applications. For example, the application *black start* could be serviced for 80US$/$kW_{year}$ by 2015 and 25US$/$kW_{year}$ by 2040. Storage technologies in power applications get reimbursed for available power capacity, which forms the denominator in the ACC equation. That means any additional energy capacity increases ACC as well as any additional annual cycle, which reduces lifetime without leading to additional revenues.

Similar to Figure 6.5 and Figure 6.6, Figure 6.7 and Figure 6.8 provide 'maps' of future electricity storage lifetime cost. For the first time, these costs for any possible application can be drawn from one graph.

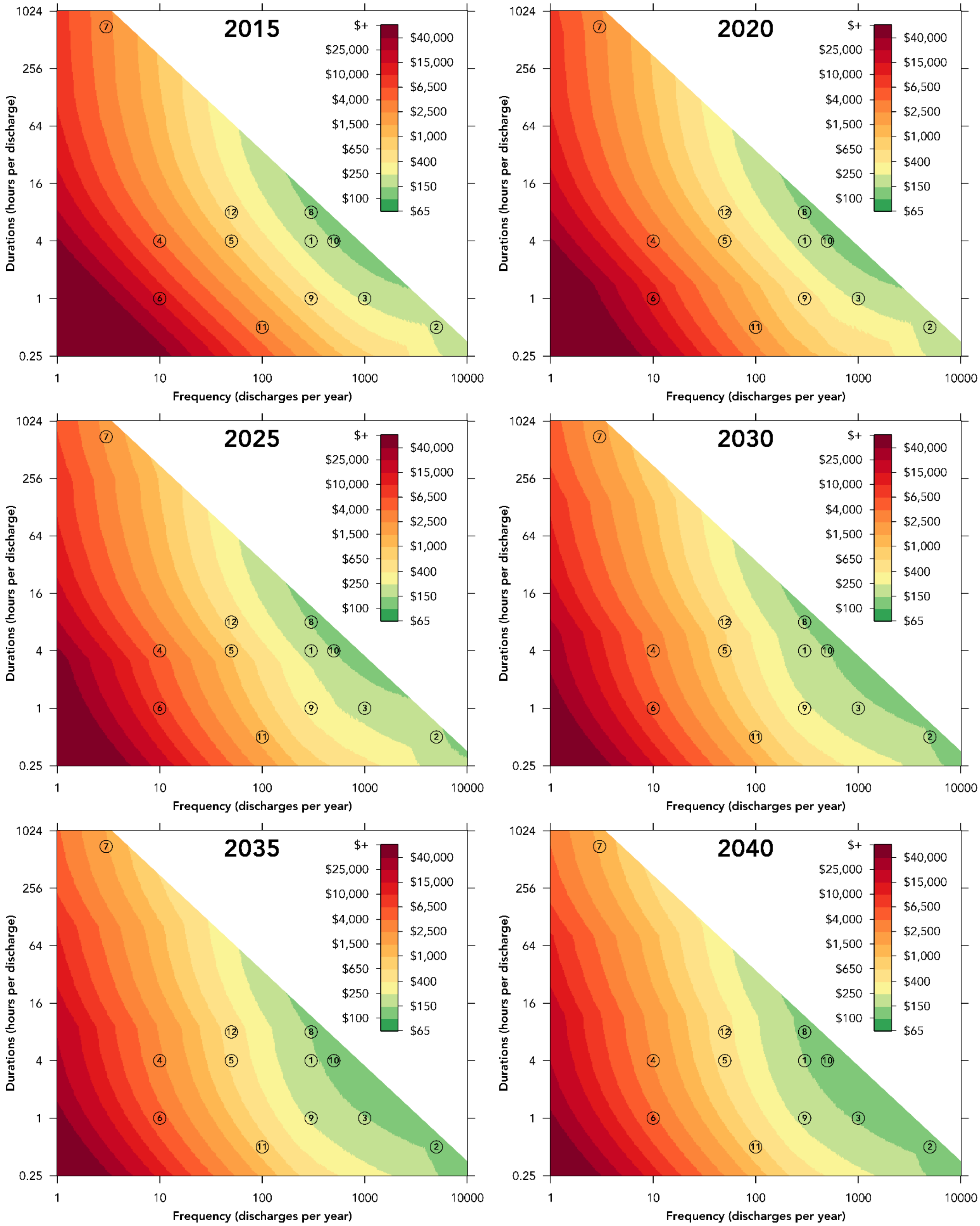

Figure 6.7 – LCOS discharge duration and annual cycle sensitivity – LCOS of most cost-efficient technologies. Chart displays LCOS of most cost-efficient technologies relative to discharge duration and annual cycle requirements for all modelled technologies. Circled numbers represent the requirements of the 12 core applications introduced in Table 6.1: 1-Energy Arbitrage, 2-Primary Response, 3-Secondary Response, 4-Tertiary Response, 5-Peaker Replacement, 6-Black Start, 7-Seasonal Storage, 8-T&D Investment Deferral, 9-Congestion Management, 10-Bill Management, 11-Power Quality, 12-Power Reliability. Colours represent LCOS range. The modelled electricity price is 50 US$/MWh. Discount rate is 8%. All technology input parameters can be found in Table 2.3 and Appendix C. Please refer to Figure 6.8 for a similar overview on ACC (US$/$kW_{year}$) of most cost-efficient technologies.

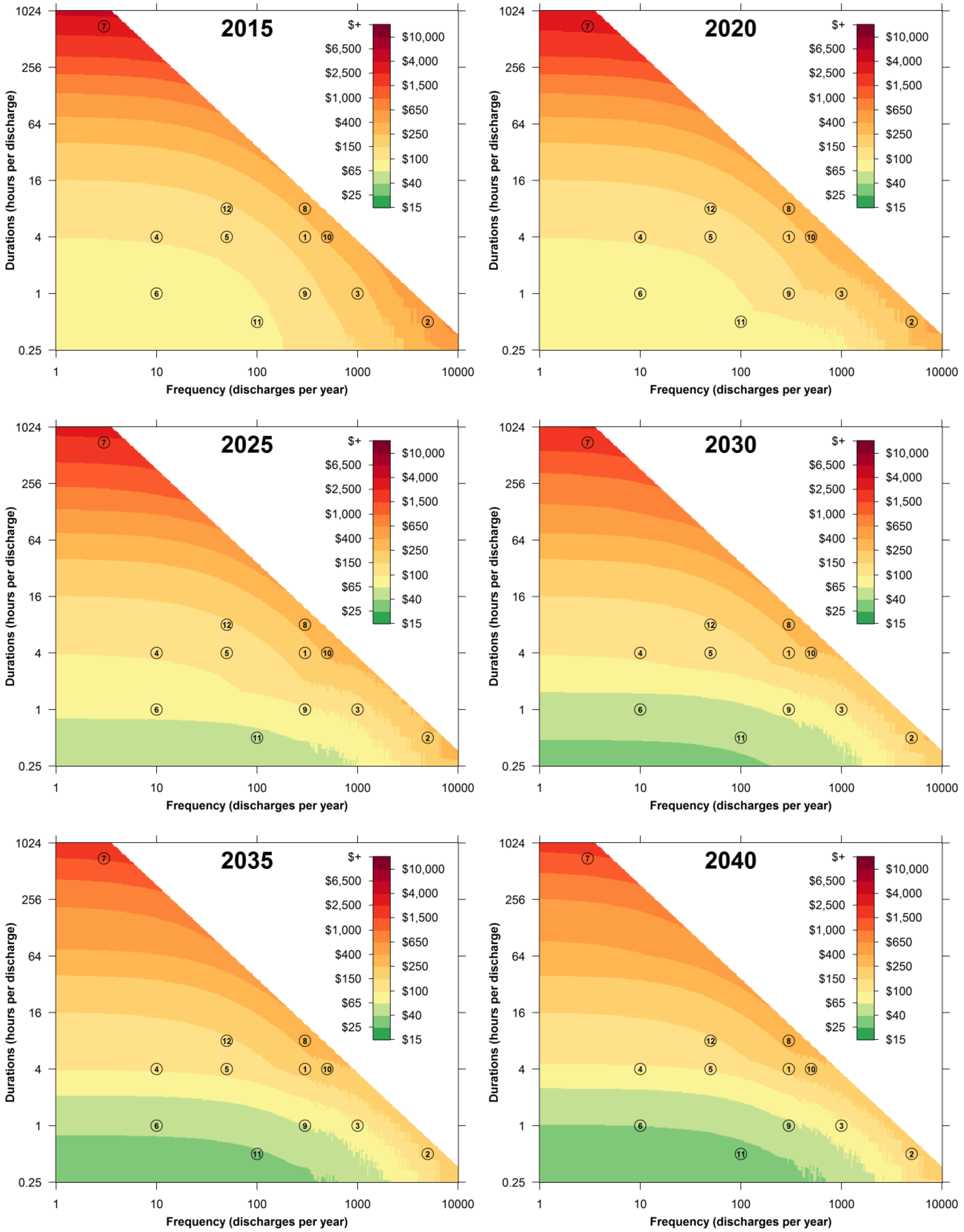

Figure 6.8 – ACC discharge duration and annual cycle sensitivity – ACC of most cost-efficient technologies. Chart displays ACC of most cost-efficient technologies relative to discharge duration and annual cycle requirements for all modelled technologies. Circled numbers represent the requirements of the 12 core applications introduced in Table 6.1: 1-Energy Arbitrage, 2-Primary Response, 3-Secondary Response, 4-Tertiary Response, 5-Peaker Replacement, 6-Black Start, 7-Seasonal Storage, 8-T&D Investment Deferral, 9-Congestion Management, 10-Bill Management, 11-Power Quality, 12-Power Reliability. Colours represent LCOS range. The modelled electricity price is 50 US$/MWh. Discount rate is 8%. All technology input parameters can be found in Table 2.3 and Appendix C.

The LCOS share attributed to charging cost is 4% averaged across technologies and discharge and frequency combinations in 2030 (9% across the 12 modelled applications). This highlights that electricity price is not a key contributor to LCOS. A ten-fold increase in electricity price from 50 to 500 US$/MWh increases the relative importance of round-trip efficiency. Consequently, efficient lithium ion would replace pumped hydro at high cycles, which in turn would become more competitive than compressed air and hydrogen storage at high discharge durations. The average share of charging cost in LCOS increases to 19% (35% across the 12 modelled applications) (Figure 6.9). The impact of charging cost on LCOS increases with the number of full operation hours per year (i.e., product of discharge duration and frequency).

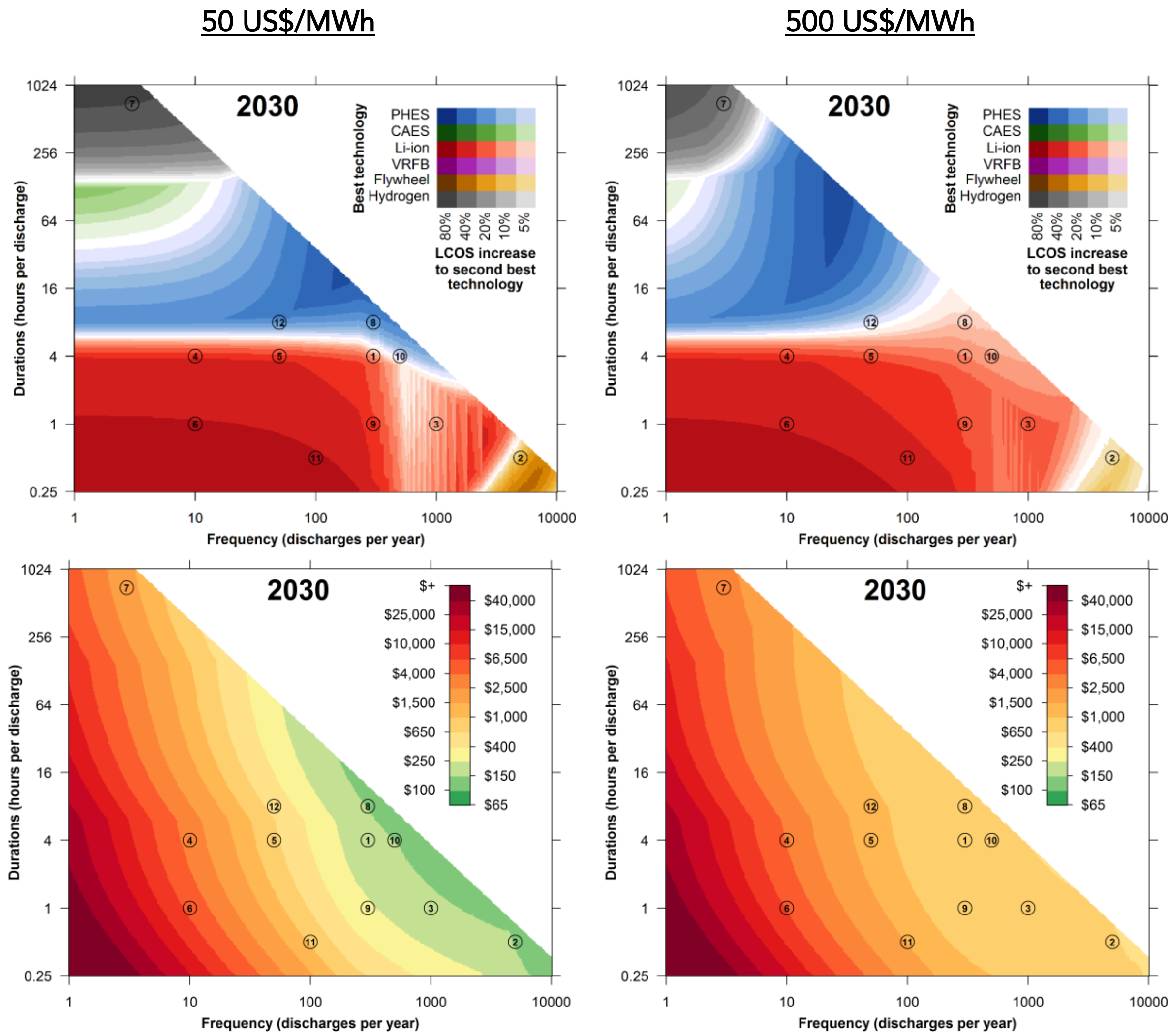

Figure 6.9 – Technology cost-effectiveness (top) and absolute LCOS sensitivity (bottom) to power price assumption of 50 US$/MWh (left) and 500 US$/MWh (right).

6.4 Sensitivity to Technology Parameters

Electricity storage projects will use different discount rates reflecting financing cost as well as technology and business case maturity. Reducing the discount rate from 8% to 4% for all technologies, which could reflect the social cost of capital[87], has a significant impact on cost-effectiveness by 2030 (Figure 6.10). Instead of being pushed out by lithium ion, pumped hydro remains most cost-effective for all applications requiring four hours of discharge duration. This is because a lower discount rate assumption means that future revenues, determined by technology lifetime, have a larger impact on LCOS. The long lifetime of pumped hydro is valued more at a discount rate of 4%, making it more competitive than lithium ion for the majority of modelled applications by 2030.

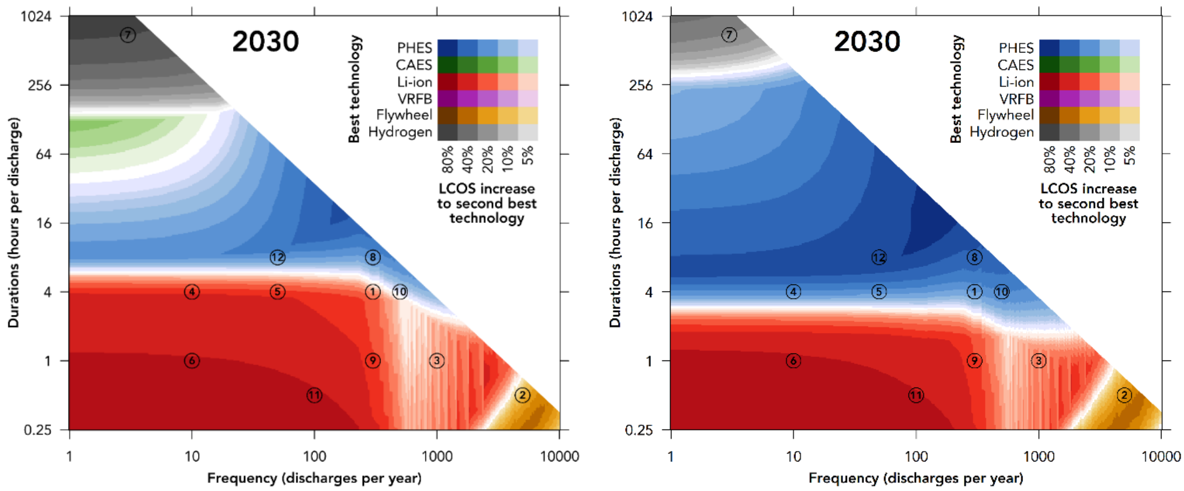

Figure 6.10 – Sensitivity of technology cost-effectiveness to discount rate. Left: 8% discount rate. Right: 4% discount rate.

When applying a 4% discount rate to vanadium redox-flow and 0% to supercapacitors, their LCOS would reduce on average by 15% and 36% respectively. In 2030, supercapacitors would displace flywheels as most cost-efficient technology above 5,000 cycles and vanadium redox flow would displace lithium ion between 500 and 1,000 cycles (Figure 6.11). However, the maturity of pumped hydro and compressed air and recent deployment levels of lithium-ion systems indicate that these technologies are more likely to benefit from lower discount rates, further increasing their cost advantage[37,64].

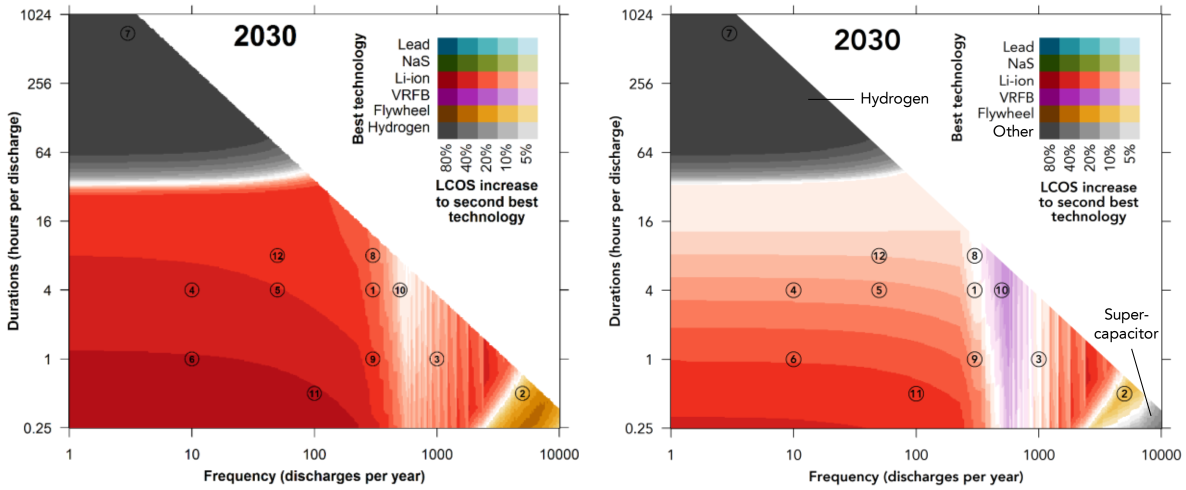

Figure 6.11 – Sensitivity of technology cost-effectiveness to discount rate. Left: 8% discount rate. Right: 4% for vanadium redox-flow, 0% for supercapacitors, 8% all others.

Another source of uncertainty are future performance improvements for the investigated technologies that could lead to lower LCOS than displayed in Figure 6.7 and Figure 6.8. LCOS is most sensitive to round-trip efficiency and cycle and shelf life. For example, a 1% annual round-trip efficiency improvement for vanadium redox-flow batteries, increasing efficiency from 73% (2015) to 85% (2030), would make the technology more cost-efficient than lithium ion at high frequencies. An annual increase in cycle and shelf life of 2.5% would have the same effect (Figure 6.12 and Figure 6.13).

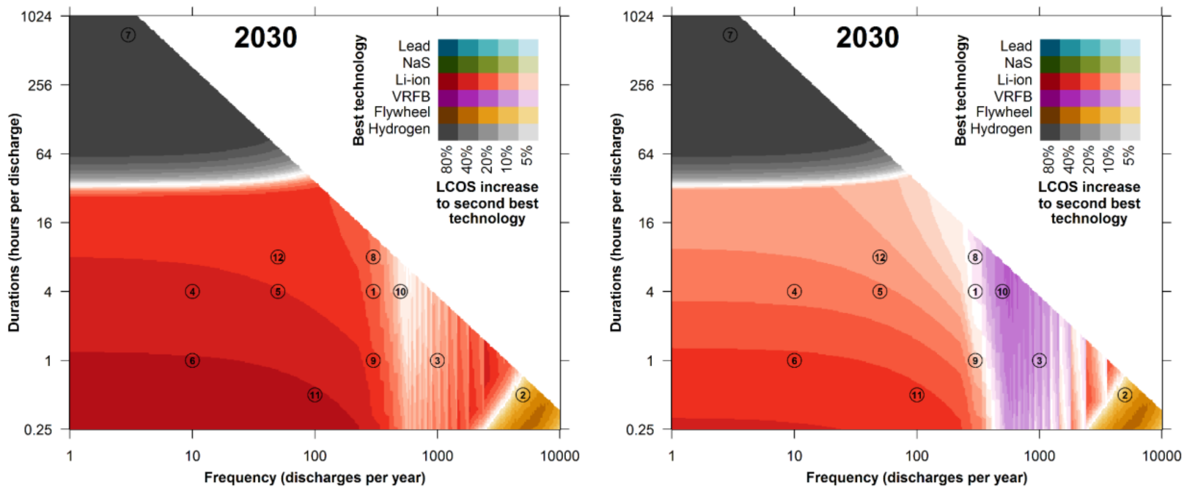

Figure 6.12 – Sensitivity of technology cost-effectiveness to round-trip efficiency. Left: Vanadium redox-flow round-trip efficiency at 73%. Right: Vanadium redox-flow round-trip efficiency at 85%. All other technology parameters for all other technologies are unchanged.

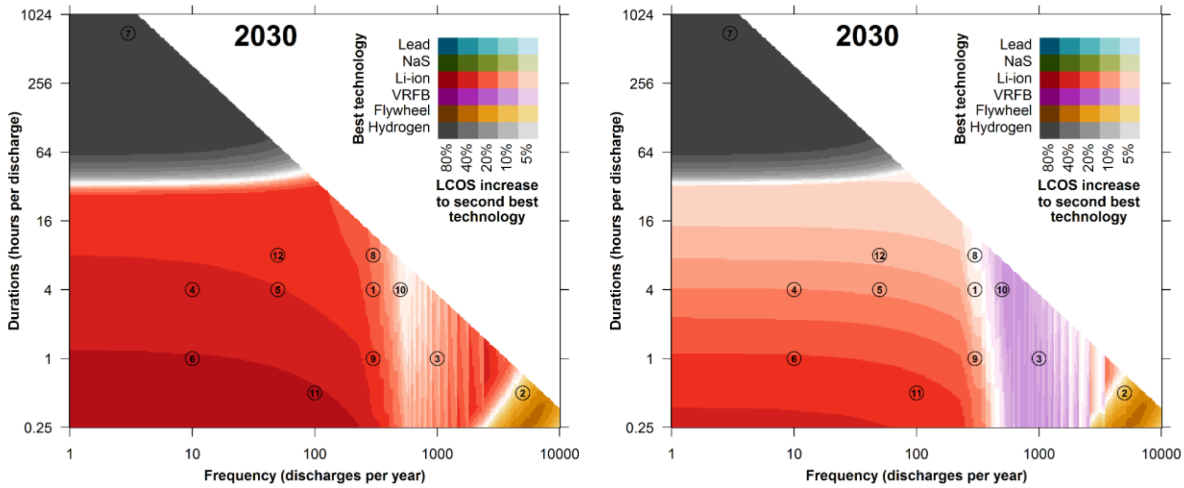

Figure 6.13 – Sensitivity of technology cost-effectiveness to cycle and shelf life. Left: Vanadium redox-flow at 8,300 cycle and 13 years shelf life. Right: Vanadium redox-flow at 12,000 cycle and 18 years shelf life. All other technology parameters for all other technologies are unchanged.

Figure 6.14, Figure 6.15 and Figure 6.16 show similar performance improvement requirements for lead acid, sodium sulphur and supercapacitor systems through which these technologies could partially outcompete lithium-ion systems by 2030. Note that these scenarios consider the impact of performance improvements for one technology in isolation. It is more likely that each technology will experience some degree of performance improvement, including lithium-ion and hydrogen storage, which may further improve their cost advantage[315,316].

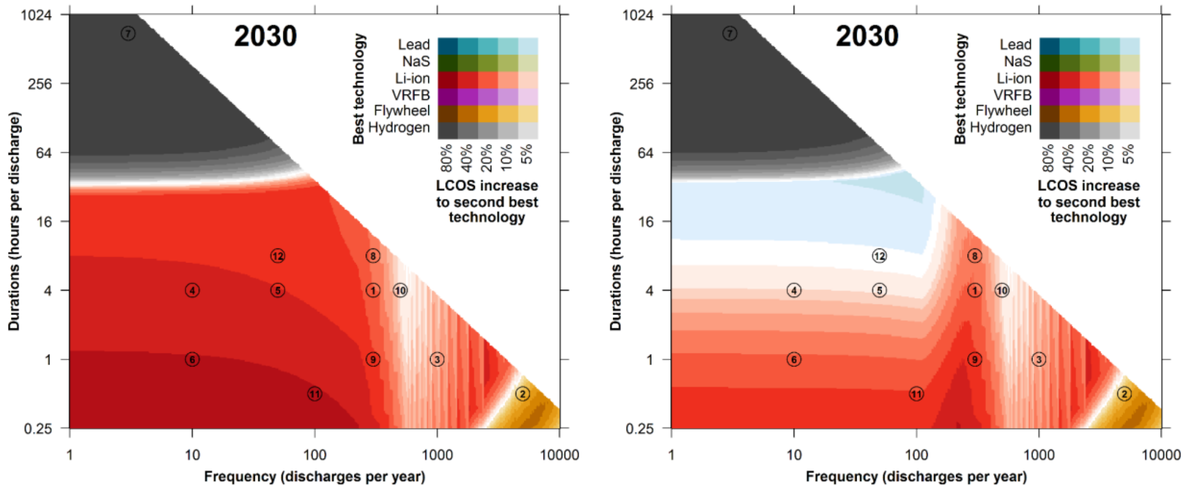

Figure 6.14 – Sensitivity of technology cost-effectiveness to various performance parameters for lead acid. Left: Lead acid at 84% round-trip efficiency and 1,200 cycle and 10 years shelf life. Right: Lead acid at 95% round-trip efficiency and 5,000 cycle and 40 years shelf life. All other technology parameters for all other technologies are unchanged.

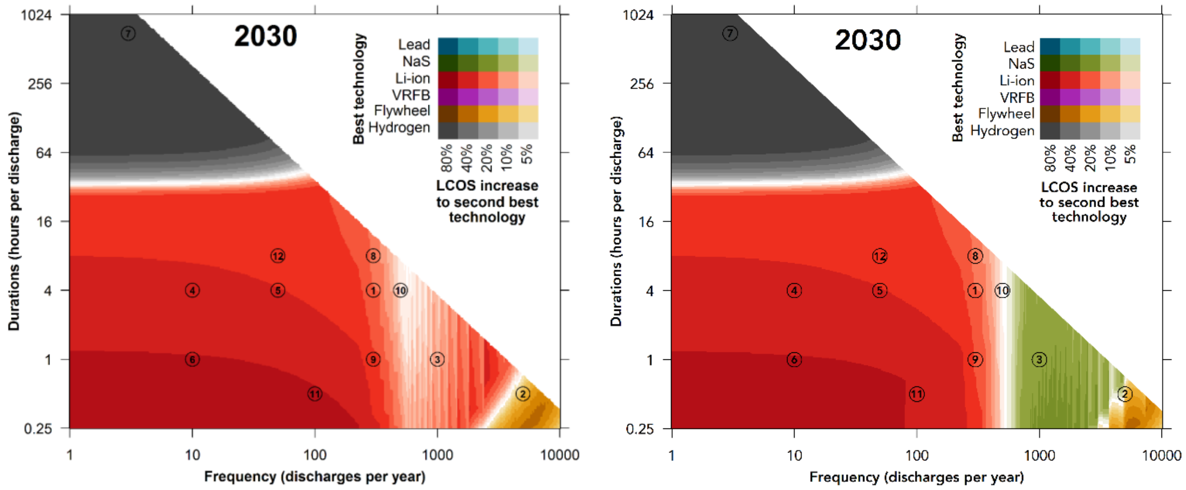

Figure 6.15 – Sensitivity of technology cost-effectiveness to various performance parameters for sodium sulphur. Left: Sodium sulphur at 81% round-trip efficiency and 4,000 cycle and 14 years shelf life. Right: Sodium sulphur at 94% round-trip efficiency and 17,000 cycle and 20 years shelf life. All other technology parameters for all other technologies are unchanged.

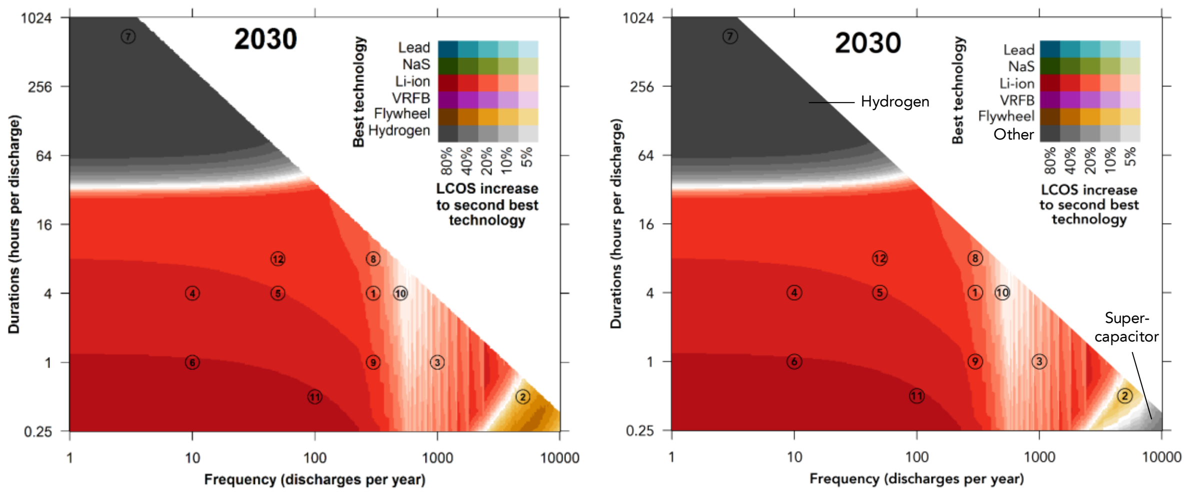

Figure 6.16 – Sensitivity of technology cost-effectiveness to various performance parameters for supercapacitors. Left: Supercapacitor at 91% round-trip efficiency and 300,000 cycle and 14 years shelf life. Right: Supercapacitor at 96% round-trip efficiency and 600,000 cycle and 58 years shelf life. All other technology parameters for all other technologies are unchanged.

It should also be noted that investment cost represent the largest LCOS component for nearly all technologies and applications from 2015 to 2050. Thus, any additional reduction in investment cost that goes beyond the experience-curve-based projections used in this study would have the most significant impact on LCOS reduction.

6.5 Discussion

The projected dominance of lithium-ion technology is the result of good performance parameters, such as high round-trip efficiency and sufficient cycle life, and strong relative investment cost reduction due to a high ER coupled with moderate levels of installed capacity for stationary systems. It follows that the development of alternative electricity storage technologies might become futile due to the challenge in matching the cost and performance advancement lithium ion has achieved to date and is expected to achieve in the future. This would mirror the continuing dominance of 1st generation (crystalline silicon) solar cells despite significant investments in alternative solar cell technologies which were initially expected to be significantly cheaper[317]. Just like crystalline silicon solar cells, 'lithium-ion' is collective for a range of technologies[43,312], offering the possibility of chemistry or design improvements that ensure the projected cost reduction for the technology group. A more detailed study could include distinct cost and performance parameters of lithium-ion technology variations.

One possible reason for the high ER for stationary lithium-ion systems could be the technology's modularity that enables knowledge spill-over from other markets like lithium-ion batteries for electric vehicles[109,131]. On performance, it should be noted that due to the recent research and deployment focus on lithium-ion batteries for portable, transport and stationary applications, the technology might be closer to its performance limits than others[318], which could suggest that performance improvements offer an avenue for alternative technologies to become more competitive than lithium ion.

Comparing application-specific LCOS to recent studies that model LCOS in applications with similar technical requirements[68,89,103,112] reveals that the modelled LCOS in this study are within the ranges identified in other studies for most technologies (Figure 6.17 to Figure 6.20). Deviations are primarily the result of different investment cost or cycle life assumptions that could not be verified by the literature and experts consulted for this study. While differences in methodology have a minor impact, the impact of slightly different application requirements among the studies is significant.

For energy arbitrage, the LCOS values identified by Jülch et al.[112] for "short-term storage" (4h discharge, 365 cycles) are within the ranges identified in this study, although often at the lower end, and for lead-acid batteries significantly below. These deviations have two main reasons. First, annual cycle assumptions differ (365 vs 300). This effect reduces LCOS by 8-15%. More significantly, distinct cycle life assumptions are higher and investment cost assumptions are lower than in the present study (lithium-ion: 7,000 vs 3,250 cycles, lead-acid: 2,700 vs 1,250 cycles; pumped hydro and compressed air: 50% lower investment cost). This also explains why Jülch et al.'s results for 2030 are at the lower end of the ranges identified in this study. Exceptions are lithium-ion and hydrogen storage. Despite the higher cycle life assumption for lithium ion (10,000 vs 3,250), respective LCOS are at the upper end of the present range, because of Jülch et al.'s higher investment cost assumptions for 2030. For hydrogen, respective LCOS are below the range identified in this study due to lower investment cost and longer shelf life assumptions. The deviations in investment cost and lifetime assumptions used by Jülch et al. could not be verified in the academic and industry literature used for this study.

In the two LCOS studies produced by Lazard[89,103], the peaker replacement application features similar requirements to energy arbitrage in this study (4h, 365 cycles). The LCOS values are also at the lower end of the results in the present study (Lazard, 2016) or even lower (Lazard, 2017). Again, the slight difference in annual cycle requirement explains part of the deviation. Lower charging cost (30 US$/MWh vs 50 US$/MWh) also have an impact. However, the most significant deviations are found for lithium ion and vanadium redox flow due to the significantly lower investment cost assumptions. This can partly be explained with the temporal difference of the studies. Lazard's investment cost values are for 2016 or 2017 and assessed against the 2015 values of this study. Especially these two technologies have experienced significant cost reductions in recent years (Figure 4.1).

The LCOS values identified by Zakeri et al.[68], are well within the ranges of the present study, apart from sodium-sulphur and lead-acid batteries. For sodium sulphur this is due to lower investment cost, and for lead acid due to higher cycle life assumptions. Both could not be verified with recent industry reports. Zakeri et al.'s range identified for hydrogen storage is at the lower end of the range in this study due to lower investment cost assumptions.

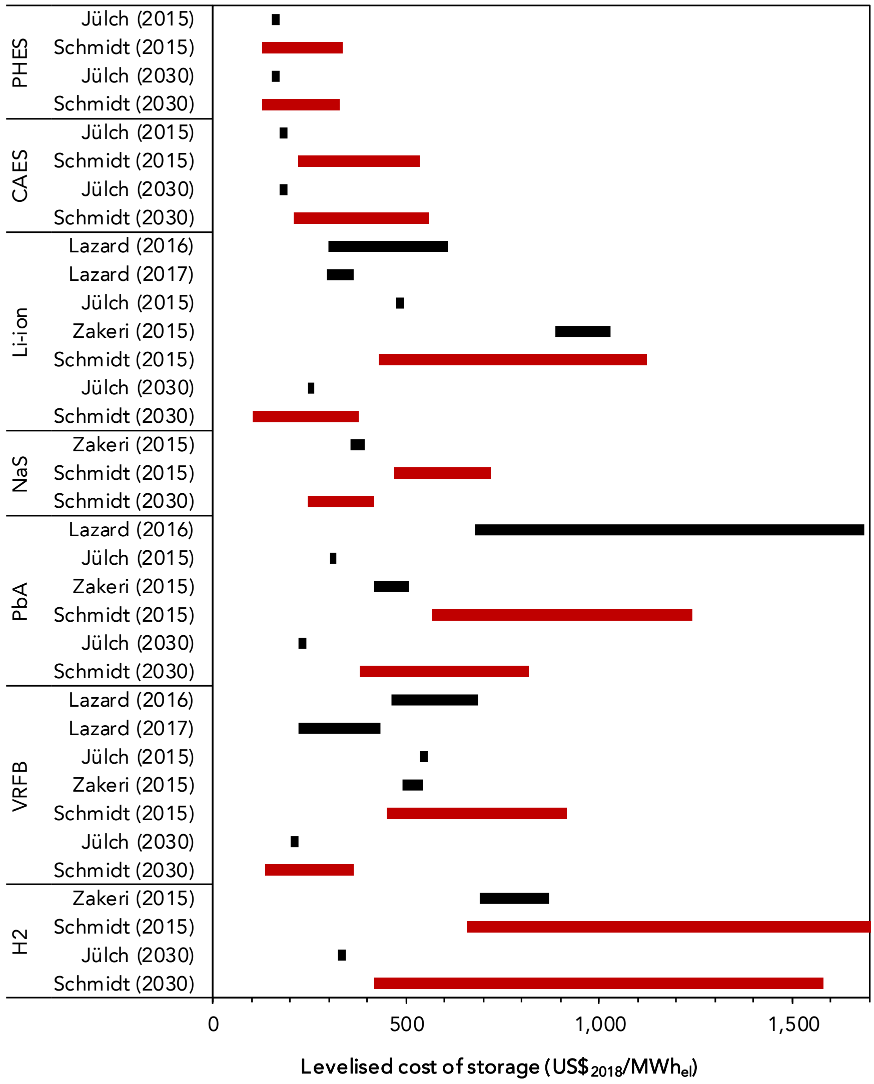

Figure 6.17 – Comparison of LCOS results for energy arbitrage to alternative studies. Application requirements are 4 hours discharge duration and 300 annual cycles for this study (Schmidt), 4 hours and 365 cycles for Jülch and Lazard, and 2 hours and 400 cycles for Zakeri. Number in brackets indicate year for which LCOS are determined. Studies: Jülch[112], Lazard[89,103], Zakeri[68], Schmidt – this study. All quantitative LCOS results for the technologies of this application in this study can be reproduced in the online webtool of the model at www.EnergyStorage.ninja. PHES – pumped hydro energy storage, CAES – compressed air energy storage, Li-ion – lithium ion, NaS – sodium sulphur, PbA – lead acid, VRFB – vanadium redox flow, H2 – hydrogen storage.

Despite slightly differing discharge duration and annual cycle requirements, the LCOS results of T&D investment deferral are compared to the LCOS results of Lazard 2016[89] (application: transmission), Lazard 2017[103] (application: distribution substation) and Zakeri et al.[68] (application: bulk storage). For most technologies there is broad agreement in the LCOS identified in all studies. An exception is compressed air due to the high round-trip efficiency assumption made by Lazard in 2016. The low LCOS for lithium ion and vanadium redox flow by Lazard are again the result of significantly lower investment cost assumptions, which can be the result of the temporal difference of the studies, given recent cost reductions for both technologies (Figure 4.1). Zakeri et al.'s results are lower for lead acid and sodium sulphur, which is the result of lower investment cost assumptions. Again, these investment cost could not be verified in the academic and industry literature used for the present study.

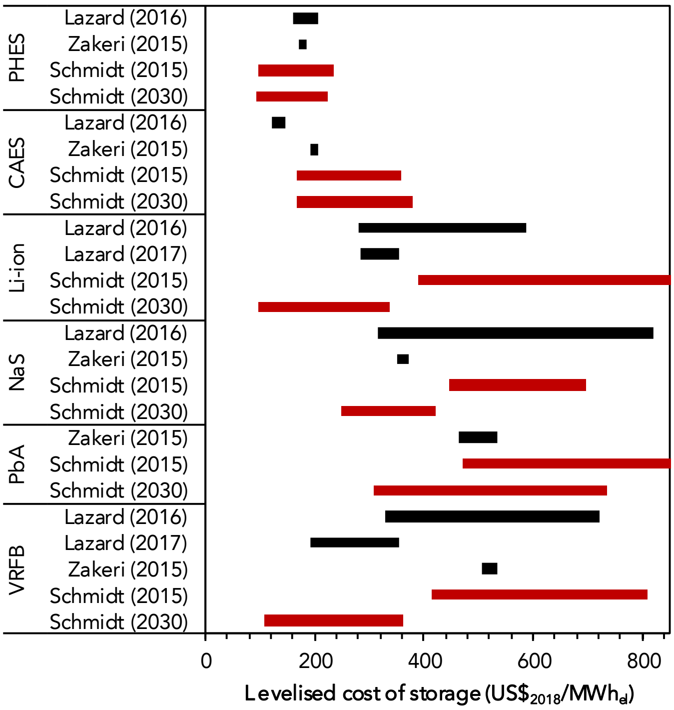

Figure 6.18 – Comparison of LCOS results for network investment deferral to alternative studies. Application requirements are 8 hours discharge duration and 300 annual cycles in this study (Schmidt), and 6-8 hours and 350-365 cycles for Lazard and 8 hours and 250 cycles for Zakeri. Number in brackets indicate year for which LCOS are determined. Studies: Jülch[112], Lazard[89,103], Zakeri[68], Schmidt – this study. All quantitative LCOS results for the technologies of this application in this study can be reproduced in the online webtool of the model at www.EnergyStorage.ninja. PHES – pumped hydro energy storage, CAES – compressed air energy storage, Li-ion – lithium ion, NaS – sodium sulphur, PbA – lead acid, VRFB – vanadium redox flow, H2 – hydrogen storage.

Lazard[89] and Zakeri et al.[68] model ACC for flywheels, lithium-ion and lead-acid batteries for a primary response application, albeit significantly different annual cycle requirements (1,000-5,000 cycles). ACC reflect the provision of capacity instead of discharged electricity. As such, an increase in discharged electricity is not valued and multiple annual cycles only limit the technology's lifetime. As a result, ACC are lowest for the study assuming fewest annual cycles. Deviations beyond this effect are the result of differing lifetime assumptions.

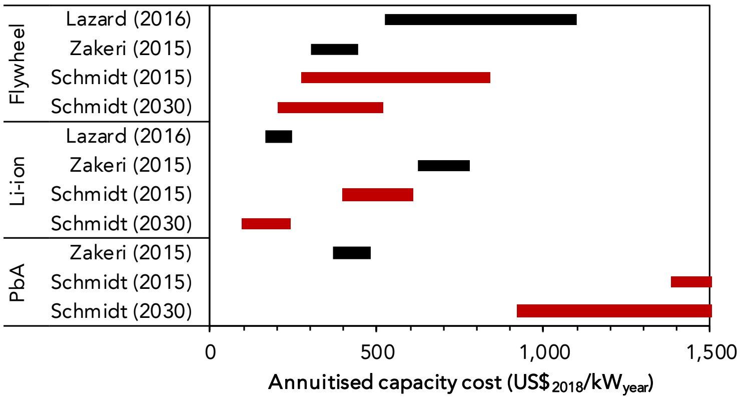

Figure 6.19 – Comparison of ACC results for primary response to alternative studies. Application requirements are 0.5 hours discharge duration and 5,000 annual cycles for this study (Schmidt), 0.5 hours and 1,700 cycles for Lazard and 0.25 hours and 1,000 cycles for Zakeri. Number in brackets indicate year for which ACC are determined. Studies: Lazard[89,103], Zakeri[68], Schmidt – this study. All quantitative ACC results for the technologies of this application in this study can be reproduced in the online webtool of the model at www.EnergyStorage.ninja. PHES – pumped hydro energy storage, CAES – compressed air energy storage, Li-ion – lithium ion, NaS – sodium sulphur, PbA – lead acid, VRFB – vanadium redox flow, H2 – hydrogen storage.

LCOS for seasonal storage are also modelled by Jülch et al.[112]. For pumped hydro and compressed air, the results match with the ranges identified in this study. This is the result of two contrasting effects. Jülch et al. only assume one annual cycle, which would mean LCOS should be around 3 times higher than in this study. However, the 50% lower investment cost and longer lifetime assumptions mean that LCOS fall back into the ranges identified in this study. For hydrogen, the relevant energy-specific investment cost in Jülch et al. are 50 times lower, which explains their LCOS result at the far low end of the range.

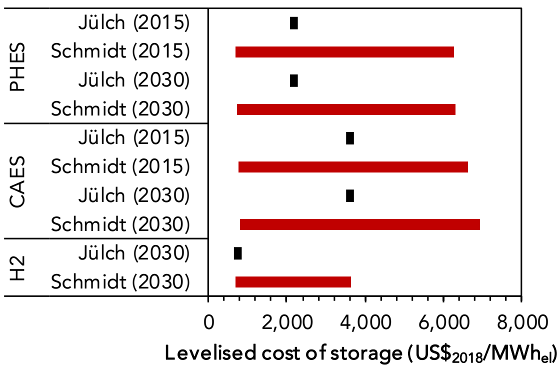

Figure 6.20 – Comparison of LCOS results for seasonal storage to alternative studies. Application requirements are 700 hours discharge duration and 3 annual cycles in this study (Schmidt), and 700 hours and 1 cycle for Jülch et al.[112]. Number in brackets indicate year for which LCOS are determined. All quantitative LCOS results for the technologies of this application in this study can be reproduced in the online webtool of the model at www.EnergyStorage.ninja. PHES – pumped hydro energy storage, CAES – compressed air energy storage, H2 – Hydrogen storage.

In addition, the LCOS ranges identified in this study tend to be slightly higher than the results in the discussed studies due to differences in the LCOS modelling approach (Chapter 2.2.2). Neglecting construction time, capacity degradation and self-discharge artificially reduces

LCOS in these studies. However, the effect is marginal compared to the impact of the described differences in investment cost and lifetime assumptions.

Chapter 6.4. reveals the sensitivity of LCOS to the underlying discount rate, also affecting which technologies are most cost-effective. Although there is a debate about whether the discount rate reflects the opportunity cost of an investment or the weighted average cost of capital (WACC) for the investor, the latter is assumed to implicitly reflect the discount rate in most levelised cost studies[87,103]. The cost of capital for an investor is determined by the financing structure of the project (e.g., debt vs equity) and usually affected by country (e.g., regulatory and fiscal policy), technology (e.g., capital-intensity, maturity), project (e.g., local authority permission) and market risks (e.g., electricity price volatility). Depending on investor type and market environment, the financing structure and exposure to these risks varies. For example, a government-owned utility in countries with good bond ratings may obtain debt funding close to the social cost of capital at around 4%[87]. In contrast, investors with low risk of default in stable investment environments, such as electricity utilities in regulated markets, or investors facing substantial finance, technology and market risks, such as utilities in liberalised markets, may face weighted average cost of capital of 7% or 10% respectively[87]. This leads to an interesting discussion about who should invest in electricity storage technologies and what policy could do to reduce financing cost. In effect, Figure 6.10 indicates that government-owned utilities would build pumped hydro plants and private utilities would build lithium-ion battery systems for peaker replacement in 2030. As such, the cost and technologies driving electricity system transformation are not primarily determined by technology parameters, but rather the investment conditions. To limit this effect, governments could ensure the existence of stable, transparent policy frameworks or offer debt guarantees[87]. In addition, public financial institutions can provide finance at low cost[319]. These could be the most effective contributions to the sustainable transformation of the electricity system, because the future should not be discounted too much when aiming for "development that meets the needs of the present without compromising the ability of future generations to meet their own needs"[320].

A possible route to improving the business case for electricity storage is by providing multiple services with one device and thereby stacking multiple revenue streams[167,321]. The presented methodology can also be used to assess LCOS for these "benefit-stacking" use cases by determining application requirements that reflect the provision of multiple services with the same device. Nominal power capacity would be based on the largest service (i.e., sequential stacking) or the sum of all service provided at the same time (i.e., parallel stacking). Discharge duration should reflect the sum of durations required by all services to ensure sufficient energy capacity when all services are required in parallel or directly one after another. Full equivalent cycles also reflect the respective sum for all services provided. Average electricity price could be the sum of prices captured when charging for individual services weighted by the full equivalent cycles attributed to them.

It should be reiterated that all presented results are subject to the investment cost projections made with experience curves (Chapter 4). These are based on historic price reduction trends and are thus uncertain. Another limitation of this study is that the experience-based cost reductions are exogenous, assuming that all technologies take the entire future stationary storage market individually. It thereby explores the full LCOS reduction potential for each technology based on investment cost reductions. In reality, a mix of technologies will be deployed, limiting individual investment cost reductions along experience curves[322]. Modelling this complex dynamic could be attempted in future studies.

Similarly, this study only approximates degradation and lifetime of electrochemical storage technologies in modelled applications. While it accounts for depth-of-discharge, it does not explicitly model mean state of charge, charge rates and temperature as additional parameters that affect cycle and time degradation and thereby limit cycle and shelf life[76,323,324]. However, the online version of the presented LCOS model (www.EnergyStorage.ninja) allows the cycle and shelf life values to be modified to account specifically for the named degradation parameters and their variation. The same customisation can be applied to all other technology and application parameters.

The results in this chapter explore future LCOS potentials for the most widely deployed stationary storage technologies and establish a quantitative foundation for the discussion of storage competitiveness and its drivers. These insights can help guide research, policy and investment activities to ensure a cost-efficient deployment of electricity storage technologies for a successful transition to a secure and affordable low-carbon energy system.

7. Value of Storage in Low-Carbon Power Systems

A techno-economic analysis of electricity storage technologies is incomplete without considering its value in low-carbon power systems. This chapter analyses the economic value of electricity storage in various applications and its profitability when considering lifetime cost. It also investigates the system value of electricity storage as the capacity requirement to integrate low-carbon electricity generation.

7.1 Market Value

Assessing the economic value of electricity storage requires transparency around the variation of this value along application requirements. Figure 7.1 matches the potential revenues for electricity storage in different applications (Chapter 2.4.1) to their discharge duration and cycle frequency requirements[170,241].

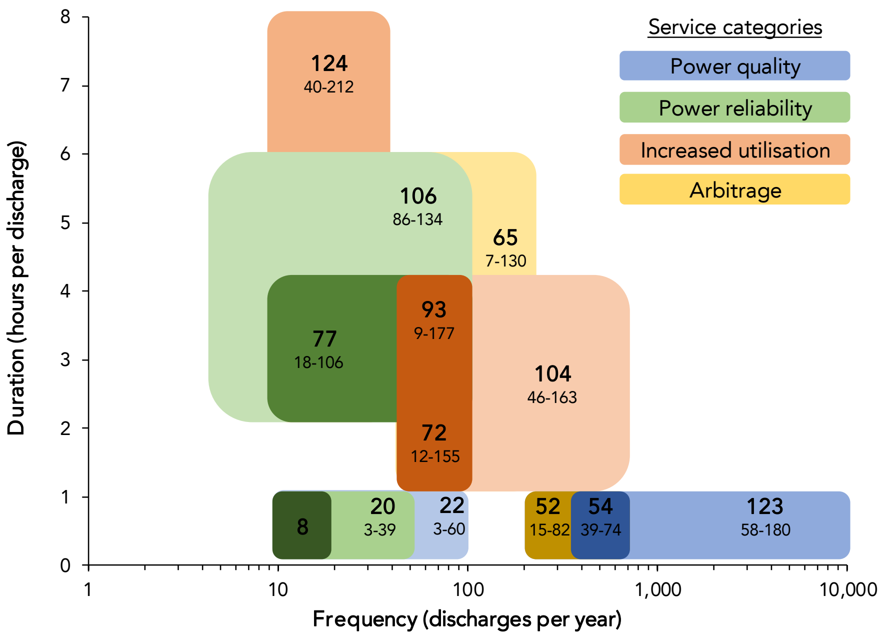

Figure 7.1 – Mean economic value for different electricity storage applications in US\$/kW$_{year}$ (Figure 2.23) plotted along respective discharge duration and frequency application requirements[170,241]. 25th and 75th percentile economic values shown in small font. Colour coding reflects fundamental service categories of applications (Figure 2.22). Services: 124 US\$/kW$_{year}$ – transmission upgrade deferral, 106 US\$/kW$_{year}$ – capacity reserve, 65 US\$/kW$_{year}$ – time-of-use charge reduction, 77 US\$/kW$_{year}$ – power reliability, 93 US\$/kW$_{year}$ – distribution upgrade deferral, 104 US\$/kW$_{year}$ – demand charge reduction, 72 US\$/kW$_{year}$ – congestion management, 123 US\$/kW$_{year}$ – frequency regulation, 54 US\$/kW$_{year}$ – frequency response, 52 US\$/kW$_{year}$ – energy arbitrage, 22 US\$/kW$_{year}$ – voltage support, 20 US\$/kW$_{year}$ – spin/non-spin reserve, 8 US\$/kW$_{year}$ – black start[170].

While power reliability applications have up to six hours discharge duration but less than 100 full discharges per year, power quality applications are characterised by less than one-hour discharge duration at various discharge frequencies. Applications that deliver increased asset utilisation have between one and eight hours and up to 500 discharges. For arbitrage, there are two types: discharge duration below one hour at up to 350 cycles and discharge duration up to six hours at below 250 annual cycles.

There seems to be a positive relationship between economic value and increasing discharge and frequency requirements (i.e., increasing number of running hours). Services with up to eight hours discharge duration or 10,000 cycles are valued at 124 (40-212) or 123 (58-180) US$/kW$_{year}$ respectively. Applications with a moderate mix of discharge duration and cycle frequency are valued at 104 (86-134) and 106 (46-163) US$/kW$_{year}$. The values reduce with a reduction in discharge duration and annual cycle frequency, down to 8 US$/kW$_{year}$ for *black start* at only one hour and 10 to 20 cycles. The residential arbitrage application *time-of-use charge reduction* represents an outlier with only 65 (7-130) US$/kW$_{year}$ at up to six hours discharge and 250 annual cycles. However, a detailed review of the respective studies reveals that those valuing storage at the lower end of this range assume discharge durations below four hours[170], more in line with the identified value-requirement relationship.

Figure 7.2 expands this value analysis for electricity storage power capacity to the entire spectrum of possible discharge duration and frequency requirements from 1 to 1,024 hours and 1 to 10,000 cycles. A Monte-Carlo analysis accounts for the ranges in economic value and discharge and frequency requirements (Figure 7.1) and each discharge-frequency combination on the spectrum is assigned an economic value for each trial before computing their mean value (Chapter 3.4.1). The 25th and 75th percentiles of the economic values on this spectrum can be found in Appendix D.1.

This enables an entirely novel analysis, indicating that up to 125 US$/kW$_{year}$ (25th: 100, 75th: 150) can be earned for applications below 1-hour discharge duration and more than 5,000 full equivalent discharge cycles per year. The value reduces with reducing frequency to below 100 US$/kW$_{year}$ (120, 60) at 1,000 cycles. The sharp reduction down to 50 US$/kW$_{year}$ (60, 30) at 100 cycles and 10 US$/kW$_{year}$ below 10 cycles only applies for discharge durations below 1 hour. For applications with more than 1-hour discharge, the value is at 80-125 US$/kW$_{year}$ for all cycle frequencies, until it reduces again from 64 hours discharge duration down to 50 US$/kW$_{year}$ (40, 80) at 700 hours.

In the UK, successful bids for enhanced frequency response for 2017-2021 are awarded 90 to 160 US$$_{2018}$/kW$_{year}$, while in Germany primary control reserve in 2018 was valued at 100 to 150 US$$_{2018}$/kW$_{year}$, both reflecting the findings in Figure 7.2 above 1,000 full equivalent annual charge-discharge cycles[176,325]. Similarly for the US, a detailed grid simulation model of the balancing areas in Colorado and Missouri reveal a market value of 147 $US\$_{2018}/kW_{year}$ for a short-duration electricity storage device providing regulation services[180]. Residential time-of-use bill management in the UK with the *Economy 7* tariff for cheap night-time electricity is valued at 65 $US\$_{2018}/kW_{year}$, which is just below the average value identified for 3 hours discharge and 350 annual cycles[174].

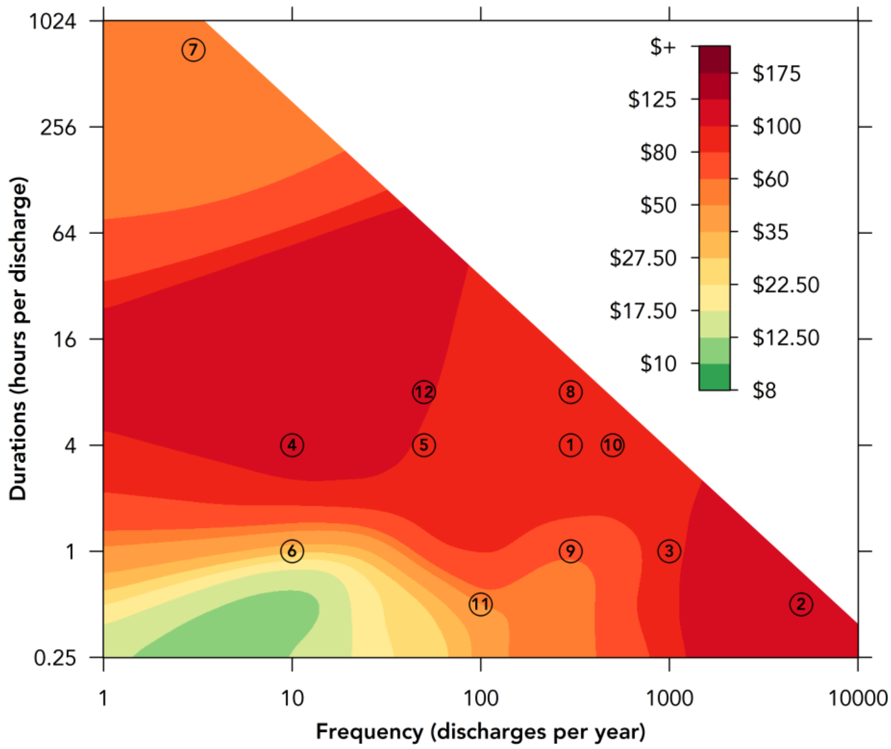

Figure 7.2 – Economic market value for electricity storage power capacity in applications with various discharge duration and discharge frequency combinations. Colours refer to economic market value in $US\$/kW_{year}$. Circled numbers represent the requirements of the 12 core applications introduced in Table 6.1: 1-Energy Arbitrage, 2-Primary Response, 3-Secondary Response, 4-Tertiary Response, 5-Peaker Replacement, 6-Black Start, 7-Seasonal Storage, 8-T&D Investment Deferral, 9-Congestion Management, 10-Bill Management, 11-Power Quality, 12-Power Reliability. Frequency refers to full equivalent charge-discharge cycles per year.

The value-requirement relationship for discharged energy (US$/MWh) is reverse to power capacity (Figure 7.3). Services requiring more than 5,000 annual cycles are valued below 50 US$/MWh ($25^{th}$: 30, 75^{th}: 50). This increases uniformly with lower frequency requirements to 150 US$/MWh at 1,000 (40, 250) and up to 640 US$/MWh (330, 880) at 100 cycles. A further increase beyond 700 US$/MWh (500, 1000) below 100 cycles is limited to applications with less than 1-hour discharge duration. The values above 1-hour duration and below 100 cycles remain within 500 and 700 US$/MWh until sharply reducing to below 25 US$/MWh (20, 40) beyond 64 hours duration.

The mean price difference between the 1,000 highest and 1,000 lowest wholesale market half-hour periods in the UK is 160 US$/MWh[15]. While only a high-level approximation of an energy arbitrage service with 500 discharge cycles, the value matches the range in Figure 7.3 above 1-hour discharge duration and between 300 and 1,000 cycles. The value increase for low duration and frequency applications is confirmed by customer willingness to pay to avoid an one hour electricity outage, determined at 4,000- 44,000 US$/MWh for the UK[326,327]. While above the range in this study, cost-plus pricing strategies based on service cost in contrast to market willingness to pay may lead to lower economic values closer to the ones identified here.

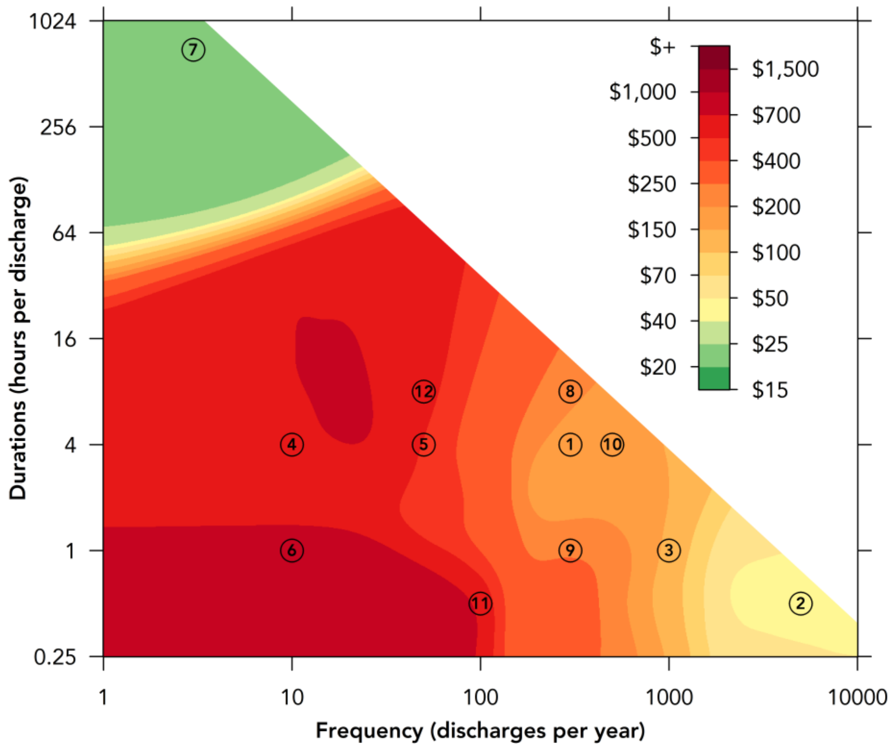

Figure 7.3 – Economic market value for electricity storage energy capacity in applications with various discharge duration and cycle frequency combinations. Colours refer to economic market value in US$/MWh. Circled numbers represent the requirements of the 12 core applications introduced in Table 6.1: 1-Energy Arbitrage, 2-Primary Response, 3-Secondary Response, 4-Tertiary Response, 5-Peaker Replacement, 6-Black Start, 7-Seasonal Storage, 8-T&D Investment Deferral, 9-Congestion Management, 10-Bill Management, 11-Power Quality, 12-Power Reliability. Frequency refers to full equivalent charge-discharge cycles per year.

Applying a different methodology to computing economic market values using random sampling within 25th and 75th percentiles instead of sampling among actual values (Chapter 3.4.1), returns similar results, confirming the robustness of this analysis (Appendix D.2).

Figure 7.4 displays these sensitivities of storage market value with varying frequency and duration requirements more explicitly. The values for power capacity vary from 5 to 125 US$/kW$_{year}$ below 10 cycles and sharply increase to a narrow band of 120-125 US$/kW$_{year}$

above 1,000 cycles. Similarly, for discharge duration, the wide range below 0.5 hours increases to a band of 90-125 $\text{US\$/kW}_{year}$ between 1 and 64 hours, beyond which it reduces again to 50 $\text{US\$/kW}_{year.}$ With increasing utilisation (product of frequency and duration) the market value increases to 60-125 $\text{US\$/kW}_{year}$ above 50 discharge hours per year.

For energy provision, an increase in frequency means a narrowing of the 10-800 US$/MWh range below 10 cycles to 400-900 US$/MWh at 100 cycles, followed by a sharp reduction to 50 US$/MWh beyond 5,000 cycles. Similarly, an increase in discharge duration means a contraction of the wide range below 1 hour to 400-700 US$/MWh at 16 hours, followed by a reduction to 25 US$/MWh beyond 64 hours. Overall, the value per MWh expands as utilisation increases from above 600 US$/MWh to 25-700 US$/MWh above 20 hours operation.

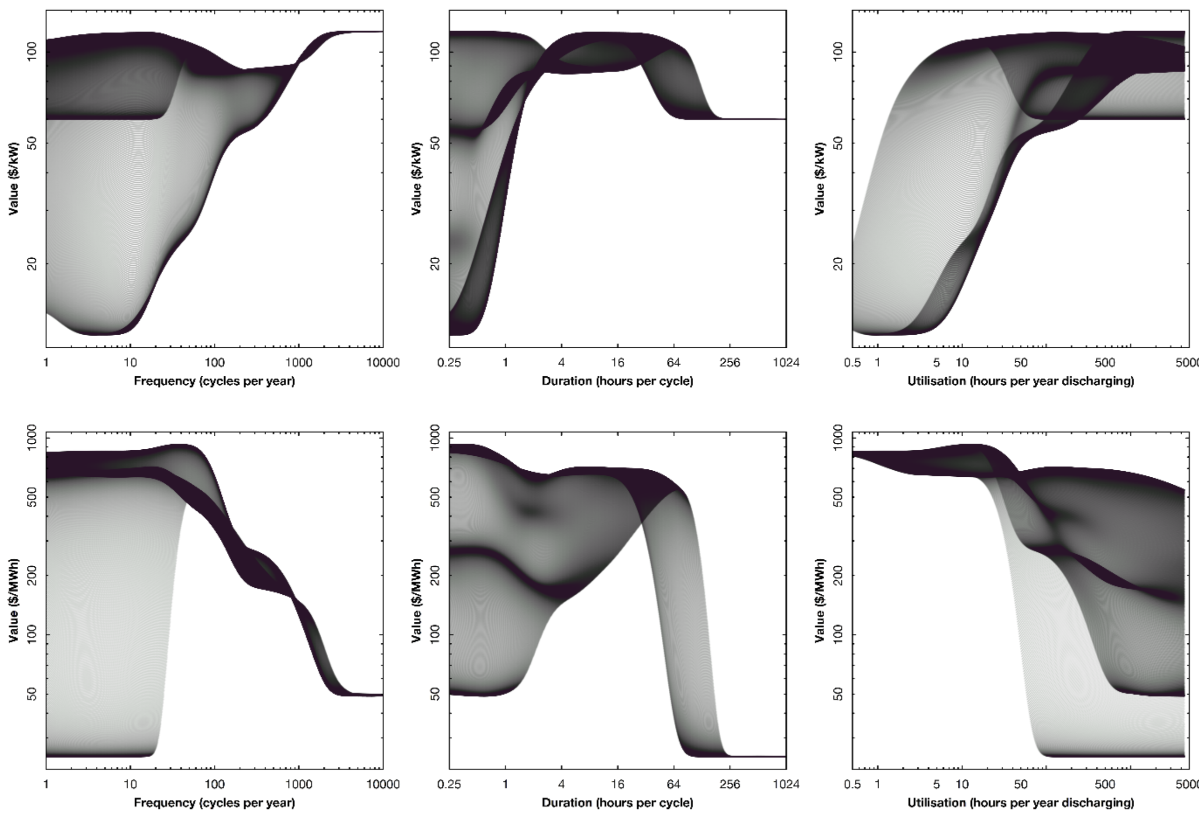

Figure 7.4 – Sensitivity of economic market value for electricity storage power capacity (top) and discharged energy (bottom) with variation in discharge frequency (left), duration (centre) or utilisation (right), the product of both. The maximum value for utilisation is 4,380 discharge hours, half of the 8,760 hours in a year.

Matching the distribution of economic market values for the 12 core applications that are introduced in Chapter 6 (Appendix D.3) to the distribution of annuitised capacity cost (ACC) or levelised cost of storage (LCOS) of those technologies with highest probability to be most cost-efficient (Chapter 6.2) returns their profitability probability. Figure 7.5 and Figure 7.6

display these probabilities for reimbursement of power capacity and discharged electrical energy respectively.

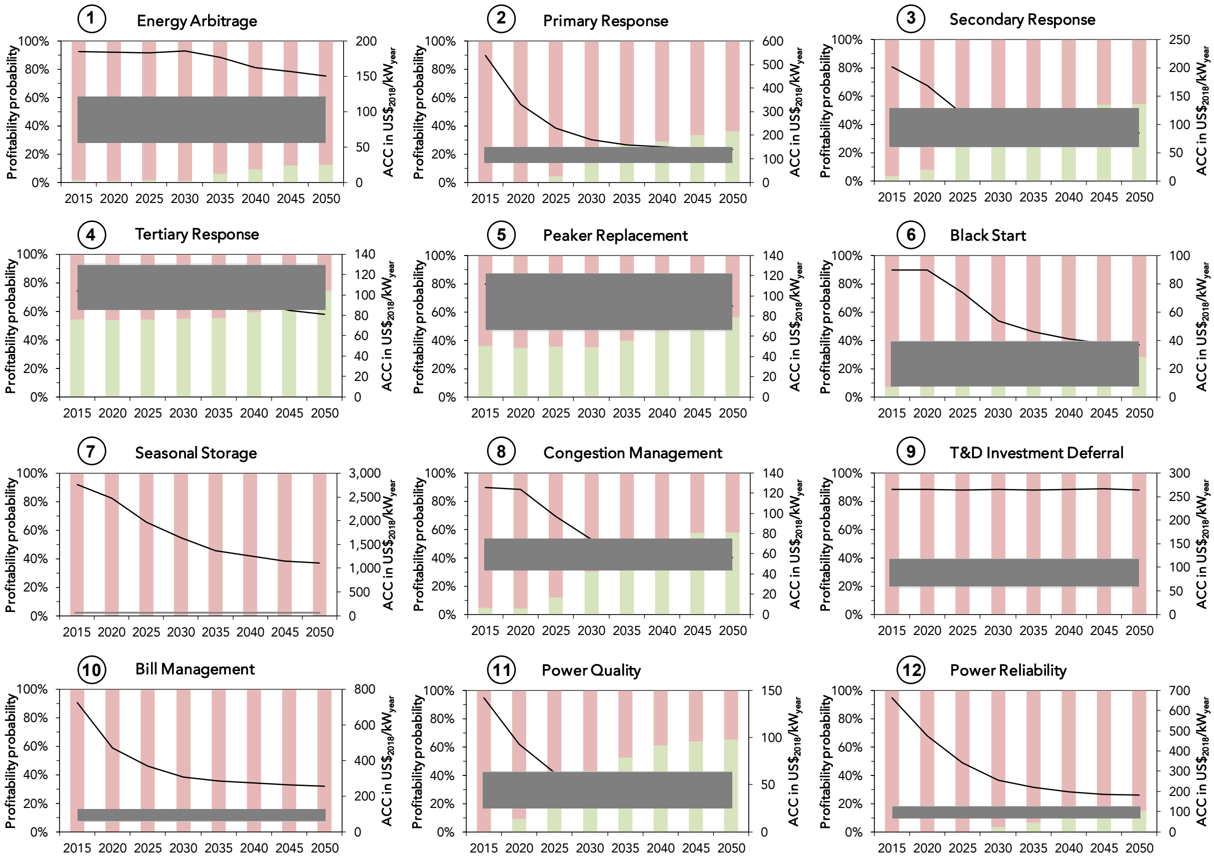

Figure 7.5 – Profitability probabilities for electricity storage power in 12 core applications from 2015 to 2050. Left axis displays probability that electricity storage will be profitable in specific application (green bar: profitable; red bar: unprofitable). Right axis displays mean annuitised capacity cost (ACC) of technology with highest probability for lowest ACC (black line). Note the different scales between panels. Probabilities reflect the frequency with which ACC of the technology with highest probability for lowest ACC (500 LCOS Monte-Carlo simulations) is below economic market value in specific application (500 economic value Monte-Carlo simulations). Shaded area represents range between 25th and 75th percentile of economic market value in specific application. Circled numbers in panel titles correspond to applications in Table 6.1. Note that most applications are usually reimbursed for energy output, not power capacity. Refer to Figure 7.6 for probability analysis in energy terms. Application requirements are displayed in Figure 6.1. Discount rate is 8%. All technology input parameters can be found in Table 2.3 and Appendix C.

Tertiary response and peaker replacement appear to be the only profitable services in terms of power capacity payments today. These services have medium discharge duration (4 hours) and frequency requirements (10 to 50 full equivalent annual cycles). Services with low duration and high cycles like primary and secondary response, power quality, congestion management and black start follow with profitability probabilities larger than 20% by 2030. All other services seem unlikely to ever have profitability probabilities larger than 20% when paid for providing power capacity. However, it should be noted that only applications with short discharge durations (<1 hour) like primary response and end-customer power quality are valued for the provision of power capacity.

Figure 7.6 displays profitability probability for the 12 core applications when reimbursed for discharged electrical energy. Transmission and distribution investment deferral with 8 hours discharge and 300 annual cycles is likely to be profitable already today. Services with shorter duration and more cycles like energy arbitrage (4 hours, 300 cycles) and secondary response (1 hour, 1000 cycles) can be profitable in specific markets with highest values for these services. Peaker replacement, congestion management and customer services like bill management or power reliability with requirements at or below 300 annual cycles and 4 hours discharge are at least 20% likely to be profitable by 2030. In contrast, applications with 10 annual cycles or less like tertiary response, black start and seasonal storage are unlikely to ever become profitable at current economic valuation.

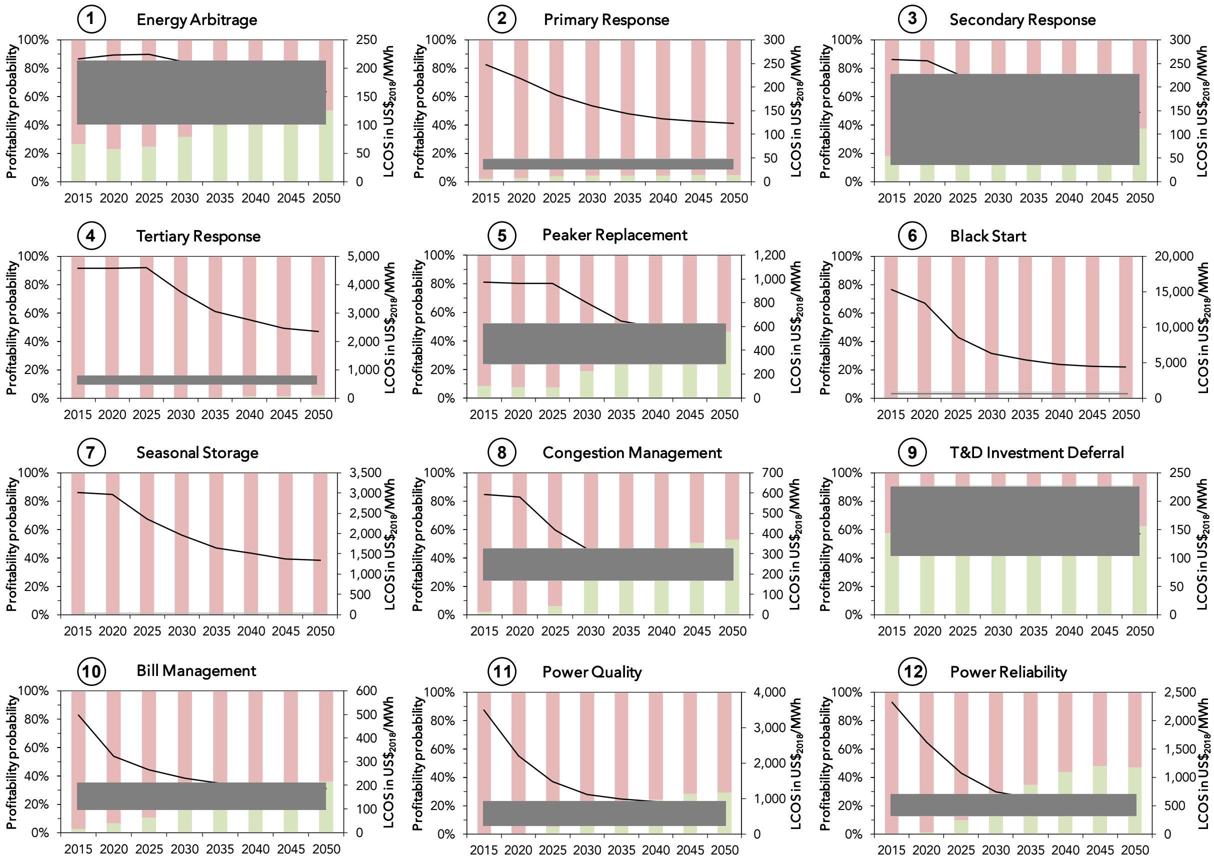

Figure 7.6 – Profitability probabilities for electricity storage energy in 12 core applications from 2015 to 2050. Left axis displays probability that electricity storage will be profitable in specific application (green bar: profitable; red bar: unprofitable). Right axis displays mean LCOS of technology with highest probability for lowest LCOS (black line). Note the different scales between panels. Probabilities reflect the frequency with which LCOS of the technology with highest probability for lowest LCOS (500 LCOS Monte-Carlo simulations) is below economic market value in specific application (500 economic value Monte-Carlo simulations). Shaded area represents range between 25^{th} and 75^{th} percentile of economic market value in specific application. Circled numbers in panel titles correspond to applications in Table 6.1. Note that profitability probability differs from reimbursement for power output, because economic values are not converted from power to energy terms using application requirements of the 12 applications, but requirements of applications in review study[170] and Monte-Carlo analysis of resulting value, discharge and frequency ranges (Chapter 3.4.1). Requirements of the 12 core applications are displayed in Figure 6.1. Discount rate is 8%. All technology input parameters can be found in Table 2.3 and Appendix C.

The ability to cluster profitability probability for power capacity and discharged energy along duration and frequency requirements of the 12 applications reveals overarching trends along these requirements. Figure 7.7 and Figure 7.8 visualise these trends for power and energy values within the duration-frequency spectrum of any possible application and over time.
For power capacity, this novel type of analysis reveals a particular set of requirements for profitable business cases at 4-hours discharge duration and between 10 and 100 annual cycles. From 2025 applications with below 1-hour duration and between 100 and 2,000 annual cycles become profitable as well, confirming the current observation of frequency regulation services being amongst the first positive business cases for electricity storage[172,325,328]. The consideration of mean economic values across a range of markets may explain the temporal delay between modelled result and current trends in specific markets. With reducing investment cost over time and reducing lifetime cost as a result (Chapter 6), the profitability range expands to applications with 1- to 4-hour discharge duration below 300 cycles and below 1-hour duration above 300 cycles.

For energy provision, profitable use cases have between 8 and 64 hours discharge duration at 50 to 300 cycles or more than 4 hours duration between 300 and 1,000 cycles in 2015. These services maximise annual operating hours, minimising LCOS. This applies to transmission and investment deferral and bill management. Note that charging cost for the customer service bill management is modelled at 100 US$/MWh in Figure 7.6, compared to 50 US$/MWh in Figure 7.8, making it profitable only in the latter. With reducing investment cost over time, the profitability boundary expands to lower cycle and duration requirements, including power reliability (50 cycles, 8 hours), energy arbitrage (300 cycles, 4 hours), congestion management (300 cycles, 1 hour) and secondary response (1,000 cycles, 1 hour) by 2035.

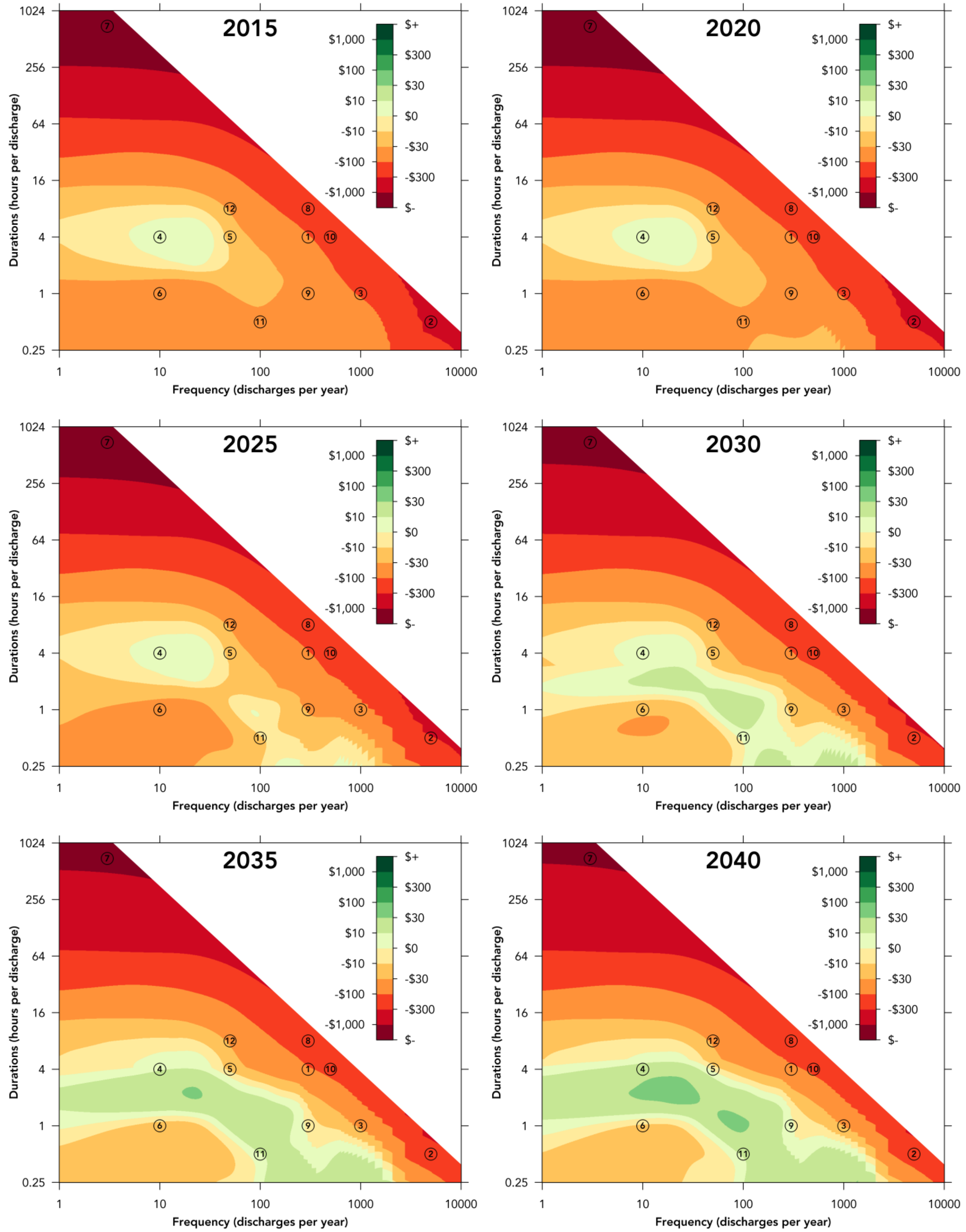

Figure 7.7 – Profitability for provided electricity storage power capacity (US$/kWyr) in applications with various discharge duration and annual cycle requirements from 2015 to 2040. Colours indicate revenue for power capacity provision in applications with respective discharge duration and frequency requirements (green: profitable, other: unprofitable). Values are determined by assessing mean ACC of most cost-efficient technology in any duration-frequency combination against mean economic market value. The modelled electricity price is 50 US$/MWh. Discount rate is 8%. All technology input parameters can be found in Table 2.3 and Appendix C. Circled numbers represent the requirements of the 12 core applications introduced in Table 6.1: 1-Energy Arbitrage, 2-Primary Response, 3-Secondary Response, 4-Tertiary Response, 5-Peaker Replacement, 6-Black Start, 7-Seasonal Storage, 8-T&D Investment Deferral, 9-Congestion Management, 10-Bill Management, 11-Power Quality, 12-Power Reliability.

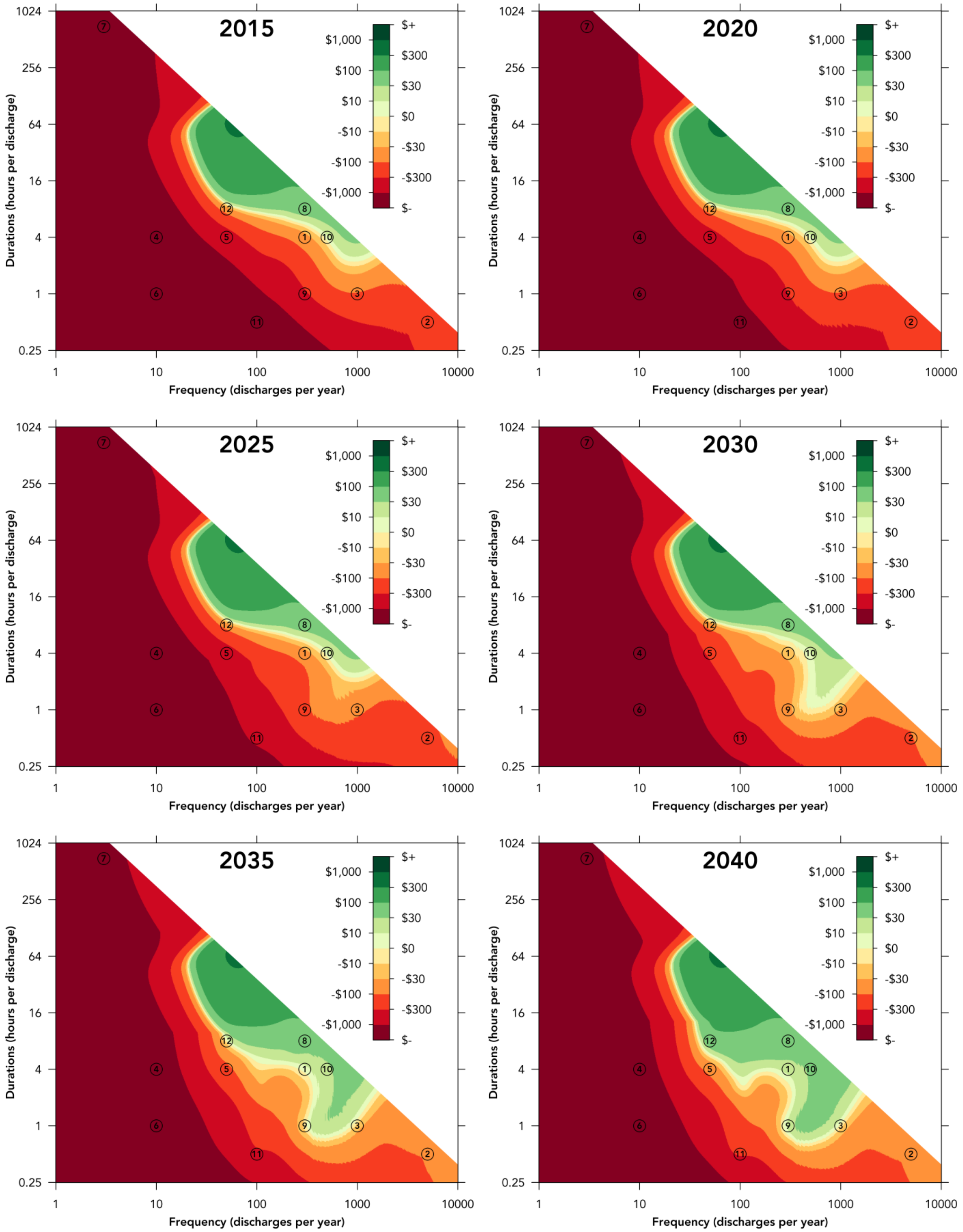

Figure 7.8 – Profitability for discharged electricity storage energy (US$/MWh) in applications with various discharge duration and annual cycle requirements from 2015 to 2040. Colours indicate revenue for each discharged unit of electrical energy in applications with respective discharge duration and frequency requirements (green: profitable, other: unprofitable). Values are determined by assessing mean LCOS of most cost-efficient technology in any duration-frequency combination against mean economic market value. The modelled electricity price is 50 US$/MWh. Discount rate is 8%. All technology input parameters can be found in Table 2.3 and Appendix C. Circled numbers represent the requirements of the 12 applications introduced in Table 6.1: 1-Energy Arbitrage, 2-Primary Response, 3-Secondary Response, 4-Tertiary Response, 5-Peaker Replacement, 6-Black Start, 7-Seasonal Storage, 8-T&D Investment Deferral, 9-Congestion Management, 10-Bill Management, 11-Power Quality, 12-Power Reliability. Note that service 10-Bill Management is profitable in 2015, different to Figure 7.6, due to the lower electricity price assumption.

7.2 System Value

As outlined in Chapter 2.4.2, there is interest in analysing the system value of electricity storage as the financial value in reducing total system cost as well as the quantity required to enable low-carbon power systems. This study investigates the latter.

Previous studies analysed electricity storage power and energy requirements relative to wind and solar energy penetration for the US, the EU and Germany[197,198,207]. In the context of Great Britain's (GB) power system, the share of nuclear generation should also be considered. In contrast to other countries, this technology is projected to play a significant role in power system decarbonisation. However, its impact on flexibility capacity requirements is uncertain given its strong incentive for constant power output (Chapter 1.2). In addition, not only low-carbon electrical energy penetration, but also power capacity should be considered when assessing system adequacy to meet peak demand.

Figure 7.9 displays electricity storage requirements as a function of wind, solar and nuclear penetration as modelled by various studies for the future GB power system. The required absolute power capacity in a system with up to 90% low-carbon generation capacity could remain at the 3 GW installed in 2017 or increase to 35 GW. The same wide range is observed for energy capacity as a function of low-carbon electricity penetration. At 90%, required capacity could be as low as today at 30 or up to 140 GWh.

The electricity storage requirement range becomes more defined when accounting for peak and annual demand assumptions across the studies. While the current power system at 42% penetration of wind, solar and nuclear power has 5% electricity storage power capacity relative to peak demand, it could range from 5-20% at 60% and 5-40% at 80% penetration. These values are equivalent to 2.7 to 10 GW (60%) and 2.7 to 21 GW (80%) electricity storage power capacity at current peak demand. The range matches the findings of various integrated assessment models for the EU[197] and a separate review of non-GB focussed studies[207]. Similarly, electricity storage energy capacity relative to annual electricity demand could remain at the current level of 0.008% or increase to 0.015% or 0.025% at 60% or 80% wind, solar and nuclear energy penetration respectively, depending on the scenario. Equivalent values are 30 to 50 GWh (60%) and 30 to 80 GWh (80%) electricity storage energy capacity at current annual demand. Here, the non-GB focussed review finds a higher and larger range of 0.030% to 0.100% at 80% penetration[207].

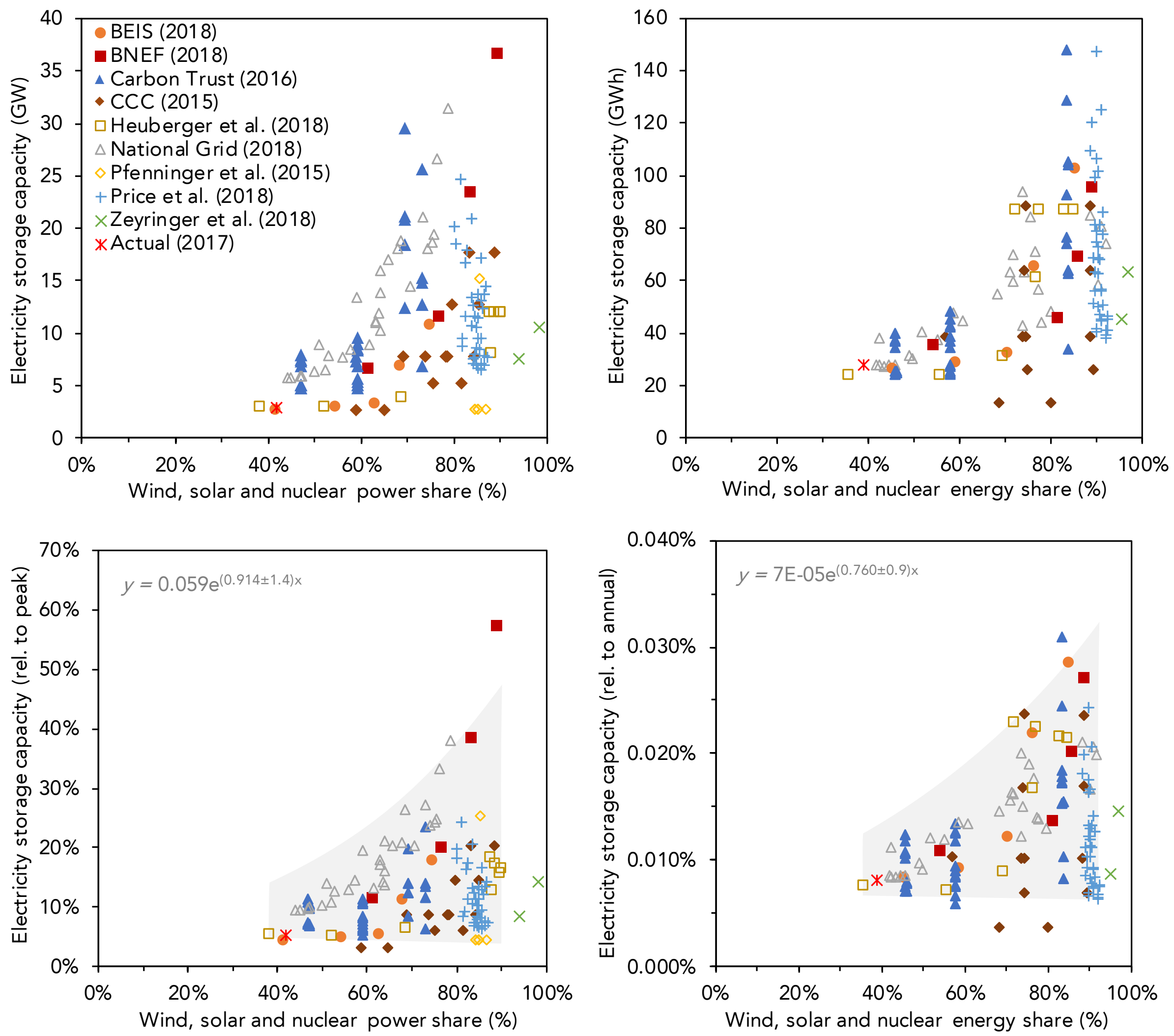

Figure 7.9 – Electricity storage capacity requirements as a function of wind, solar and nuclear penetration in the GB power system. Top: Absolute electricity storage power (left) and energy capacity (right) as a function of wind, solar and nuclear power (left) and energy share (right). Bottom: Electricity storage power capacity relative to peak power demand (left) and energy capacity relative to annual electricity demand (right) as a function of wind, solar and nuclear power (left) and energy share (right). Power and energy share refer to penetration of respective power capacity or generated energy compared to total generation capacity or electricity generated, excluding dedicated flexibility technologies (Chapter 3.4.3). Shaded areas represent exponential fit to data sets with uncertainty range containing all but 5 data points. Respective formulae are given in the top left corner of each chart. Studies: BEIS (2018)[187], BNEF (2018)[188], Carbon Trust (2016)[20], CCC (2015)[189], Edmunds et al. (2014)[190], Heuberger et al. (2018)[191], National Grid (2018)[192], Pfenninger et al. (2015)[193], Price et al. (2018)[194], Zeyringer et al. (2018)[195].

The shaded areas in Figure 7.9 identify possible maximum and minimum deployment levels for electricity storage subject to the assumptions in the various studies and scenarios. They thereby mark off the electricity storage capacity requirements to enable low-carbon power systems with up to 90% wind, solar and nuclear power and energy penetration in GB.

However, the wide ranges also highlight that low-carbon power systems do not necessarily depend on electricity storage; rather, it can be a valuable enabler under certain conditions. This insight is supported by the fact that the observed variations in electricity storage requirements are not study-specific but vary by individual scenario. For example, Pfenninger et al.[193] feature one scenario with 15 GW storage (25% relative to peak) at 85% wind, solar and nuclear power share, compared to 3 GW (5%) in all other scenarios, where alternative flexibility technologies (i.e., interconnection, DSR, OCGT, hydro, oil, diesel) balance intermittent or relatively inflexible generation with demand.

A more comprehensive approach to assessing the system value potential of electricity storage in integrating low-carbon power is to analyse the overall flexibility capacity requirements, regardless of which technology provides them, as a function of wind, solar and nuclear power penetration (Figure 7.10, left panel). It shows that up to 40% penetration, less than 20% flexibility capacity relative to peak demand is required. This increases to a range of 40-100% above 80% penetration.

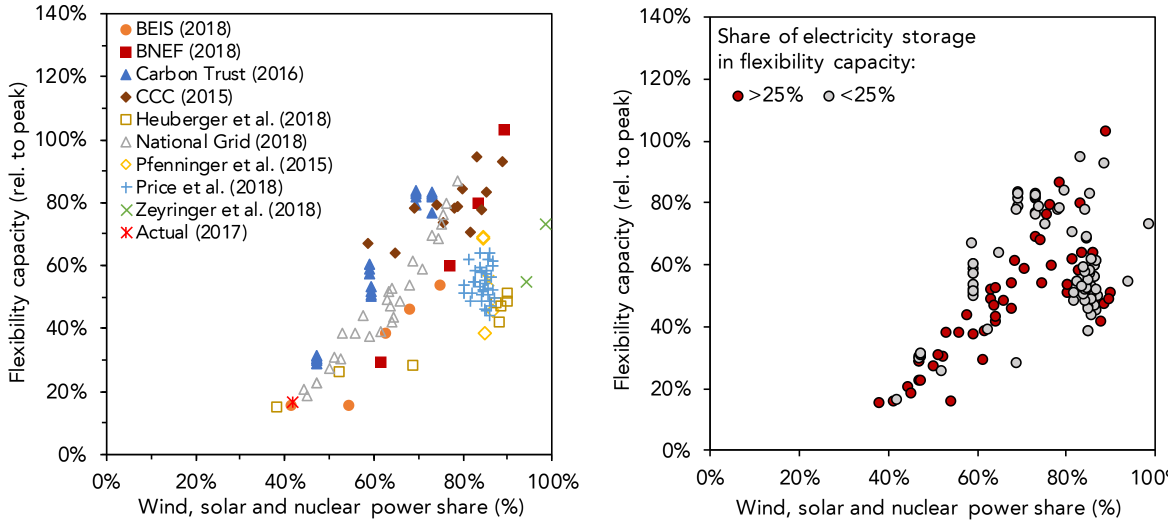

Figure 7.10 – Flexibility capacity requirements relative to peak demand and as a function of wind, solar and nuclear power penetration for the GB power system. Left: Results from individual studies. Right: Differentiation of studies along share of electricity storage power capacity as part of flexibility capacity (i.e., storage, interconnection, DSR, OCGT, hydro, oil, diesel).

The right panel in Figure 7.10 shows that the electricity storage share in flexibility capacity has no impact on requirements, confirming that flexibility technologies can be used relatively interchangeably to fulfil capacity requirements. Therefore, this approach assesses the full theoretical capacity requirement for electricity storage to enable low-carbon power systems. Technology constraints of electricity storage and alternative flexibility options (Chapter 7.3.2) and their economic market value (Chapter 7.1) can then be used to define practical requirements.

Analysing flexibility capacity requirements in more detail reveals three insights. First, flexibility requirements appear to increase linearly, which was previously observed for electricity storage power capacity[198]. Figure 7.11 (left) displays linear regression trendlines as visual guides for studies with more than two data points and a coefficient of determination of $R^2 \geq 0.85$. Note that the exponential fit for electricity storage power capacity in Figure 7.9 includes scenarios of all studies and thereby distorts study-specific results.

Second, there appears to be a flexibility baseline at 20% capacity of peak demand which holds from a wind, solar and nuclear penetration of 0% up to 40% in all studies, indicating that nearly half of power system electricity can come from relatively inflexible or intermittent sources before there are additional needs for flexibility. The trendlines appear to even suggest that no flexibility capacity is needed for penetrations under 20% or under 50%.

Third, there seems to be a difference in the flexibility capacity requirements modelled in industry or government compared to academic studies (Figure 7.11, right). Academic studies mostly model requirements at high low-carbon penetration and identify less than 75% flexibility capacity required beyond 80% penetration compared to above 75% in the other studies. This is the result of modelling dispatchable capacity system margins below 20% (Appendix D.4). That means the amount of firmly reliable capacity (i.e., all capacity except wind and solar) is only slightly above peak demand, for some studies even below. The increase in flexibility requirements in both approaches is due to the low capacity credit of intermittent wind and solar. When aggregated, the studies suggest a capacity credit of 10%, as each additional GW of wind and solar displaces 0.1 GW of other capacity (Appendix D.5).

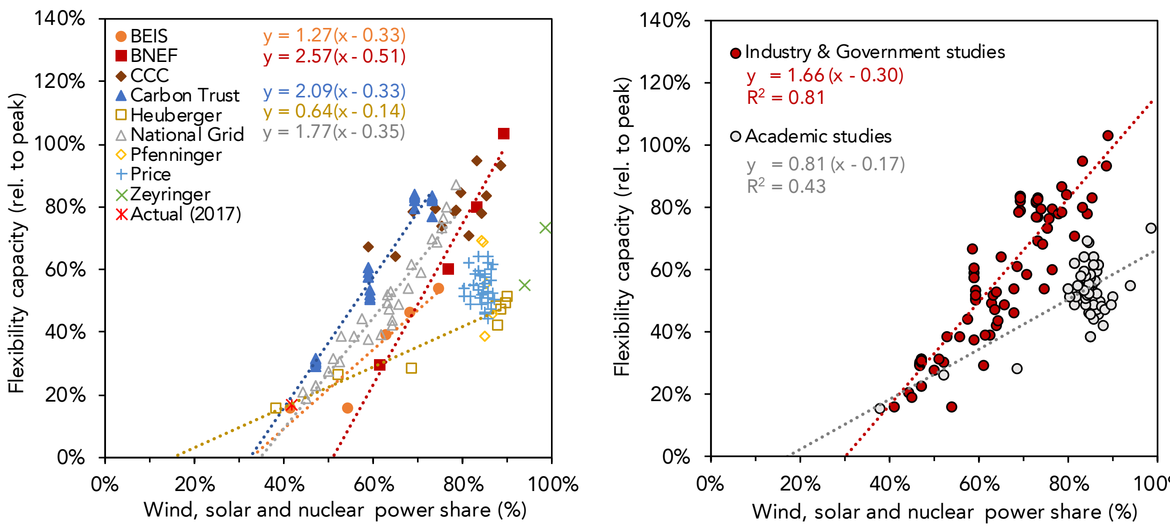

Figure 7.11 – Analysis of flexibility capacity requirements relative to peak demand and as a function of wind, solar and nuclear power penetration for the GB power system. Left: Results from individual studies. Right: Differentiation of studies along commissioning institution. Trendlines in left panel displayed for data series with more than two data points and coefficient of determination of $R^2 \geq 0.85$. Trendline formulae in both panels displayed in respective colour code. Negative term in bracket denotes trendline intersection with x-axis. Trendline coefficients of determination (R^2) shown in right panel only. Industry & Government: BEIS (2018)[187], BNEF (2018)[188], Carbon Trust (2016)[20], CCC (2015)[189], National Grid (2018)[192]. Academia: Heuberger et al. (2018)[191], Pfenninger et al. (2015)[193], Price et al. (2018)[194], Zeyringer et al. (2018)[195].

The linear regression of both data sets reveals two potential approaches for planning low-carbon power systems. The more conservative one based on industry and government studies suggests that flexibility capacity is only needed once wind, solar and nuclear make up 30% of the generation portfolio and will then increase by 1.7% relative to peak demand with each additional 1% of low-carbon capacity. According to this approach, a power system based only on wind, solar and nuclear power would have flexibility capacity at 115% of peak demand.

The less conservative approach in academic studies suggests that no flexibility capacity is needed below 17% wind, solar and nuclear power penetration and will increase by 0.8% of peak demand for each additional 1% low-carbon capacity in the power mix. According to this approach, a power system based only on wind, solar and nuclear power would have flexibility capacity at 65% of peak demand.

These two approaches can be useful in planning low-carbon power systems to assess flexibility capacity requirements that could be fulfilled with electricity storage. This idea is implemented in Figure 7.12 as a "thought experiment" on the amount of flexibility capacity required globally if the power generation mix changes in line with projections made in the IPCC 1.5°C report to keep global average temperature increase below 2°C[1,245,246].

In 2015, less than 20% wind, solar and nuclear power penetration relative to all other regular generation capacity would require no flexibility capacity. However, 1,400 GW hydro and oil-based capacity and around 370 GW electricity storage, demand-side response and interconnection amount to nearly 40% of the 4,200 GW noncoincident peak. As the power penetration of wind, solar and nuclear increases to 76% by 2050, the flexibility capacity decreases from 40% to 20%. This is because peak demand (10,000 GW) increases faster than projected additions for hydro and oil-based generation (total: 2,000 GW), the only flexibility technologies which have explicit capacity data in the respective IAMC database[245,246]. This means there is an increasing gap between flexibility capacity requirements and installed capacity from the early (conservative) or late 2030s (optimistic approach). While only the conservative approach requires additional 400 GW flexibility capacity by 2035, 2,200 GW are suggested optimistically, and another 2,600 GW conservatively by 2050. At even higher penetration of low-carbon generators, Jacobson et al.'s roadmap for a 100% renewable energy system in 139 countries in 2050 finds flexibility capacity requirements at 60% of peak demand, which would be just below the suggestion of the optimistic approach[249].

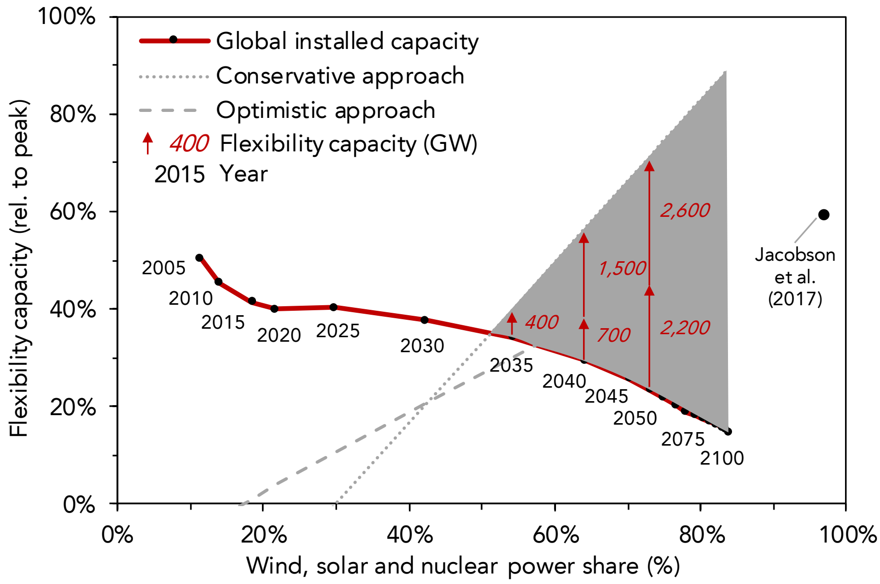

Figure 7.12 – "Thought experiment" on global flexibility capacity requirements. Global installed capacity based on Integrated Assessment Modelling Consortium (IAMC) projection in IPCC 1.5°C report for scenarios with 50% probability to keep global average temperature increase below 2°C[1,245,246]. Conservative and optimistic approaches reflect flexibility capacity requirements as identified in Figure 7.11. Red numbers indicate additional flexibility capacity required on top of projected capacities for hydro and oil-based generation and 2015 capacity levels for electricity storage (153 GW), interconnection (177 GW) and demand-side response (40 GW)[11]. In 2050, global annual electricity demand is modelled at 48,000 TWh, noncoincidental peak demand at 10,000 GW, total capacity at 15,700 GW with 2,000 GW hydro and oil-based generation. For comparison, 2015 values are 20,500 TWh (annual demand), 4,200 GW (peak), 5,500 GW (total capacity), 1,400 GW (hydro, oil). The result from a study by Jacobson et al.[249] for a 100% wind, water and solar power based energy system for 139 countries is also displayed for comparison (peak: 11,800 GW; Hydro and 'peaking/storage' capacity: 7,060 GW)

This "thought experiment" shows that, notwithstanding the limitations discussed later in Chapter 7.3.2, these two approaches can be used for a high-level approximation of maximum and minimum flexibility capacity requirements for low-carbon power systems based on wind, solar and nuclear power. They thereby assess theoretical electricity storage requirements to integrate intermittent and relatively inflexible low-carbon generators, form the basis to assess its total financial system value, and can guide future power system planning while ensuring sufficient flexibility capacity.

7.3 Discussion

This analysis on economic market value of electricity storage in various applications and its system value in integrating low-carbon generation capacity is subject to limitations.

7.3.1 Market Value

The economic market value analysis for various applications across power markets serves to explore overarching trends in the valuation of electricity storage services in decarbonising power systems. Its applicability is shown through comparison with actual sample values for electricity storage in current power markets. It is an attempt to map the economic value of electricity storage services and can inform the identification of business cases for industry in distinct markets or the requirement of policy intervention for desired market-based system services.

However, the generalising nature of the analysis means that identified economic market values will rarely match the actual values in specific power markets for use cases with similar application requirements. That means the analysis of distinct business cases in specific power markets requires detailed consideration of the specific market conditions, for example regulatory policies or generation mix, and cannot rely on the presented findings. Moreover, this analysis is based on historic data. The ongoing transformation of power systems might lead to changes in the economic market values that reflect the changing importance of respective services.

In terms of profitability for energy services, the widespread penetration of network investment deferral use cases across power markets (20% in Italy, 10% in US PJM, Germany, GB and Japan) affirms the identified probability of this application[26] (Figure 7.6). The potential profitability of energy arbitrage in distinct markets is also confirmed by the strong penetration of this application in the New York (NYISO), California (CAISO), Texas (ERCOT) and Japanese power markets[26]. The potential future profitability of applications like bill management or peaker replacement matches the expectation that increasing penetration of variable renewable generation like solar PV will lead to 'peakier' net demand patterns in the coming decade[329].

Regarding power provision, primary response is found to be unprofitable before 2030 (Figure 7.5) However, this seems to contradict sizable electricity storage installations for this application in recent years[26]. There are four potential explanations.

First, application requirements for the 12 core applications might not match real-world use cases. For example, primary response is modelled with 5,000 full equivalent annual charge-discharge cycles, which is more than the cycle lifetime of most battery storage technologies (Table 2.3). Profitable primary response use case for electricity storage are likely to require only around 1,000 cycles[89], which significantly enhances lifetime and cost efficiency.

Second, the value for these services in distinct power markets might be higher than the range identified in this study. This is shown by the wide distribution of sample values for this service in US markets (Figure 2.23, frequency regulation) and its varying penetration in different power markets in general[26].

Third, economic parameters might differ from the assumptions in this study, leading to lower ACC in real-world use cases. The successful bids for enhanced frequency response (EFR) in the UK (90-160 US$/$kW_{year}$) are significantly below modelled ACC for primary response in 2015 but match the identified economic value range (50-200 US$/$kW_{year}$), reaffirming the positive business case. One hypothesis is the use of discount rates below the 8% assumed in this study, for example through access to cheaper cost of capital[330]. In fact, the majority of EFR projects are realised by multinational energy utilities which can limit risk exposure and access low cost of capital[325].

Finally, electricity storage system operators could provide multiple services with one device to stack multiple values, also called benefit-stacking, to achieve profitability (Chapter 2.4.1). Indeed, two of the successful EFR projects bid only for 8,440 service hours per year[325]. The remaining 320 hours are used to avoid network demand charges by attempting to reduce the demand of industrial customers during the three non-consecutive half hours of highest peak demand in the UK (i.e., Triads)[330].

More generally, the combination of multiple services and stacking of respective revenue streams is widely seen as strategy for profitable electricity storage business cases with the aim to optimise usage of available storage capacity for profit maximisation[27,166,167]. The limited profitability of most modelled electricity storage services confirms this interest in benefit-stacking.

For provision of energy services, the results could be interpreted such that maximising utilisation of a 4- to 64-hour discharge duration storage device through operation at 100-1,000 cycles is most profitable. This could resemble a sweet spot between LCOS minimisation through large quantities of discharged energy within feasible cycle life limits and sufficiently high revenues for long energy discharge (compare Figure 6.7 and Figure 7.3).

For power provision there seem to be two sweet spots. The first at 10-100 cycles and 4 hours discharge duration optimises a sharp revenue increases at discharge durations beyond 1 hour with moderate cost mark-ups of increasing energy capacity for the most cost-efficient technology in this application range. Similarly for applications below 1-hour discharge duration and between 100 and 2,000 cycles, where sharply increasing revenues partly exceed increasing ACC due to shorter technology lifetime at higher discharge frequencies (compare Figure 6.8 and Figure 7.2).

It should be noted, however, that no original data was available for the economic market value of applications with more than 8 hours discharge (Figure 7.1). The modelling of seasonal storage revenues as arbitrage service with market wholesale price data serves to define a realistic boundary for discharge durations beyond 500 hours. However, there is significant uncertainty on the economic value of electricity storage services between 8 and 500 hours, because they currently do not exist, and identified values within that range should be considered with caution. In terms of profitability, this affects applications with more than 50 cycles and 8 to 64 hours discharge duration that are currently identified as profitable. The economic values are largely based on applications with 8 hours discharge duration or less. It seems intuitive that the economic value will reduce at some point with increasing discharge duration, but the location and steepness of that threshold is uncertain and would affect profitability.

7.3.2 System Value

The analysis of modelled flexibility capacity requirements for low-carbon GB power systems with data from various studies and scenarios reveals a more conservative approach in industry and government compared to academia. It is arguable whether the approach taken by academics is “smart” or “naïve”. These studies place a focus on accurate representation of wind and solar variability using resource data from multiple years[195] and high spatial[193,194] and temporal resolution[191], potentially ensuring system adequacy without the need for excessive capacity margins. However, temporal resolution is always above one hour, potentially underestimating flexibility requirements for short-term system balancing.

The role of nuclear in low-carbon power systems is important in this discussion. The study by Zeyringer et al.[195] with only 55% flexibility capacity relative to peak demand at 94% wind, solar and nuclear power penetration models nuclear capacity at 38% of peak demand, actually raising combined flexibility and nuclear capacity to 93% (rel. to peak). BNEF's scenario[188] at 89% low-carbon penetration and 103% flexibility capacity (rel. to peak) includes nuclear capacity at only 10%, increasing flexibility and nuclear capacity to 113% (rel. to peak). This could suggest reduced flexibility capacity requirements with high nuclear capacity.

When analysing all data for nuclear power share such a trend cannot be observed, however (Appendix D.6). This is because the ability to meet peak demand does not justify technology deployment economically. Balancing renewable supply and matching consumer demand cost-effectively also requires the ability to quickly increase or reduce power output (i.e., ramping), which might make nuclear, which operates most cost-effectively at constant power output, uneconomic[14]. This contrast between providing for peak demand but not adjusting power output reflects the wider debate about the future role of nuclear in low-carbon power systems[331,332]. Recent findings suggest value in a limited amount of nuclear to decarbonise power systems with low overall flexibility, but highlight the preference to meet peak demand with flexibility capacity[333]. As such, the presence of nuclear in the studies reviewed does not appear to materially affect flexibility capacity requirements identified in this analysis. For reference, flexibility capacity requirements as a function of wind and solar power penetration only are displayed in Appendix D.7.

In terms of electricity storage energy capacity requirements, those studies for the US, EU and Germany reviewed by Zerrahn et al.[207] and displayed in Figure 2.24 that find higher values than the GB studies in Figure 7.9 do not include nuclear power (Budischak et al.[200], Pape et al.[202] and Scholz et al.[184]). This suggests a higher penetration of nuclear reduces the need for electricity storage energy capacity, which is reasonable given that the otherwise missing energy in periods with low wind and solar generation must be provided by electricity storage alone. However, it could be argued that this only applies to the small penetrations of nuclear power modelled for GB studies (<25% for nine tenths of the scenarios), since higher nuclear penetrations could lead to overproduction at times of low demand that would best be stored for later discharge from an economic perspective, and increase electricity storage energy capacity requirements[83].

Figure 7.10 shows no difference in flexibility capacity requirement between studies with more electricity storage capacity than others and it is argued that flexibility options can be used interchangeably. This insight is simplified, neglecting possible technology constraints in providing flexibility at certain times and durations. For example, flexible power provision through electricity storage is limited by its discharge duration, whereas provision through interconnection is limited by the spatial correlation of weather and demand patterns[334]. While there is no apparent impact of electricity storage discharge duration on flexibility capacity requirements in the studies analysed (Appendix D.6), the decision by the UK energy markets regulator to de-rate electricity storage capacity in the capacity market clearly highlights this limitation[335]. For example, a storage system with 0.5 hours discharge duration only receives remuneration for 17.5% of its power capacity when bidding into the one-year-ahead capacity market, while systems with 1.5 hours or above 4 hours receive 50% or 96% respectively[336]. This de-rating is supposed to reflect the equivalent firm capacity at the time and duration of peak demand[335]. Similar limitations apply to alternative flexibility options. GB interconnector capacity is de-rated at between 26% and 84% based on day-ahead price differentials with the relevant pricing zones for highest GB peak demand periods[337]. DSR is de-rated at 84% and only eligible for one-year contracts, which recently led to the annulment of the UK capacity market by the European Court of Justice for discriminating against this flexibility option[338]. For comparison, flexible generation capacity (e.g., OCGT, oil, diesel, hydro) is de-rated at 89 to 95% based on historic station availability.

For the present analysis this has two implications. First, the flexibility capacity requirements modelled by various studies appear to refer to equivalent firm capacity, because flexibility options are not de-rated. One study assumes 14.8 GW flexible EV charging is fully available at all times for example[188]. Absolute flexibility capacity requirements may therefore be higher than identified here. Second, while more work on the identification of appropriate de-rating factors is required, the low de-rating of electricity storage with more than 4 hours discharge duration implies highest system value for contribution to peak demand for this flexibility technology per unit of capacity.

This analysis finds that no flexibility capacity is required up to 17-30% wind, solar and nuclear power penetration. When only considering wind and solar power penetration, this reduces to 5% (Appendix D.7). This finding mirrors observations in actual power system transformation reflected in the phases identified by the International Energy Agency (IEA) regarding the impact of variable renewable generators on power system operation[17]. Phases 1 and 2 apply to up to 10% renewable penetration and require only updates to operating practices with existing system resources like retrofitting coal plants with modern control and measurement equipment to increase ramp rates and reduce minimum stable generation levels[339]. There is more inherent flexibility in CCGT plants, which can provide bulk energy shifting (i.e., balancing out large swings in wind output), not considered here. However, higher investment cost and technical complexity than OCGT plants make CCGT plants ill-suited to solely provide flexible services without bulk energy generation, which is why they do not count towards flexibility capacity in the present analysis.

Previous studies identified a relationship between electricity storage requirements and the ratio of wind to solar in the variable renewable generation mix with more power and energy capacity required for solar-dominated systems[198,340,341]. This relationship is not observed in the present analysis (Appendix D.6), which could be a result of the limited number of studies with solar-dominant scenarios for the GB power systems. This is one implication for the applicability of identified insights to other geographies.

Normalisation of flexibility requirements to peak or annual demand and of wind, solar and nuclear share to overall power and energy mix make identified insights applicable to power systems generally in theory. In reality, however, variations in flexibility requirements compared to this study are likely to result from three dimensions: type of renewable resource, temporal distribution of resource availability and existing power system assets. As mentioned before, flexibility capacity requirements have been found to increase in solar power dominated systems[198]. Temporal distribution refers to the ability to exploit renewable energy generation in regular intervals at different times per day. For example in power systems that span multiple time zones, solar peak production at noon in one zone might coincide with the afternoon demand peak in another[21]. This potential can only be exploited with sufficient power transmission assets, however. Also, an inherently more flexible power plant portfolio (e.g., majority CCGT rather than coal or nuclear) could reduce flexibility capacity requirements. As such, the requirements identified in this study might be lower than in power systems with less gas-based generation capacity. This means, while the quantitative insights on flexibility requirements can be applied to all power systems, these three dimensions should serve to qualify results and thereby guide future power system planning to ensure sufficient flexibility capacity.

This also applies to the "thought experiment" of global flexibility capacity requirements, which would of course be more valid with comparable studies of other regions, to improve the representativeness of the underlying low-carbon and flexibility capacity relationships.

Nevertheless, the identified requirements can serve as a guide for the need of fully flexible capacity (e.g., storage, interconnection, DSR, flexible generation) in a global low-carbon power system. For example, Jacobson et al.'s roadmap for a 100% renewable energy system in 139 countries, which aligns with the optimistic approach for flexibility capacity planning, relies on hydro generation (15%) and thermal storage (85%), underground or in concentrated solar power plants, as flexibility capacity[249]. Similar studies by the same author use pumped hydro, battery or hydrogen storage without impact on the overall flexibility capacity requirement[342]. For the 2,200 GW (optimistic) or 4,800 GW (conservative) additional flexibility capacity required by 2050 in the "thought experiment", this share of electricity storage would probably be an overestimate since interconnection and DSR are likely to provide flexibility capacity as well. As such, this analysis that reaches across the breadth of techniques and assumptions can still serve as interesting counterbalance to bottom-up technical studies to shed more light on the role and need for flexibility capacity.

8. Conclusions

The energy sector needs to transform rapidly to reduce carbon emissions and limit global climate change. Electricity storage is one option to provide the required flexibility in low-carbon power systems with intermittent and relatively inflexible generators. To assess this technology against alternatives and enable further investment in low-carbon technologies, policy-makers and industry need certainty on electricity storage cost reduction potentials and drivers, its market value and the capacity required to enable the deep decarbonisation of power systems.

However, cost estimates span a wide range and are often outdated or limited to only a few technologies. The use of different methodologies for different technologies, intransparency on included cost components and focus on investment cost further increases uncertainty. The quantification of lifetime cost lacks a common methodology often excluding relevant cost and performance parameters. As a result, comprehensive assessments of the future economic value of electricity storage cannot be made.

Therefore, the motivation of this PhD thesis is to reduce uncertainty on the future cost of electricity storage and increase transparency on its economic value and role in enabling low-carbon power systems.

8.1 What's new? – Summary of Contributions

This thesis creates a dataset that enables future investment cost projections for the most promising electricity storage technologies and provides insights from expert interviews on the development potential of two key technologies. It derives a comprehensive formula for and quantifies future lifetime cost of electricity storage in various applications. This forms the basis to determine its future economic value. In addition, electricity storage and flexibility capacity requirements in low-carbon power systems more generally are identified. The contributions are categorised along the initial objectives of the PhD thesis in more detail below.

Objective A: Identify cost reduction trajectories for electricity storage technologies and underlying cost reduction drivers.

A dataset of experience curves for 11 electricity storage technologies is created. The dataset allows methodologically coherent analyses of future investment cost, is clear about included cost components and publicly available for continuous updating. It is used to derive technology-independent cost trajectories down to 200-450 US$/kWh (systems) and 110-200 US$/kWh (packs) at 1 TWh installed capacity. These ranges are not infeasible based on raw material cost and availability. Investment required in individual technologies to achieve that price range is quantified at US$120-630bn. In terms of time, price ranges of 280-480 US$/kWh (systems) and 70-270 US$/kWh (packs) can be reached by 2030, indicating that electric vehicles could become competitive between 2020 and 2024, but residential storage only between 2024 and 2040.

Detailed insights on the development potential for two prominent storage technologies, water electrolysers and lithium-ion batteries, are drawn from expert interviews. Investment cost are estimated at 50-320 US$/kWh for lithium-ion packs and 400-2,200 US$/kW for PEM electrolysers in 2030 at current R&D funding and production scale-up. These could experience further reduction of 12-17% (lithium ion) or 23-27% (electrolysis) with production scale-up compared to 5-22% (lithium ion) and 0-24% (electrolysis) with increased R&D funding. A detailed list of technical and value chain innovations highlights the drivers for cost reduction and performance improvement.

A comparison of the experience curve and expert elicitation methodology to assess future investment cost is made as well.

Objective B: Quantify future cost of storage in specific use cases, accounting for differences in technology cost and performance and application requirements.

A novel formula is derived to assess application-specific lifetime cost for storage technologies incorporating experience-based investment cost reductions and accounting for all relevant cost and performance parameters. The formula is used to quantify future lifetime cost for 9 technologies in various applications. It shows that lithium ion is most cost-efficient for most applications by 2030, outcompeting pumped hydro below 4 hours discharge duration due to strong cost reductions and sufficient performance. Hydrogen-based storage outcompetes compressed air and pumped hydro at long discharge durations.

The analysis shows that levelised cost of storage (LCOS) are lowest at high frequency (1,000 cycles) and moderate duration applications (4 hours), while annuitised capacity cost (ACC) are lowest at low frequency (10 cycles) and duration (0.5 hours). By 2030 lowest LCOS and ACC are 150 US$/MWh and 50 US$/kW$_{year}$ respectively at an electricity price of 50 US$/MWh. A lower general discount rate means pumped hydro remains most cost-competitive for most applications by 2030. Similarly, performance improvements in lifetime or efficiency of 1.0-2.5% per year mean redox-flow and sodium-sulphur batteries can outcompete lithium ion in 2030.

The novel formula is made available as online webtool to foster usage of the lifetime cost methodology for electricity storage technology comparison or competitiveness assessment.

Objective C: Assess the economic market value of electricity storage in specific use cases and its value in enabling low-carbon power systems.

The economic market value (i.e., revenue potential) of electricity storage applications is determined for any discharge duration and frequency requirement. While the value of discharged energy reduces with high discharge frequency and long duration, the value for power provision increases with high frequency and duration.

The profitability of electricity storage is quantified by matching its economic market value to future lifetime cost, accounting for investment cost reductions. There seem to be two initial sweet spots for profitable business cases: for reimbursement of discharged energy above 4 hours duration and 300-1,000 cycles, and for reimbursement of power capacity at 4 hours duration and 10-100 cycles. With reducing investment cost, profitability for energy services expands to applications with 1-hour duration, and for power provision to services requiring 100-2,000 cycles at less than 1-hour discharge.

Regarding the role of electricity storage in enabling low-carbon power systems, modelled capacity requirements for Great Britain are analysed, identifying an envelope of respective power and energy capacities with increasing low-carbon generation.

In addition, flexibility capacity requirements with increasing wind, solar and nuclear power penetration are assessed, showing that electricity storage is used relatively interchangeably with other flexibility options. There are also two approaches to assess flexibility requirements: academics model flexibility capacity below 75% of peak demand above 80% low-carbon penetration, while industry or government studies find flexibility capacity above 75% of peak demand.

8.2 Why does it matter? – Key Conclusions

The key conclusions are listed with reference to the thesis objectives below.

A.1 Today's promising electricity storage technologies will cost US$325±125/kWh (systems) and US$155±45/kWh (packs) once 1 TWh is installed for each.

These price ranges are identified with experience rates based on historic price reductions for 11 promising electricity storage technologies. Raw material cost are significantly below these ranges and investment requirements appear reasonable compared to global investments in renewable energy technologies or network infrastructure.

A.2 The technology that brings most capacity to market is likely to exhibit lowest investment cost, giving an advantage to modular technologies that can be used in multiple applications.

The similar cost reduction trajectories for electricity storage technologies relative to installed capacity suggest that cumulative capacity is a key cost reduction driver. It explains the rapid cost reduction of lithium ion, which is deployed in multiple applications, such as consumer electronics, electric vehicles and stationary systems.

A.3 Production scale-up has a stronger impact on investment cost reduction than doubling R&D funding for lithium-ion batteries and water electrolysers.

Experts identify higher relative cost reduction potentials through production scale-up than doubling R&D funding for lithium ion and electrolysis. This is driven by manufacturing improvements and supply chain optimisation. Combined with A.2, it could mean policy-makers should focus on facilitating electricity storage markets to reduce cost.

A.4 Experts appear to overestimate future investment cost at low deployment rates, and underestimate at high rates, compared to experience curve estimates.

This results from comparing expert to experience curve projections. The higher complexity of cost-efficiency potentials when moving from small-scale to mass manufacturing appears more difficult to comprehend for experts than specific technical advances, a potentially useful consideration in future expert interviews.

B.1 Application-specific lifetime cost account for all relevant cost and performance parameters and must be used to assess technology competitiveness.

The wide ecosystem of most cost-efficient technologies across the spectrum of discharge duration and discharge frequency requirements highlights the complex interplay between technology parameters and application requirements. This complexity is not reflected in investment cost.

B.2 Lowest levelised cost of storage are achieved by operating systems with moderate energy-to-power ratios at high annual cycle frequencies.

Despite varying performance parameters and reducing investment cost of different technologies, the lowest levelised cost are consistently achieved for systems with 1-16 hours discharge duration (i.e., energy-to-power ratio) operated at 250-4,000 full equivalent annual discharge cycles. The combination maximises discharged energy while optimising between total investment cost and operational lifetime.

B.3 Matching the cost-efficiency of lithium ion is becoming increasingly difficult for alternative electricity storage technologies.

The further increasing cost advance of lithium ion combined with sufficient performance parameters make the technology most cost-efficient for most applications by 2030. Alternative technologies may struggle to gain market share and achieve cost reductions under these conditions. This would mirror the continuing dominance of 1st generation solar cells despite significant investment in alternative solar cell technologies which were initially expected to be cheaper.

B.4 Significant performance improvements in alternative electricity storage technologies could be the key to outcompete lithium ion.

Sensitivity analyses show that lifetime and efficiency improvements could lead to alternative technologies being more cost-effective in certain applications than lithium ion. The recent research and deployment focus on lithium ion might mean the technology is reaching its performance limits. This could suggest that a focus on performance improvement is the most effective way for alternative technologies to match the competitiveness of lithium ion.

B.5 Investment conditions have a substantial impact on lifetime cost and technology choice.

Sensitivity analyses show the impact of the discount rate on lifetime cost, determining the most cost-effective technology in distinct applications. This suggests that investment conditions determine the cost and technologies for electricity system transformation. To limit this effect and enable technology-optimal choices, governments could define transparent, stable policy frameworks and provide finance at low cost.

C.1 Future business cases are likely to be profitable in three distinct application categories with specific discharge duration and discharge frequency requirements.

For reimbursement of discharged energy, applications requiring moderate discharge duration (1-16 hours) and frequency (300-1,000) are most profitable. These applications minimise levelised storage cost, while offering sufficiently high revenues. For reimbursement of power capacity, applications requiring moderate duration (1-4 hours) and low frequency (<100 cycles) or low duration (<1 hour) and moderate frequency (100-2,000) are profitable. In both cases, sharply increasing revenues for longer duration or higher frequency applications exceed the increasing annuitised capacity cost.

C.2 A low-carbon GB power system does not depend on electricity storage but with multiple hours of discharge duration it can be the most valuable flexibility option per unit of capacity.

The envelope of electricity storage capacities identified from various models of low-carbon GB power systems shows its relative interchangeability with alternative flexibility options. Combined with common de-rating factors for flexibility options, lowest for multiple-hour storage, this means it can be the most valuable flexibility option per unit of capacity.

C.3 Nearly half of GB's electricity can come from wind, solar or nuclear without additional dedicated flexibility capacity, but at full penetration it must match 65-115% of peak demand.

Both identified approaches for flexibility capacity planning indicate that up until 40% wind, solar and nuclear penetration, the baseline capacity of 20% relative to peak demand is not exceeded. At higher penetrations, the requirement increases at different rates up to 65% or 115% in a fully wind, solar and nuclear based power system.

C.4 Better collaboration between academia, industry and government is needed to identify more robust conclusions for flexibility requirements in low-carbon power systems.

The separate approaches for flexibility capacity requirements between academia and industry/government suggest siloed modelling techniques and assumptions. Improved knowledge exchange in cross-sectoral forums could overcome siloed thinking and accelerate energy system transformation through more robust conclusions. The Power Swarm initiative in the UK is an example: www.powerswarm.co.uk.

8.3 What's missing? – Limitations and Future Work

The analyses presented in this PhD thesis are rigorous and meaningful. Nevertheless, there are limitations, which could be overcome in future work.

Data availability is one limitation of the experience curve analysis. The methodology is based on product prices instead of manufacturing cost, which can distort observed cost reductions due to pricing strategies, in particular for immature technologies[125]. Future work could look at manufacturing cost directly, for example through collaboration with battery cell manufacturers. This would also provide an opportunity to assess component-specific instead of aggregate experience rates (ERs), which is particularly relevant for modular technologies that are manufactured for multiple end-products. Lithium-ion cells, for example, are used in consumer electronics, EV packs and stationary systems. Such analysis could then differentiate between types of lithium-ion cells (i.e., chemistry, format) rather than end-products.

The limitation of experience curve analysis to identify cost reduction drivers also makes it structurally uncertain[125,131,133]. Drivers beyond experience in manufacturing (learning-by-doing) could be R&D investment (learning-by-searching), customer feedback (learning-by-using), economies of scale including supply chain improvements, and spill-over effects (learning-by-interacting)[131]. Variations in all of these factors could lead to diversion from the forecasted cost reductions that are not incorporated in this analysis[120].

To account for these uncertainties, future studies should incorporate capacity growth and price development to update the analysed ERs. The complete dataset of product price and cumulative deployment data is openly released, including the respective experience curve regression parameters[78]. This enables further refining and improving of experience curves by updating with new data, explicitly incorporating the impact of R&D funding to compile two-factor ERs or identifying more specific rates for storage system components and applications.

It would also be beneficial to conduct expert elicitations on future investment cost for additional electricity storage technologies to improve understanding of the cost reduction drivers and qualify experience curve cost projections. This could be further complemented by developing bottom-up engineering models for electricity storage technologies, similar to existing ones for lithium-ion or redox-flow systems[104,217]. These could inform expert elicitations or derive future cost estimates separately with component cost and performance assumptions based on existing literature.

This thesis does not provide insights on the environmental impact of electricity storage technologies. It identifies a knowledge gap in this field among experts, however, which mandates an increase in research efforts, for example through lifecycle assessment studies or interviews targeting technology end-of-life experts.

The modelling of storage lifetime cost is limited by the amount of technologies considered. Future studies should look at additional technologies, as performed recently for gravity-based storage systems[343,344]. Moreover, this study does not model performance improvements for all technologies, which would be a valuable contribution of any future study and could be performed using the online version of the presented lifetime cost model (www.EnergyStorage.ninja). Similarly, this study only approximates degradation and lifetime of electrochemical storage technologies in modelled applications. While it accounts for depth-of-discharge, it does not explicitly model mean state of charge, charge rates and temperature as additional parameters that affect cycle and time degradation and thereby limit cycle and shelf life[76,323,324].

The economic market value analysis is based on US revenue data, verified with data from the UK and Germany. A more comprehensive analysis could review revenue data from a more diverse set of power systems. Also, the limited diversity of electricity storage applications in terms of duration and frequency requirements relative to the entire spectrum might not accurately reflect the actual variation in economic value with those parameters. A wider range of applications with more defined requirements could reveal a more granular distribution of economic values. Such an analysis is still limited to identifying overarching trends only. The assessment of specific business case profitability must be application-specific for a particular power system, including regulatory, market and investment conditions.

Another limitation of this PhD thesis is the missing consideration of benefit-stacking, which is widely perceived as strategy for profitable electricity storage business cases[27,166,167]. However, before the profitability of benefit-stacked applications can be assessed, it was first necessary to determine lifetime cost, revenue and profitability of single use cases as basis for transparency on electricity storage cost and value. For example, there is not yet a common methodology for lifetime cost, which this thesis tries to resolve. Future work should comprehensively assess which services can be provided sequentially or simultaneously with different proportions of the available capacity, the combined revenue and the impact on lifetime cost, to assess profitability potentials for benefit-stacking use cases.

The analysis of electricity storage and flexibility capacity requirements more generally is limited to models of the GB power system. To confirm the identified insights, it is essential to perform a similar analysis for other power systems. These would ideally consider the impact of future changes in demand profiles on flexibility capacity requirements and suitability of different flexibility options. And finally, the resulting insights should be used to not only quantify the amount of flexibility and electricity storage capacity required in low-carbon power systems, but also their financial system value compared to alternative decarbonised power systems without electricity storage.

These studies could further reduce uncertainty on the future cost of electricity storage and increase transparency on its value in low-carbon power systems. In addition to the contributions made in this PhD, they would support the transformation towards a more sustainable, affordable and secure energy sector that helps limiting global climate change.

Thank you for reading my PhD thesis! I hope you found it insightful and worthwhile.

“Philosophers have only interpreted the world,

in various ways.

The point, however, is to change it.”

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A. Appendix to Chapter 4

A.1 Experience curve data overview

Table A.1 – Overview of product price and cumulative installed capacity data sources, linear regression parameters, indicative power-to-energy ratios and comments on individual technology dataset.

Pumped hydro – Utility, System	
Price data	2000 – 2015: Average price data for run-of-the-river and pumped hydro plants reported to IEA by OECD member states, South Africa, Brazil and China[87,345,346]. Maximum and minimum values of 2005 – 2010 data excluded[346]. 1980 – 2000: Based on mean price and experience rate for large and small hydro[130]. Scaling factor of 0.64 applied to all data points to account for pumped hydro installations only. Factor is based on comparing full 2010 – 2015 dataset with 2010 – 2015 pumped hydro data[87]. Resulting price range of 270-300 US$/kWh in line with other findings on pumped hydro costs[65,90].
Capacity data	Capacities and commissioning dates of plants listed in DoE database[260].
Model fit	$n_{final} = 7$; $R^2 = 0.026$; $p = 0.730$; $\sigma = 0.059$ ($N_{2000\text{-}2005} = 8$, $N_{2005\text{-}2010} = 12$, $N_{2010\text{-}2015} = 28$)
P/E ratio	P/E = 1/9.7h; Weighted average discharge duration of plants listed in DoE database[260], excluding values >100 hours.
Comment	The data is biased towards OECD countries, because majority of data points come from OECD member states. This could be significant since construction of pumped hydro plants is labour-intense.

Lead-acid – Multiple, Module	
Price data	US producer price index for lead-acid batteries larger than BCI dimensional group 8D (Applications: uninterruptable power supply, heavy duty vehicles, etc.)[215].
Capacity data	Lead end-use statistics in US, assuming 80% of consumption for battery production[215]. US data scaled-up to global data based on US share of 30% in global lead end-use[347].
Model fit	$n = 21$; $R^2 = 0.105$; $p = 0.153$; $\sigma = 0.042$
P/E ratio	P/E =1/4.8h; Average of 1/3.3h (heavy-duty)[348] and 1/8h(UPS)[349]
Comment	Data taken from peer-reviewed study[215]. No economy-wide data on lead-acid battery production or sales available, so US lead consumption is used as proxy[215].

Lead-acid – Residential, System	
Price data	Observed prices for systems <30 kWh in German residential market 2013 - 2017[91].
Capacity data	Based on information from German KfW incentive program[224,350]. Scaled to global market assuming German residential storage market is ~1/3 of global[351,352].
Model fit	$n = 4$; $R^2 = 0.918$; $p = 0.042$; $\sigma = 0.042$
P/E ratio	P/E = 1/3h; Average value for residential lead-acid batteries sold in Germany[353,354].
Comment	2016 data represent first half of the year. No data for second half of year recorded, because only 4% of new installations were lead-acid (96% lithium-ion). This is down from ~50% in 2013.

Lithium-ion – Electronics, Battery	
Price data	Japanese Ministry for Economy, Trade and Industry (METI) statistics on Li-ion consumer batteries 1995–2011[255], Avicienne market reports for 2011-2016[355].
Capacity data	Annual production data for consumer electronics lithium-ion batteries[254,256,355].
Model fit	$n = 22$; $R^2 = 0.967$; $p = 3 \times 10^{-16}$; $\sigma = 0.021$
P/E ratio	P/E = 1/2h
Comment	-

Lithium-ion – Electric Vehicles, Pack	
Price data	Annual battery pack price index for 2010 - 2018[96].
Capacity data	Annual figures for EVs sold and respective battery pack size[258].
Model fit	n = 9; R^2 = 0.926; p = 3 x 10^{-5}; σ = 0.037
P/E ratio	P/E = 4/h; Average between Tesla S P85D and Nissan Leaf MY 2011/2015
Comment	Experience rate of 16% higher than recently modelled experience rate of 6-9%[23]. But, respective study claims that accounting for chemistry advances and economies of scale makes rate of 12-14% conceivable[23].

Lithium-ion – Residential, System	
Price data	Observed prices for systems <30 kWh in German residential market 2013 - 2017[91].
Capacity data	Based on information from German KfW incentive program[224,350]. Scaled to global market assuming that German residential storage market is ~1/3 of global[351,352].
Model fit	n = 5; R^2 = 0.949; p = 0.005; σ = 0.030
P/E ratio	P/E = 1/3h; Average value for residential lithium-ion batteries sold in Germany[353,354].
Comment	Dominant technology in German market with market share of 99%, up from ~50% in 2013[91].

Lithium-ion – Utility, System	
Price data	Observed prices for stationary systems for 2010 - 2017[259,288,356].
Capacity data	Systems listed in the DoE database larger than 100kWh and operational by 2017[64].
Model fit	n = 8; R^2 = 0.861; p = 9 x 10^{-4}; σ = 0.042
P/E ratio	P/E = 1/1.2h; Weighted average discharge duration of Lithium-ion systems listed in DoE database[64].
Comment	-

Nickel-metal hydride – Hybrid Electric Vehicles, Pack	
Price data	Modelled for 1997-2014 with annual car sales data and price projections for annual production levels[357]. Checked against official company statements on price reductions.
Capacity data	Toyota Prius sales figures[268] and battery specifications[358]. Toyota Prius sales make up ~50% of total global HEV sales[359].
Model fit	n = 18; R^2 = 0.977; p = 1 x 10^{-14}; σ = 0.006
P/E ratio	P/E = 15.6/h; Toyota Prius Generation III battery specification[358].
Comment	Approach taken from peer-reviewed study[98]. Price data deflated in Japanese Yen and then converted to US$$_{2015}$. Price reduction of 75% from 1997 – 2010 in line with official Toyota statement from 2010[360].

Sodium-sulphur – Utility, System	
Price data	Industry reports[65,361], news items[362,363] and manufacturer interviews[364,365] for 2007-2015.
Capacity data	Systems deployed by NGK[366,367].
Model fit	-
P/E ratio	P/E = 1/6h; System specification by NGK[65,365].
Comment	NGK dominates market for Sodium-sulphur systems[260]. No experience rate modelled due to very high standard error of underlying data (σ = 0.299).

Redox-flow – Utility, System	
Price data	Vanadium redox-flow system prices for 2008 - 2015 by two leading manufacturers and an large-scale project[368], and 2017 prices[103].
Capacity data	Vanadium redox-flow systems listed in DoE database[64].
Model fit	n = 5; R^2 = 0.943; p = 0.006; σ = 0.028
P/E ratio	P/E = 1/3.6h; Weighted average of systems listed in DoE database[64].
Comment	-

	Electrolysis – Utility, Pack	Fuel cells – Residential, Pack
Price data	1956-2002: Industry reports and academic publications[231]. 2002-2009, 2014: Manufacturer quotes[57,51].	Japanese Enefarm-type systems[105].
Capacity data	1956-2002: Industry reports and academic publications[231]. 2002-2014: Based on US$100mn market size[369], average system price for 2002-2014.	Sales numbers for Japanese Enefarm-type systems[105].
Model fit	$n_{final} = 6$; $R^2 = 0.857$; $p = 0.008$; $\sigma = 0.054$ ($N_{1956\text{-}2002} = 11$, $N_{2002\text{-}2009} = 9$, $N_{2014} = 8$)	$n = 14$; $R^2 = 0.95$; $p = 3.7 \times 10^{-9}$; $\sigma = 0.017$
P/E ratio	P/E = 1/10h assumed; appears feasible on the basis of average residential electricity consumption of 2900 - 3500 kWh/year and residential fuel cell system size of 1kW[233].	
Comment	Alkaline systems	PEM systems; >95% sold in Japan[62,370].

Solar PV Modules	
Price data	Solar PV module price data[252].
Capacity data	Global cumulative capacity[252].
Model fit	$n = 40$; $R^2 = 0.942$; $p = 4.74 \times 10^{-25}$; $\sigma = 0.015$
Comment	-

PV Inverters	
Price data	Inverter price data[253].
Capacity data	Global cumulative PV shipments[253].
Model fit	$n = 24$; $R^2 = 0.966$; $p = 1.33 \times 10^{-17}$; $\sigma = 0.012$
Comment	PV inverters < $20kW_p$

A.2 Cost contribution of storage system components

Reported price data in this analysis is given for different technology scopes (i.e., cell, battery, module, pack, ex-works system, system). The table below lists the components included within each scope alongside indicative cost contribution for a stationary lithium-ion system. Bold shaded rows give the contribution of each scope to the overall system, and unshaded rows give the contribution of individual components to that scope.

Table A.2 – Components of EES technologies and indicative cost contributions[97,217,371].

Technology Scope	Indicative contribution	Reported technologies
Cell	**19%**[97]	
Electrodes	46%[217]	- (*18650 cell costs for EV packs reported at 145 US$/kWh*[94])
Electrolyte	14%[217]	
Separators	15%[217]	
Current Collectors	19%[217]	
Terminals	4%[217]	
Cell container	2%[217]	
Battery (consumer electronics)	***no data***	
Power electronics	*no data*	Lithium-ion (Electronics)
Housing	*no data*	
Module	*Included in pack*	
Thermal conductors	9%[217]	Lead-acid (Multiple)
Cell group interconnectors	0%[217]	
State-of-charge regulator	85%[217]	
Terminals	1%[217]	
Provision for gas release	2%[217]	
Module enclosure	3%[217]	
Pack	**11%**[97]	
Wiring, interconnections and connectors	21%[97]	Lithium-ion (EV) Nickel-metal hydride (HEV) Electrolysis (Utility) Fuel cells (Residential)
Housing	15%[97]	
Temperature control	7%[97]	
Power electronics	24%[97]	
Battery Management System	33%[97]	
Ex-works System	**35%**[372]	
Inverter	*45%*[93]	-
Container	*45%*[93]	
SCADA/controller	*10%*[93]	
System	**35%**[372]	
Transport	-	Lithium-ion (Residential, Utility) Lead-acid (Residential) Redox-flow (Utility) Sodium-sulphur (Utility) Pumped hydro (Utility)
Installation	-	
Commissioning	-	
	100%	

A.3 Commodity price ranges

Table A.3 – Commodity price ranges and sources.

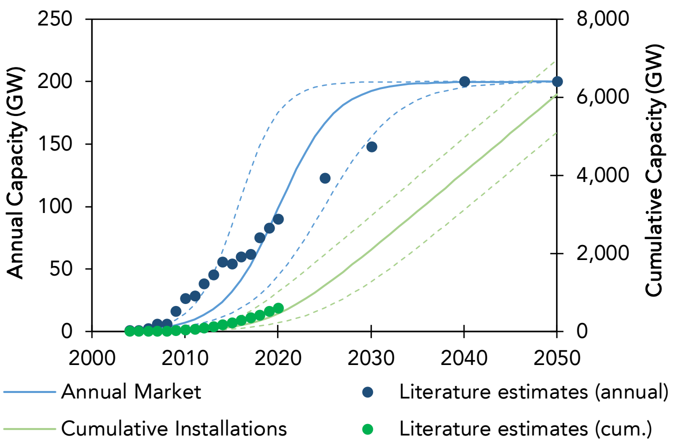
Commodity Price Database	US$/kg	US$/kg	US$/kg		
Commodity	**Mid**	**Max**	**Min**	**Comment**	**Source**
ABS -Acrylnitiril-btadienestyrene	2.00	2.00	2.00		www.roymech.co.uk/Useful_Tables/Matter/Costs_Plastics.html
Activated Carbon	1.65	1.65	1.65	1997	Mercury Study Report to Progress. United States Environment Protection Agency. December 1997
Alpha-alumina	15.60	15.60	15.60		www.inframat.com/products/26R-0806UPA.htm
Aluminium	2.04	2.80	1.51		Bloomberg[216]
Ammonium Salts in Acetonitrile	1.00	1.00	1.00	assumption	
Antimony	8.04	12.79	4.10		Bloomberg[216]
Aramid fibres	25.00	25.00	25.00		www.netcomposites.com/guide-tools/guide/reinforcements/aramid-fibrefiber/
Barium	8.33	8.33	8.33		www.ebiochem.com/product/barium-chromate-ar-9980
Beta-alumina (boehmite)	3.07	3.07	3.07	2003	www.gunnarmusan.de/Material/ZEBRA%20Battery%20-%20Material%20Cost,%20Availability%20and%20Recycling.pdf
Binder PVDF	10.00	10.00	10.00		BatPac (Cost Input)[217]
Brass	8.67	9.16	8.43		Bloomberg[216]
Cadmium	2.72	7.50	0.94		Bloomberg
Carbon	6.80	6.80	6.80		BatPac (Cost Input)[217]
Carbon Black	6.80	6.80	6.80		BatPac (Cost Input)[217]
Carbon Steel	0.72	0.83	0.49		Bloomberg[216]
Carbon, graphite	10.90	10.90	10.90	Mix Carbon, Graphite	
Cement	0.10	0.11	0.09		Bloomberg[216]
Cerium Metal	11.80	34.13	4.60		Bloomberg[216]
Chromium	9.25	13.50	6.35		Bloomberg[216]
Cobalt	29.21	38.13	24.05		Bloomberg[216]
Concrete	0.05	0.05	0.05		ocw.mit.edu/courses/materials-science-and-engineering/3-11-mechanics-of-materials-fall-1999/modules/props.pdf
Copper	6.52	9.60	3.07		Bloomberg[216]
Ethylene Carbonate	1.06	1.06	1.06		www.ihs.com/products/chemical-technology-pep-reviews-ethylene-carbonate-from-ethylene-2003.html
Ethylene Glycol Dimethyl Ether	5.00	5.00	5.00		www.alibaba.com/showroom/dimethyl-ether-prices.html
Glass	0.19	0.21	0.17		Bloomberg[216]
Glycol	1.16	1.65	0.87		Bloomberg[216]
Graphite	15.00	15.00	15.00		BatPac (Cost Input)[217]
Gravel	0.01	0.01	0.01		Bloomberg[216]
Halide salts	0.77	0.77	0.77		www.gunnarmusan.de/Material/ZEBRA%20Battery%20-%20Material%20Cost,%20Availability%20and%20Recycling.pdf
High alloy steel	2.25	2.97	1.35	see stainless steel	
Iron	0.72	0.83	0.49	see carbon steel	
Lead	2.03	2.55	1.00		Bloomberg[216]
Lead oxides	2.03	2.55	1.00	see lead	
Lithium carbonate	5.48	7.00	3.97		minerals.usgs.gov/minerals/pubs/commodity/lithium/myb1-2013-lithi.pdf, Berenberg Bank Report
Lithium hexa-fluorophosphate	13.49	13.49	13.49		BatPac (Cost Input)[217]

Lithium hydroxide	6.70	6.70	6.70		minerals.usgs.gov/minerals/pubs/commodity/lithium/myb1-2013-lithi.pdf
Lithium manganese oxide	10.00	10.00	10.00		BatPac (Cost Input)[217]
M: Ni, Ti, V, Zr	13.29	22.72	6.58	Average Price	
Magnesium	2.81	4.30	2.00		Bloomberg[216]
Manganese	2.37	3.23	1.60		Bloomberg[216]
Molybdenum	37.91	75.20	13.30		Bloomberg[216]
Nafion	176.00	176.00	176.00		www.nrel.gov/docs/fy09osti/45457.pdf
Nickel	18.05	33.33	8.82		Bloomberg[216]
Nickel Compounds	14.44	26.66	7.06	80% Ni content	
Nickel hydroxide	6.00	6.00	6.00		www.arb.ca.gov/msprog/zevprog/2003rule/03board/andermanreport.pdf
PEEK	68.33	68.33	68.33		www.roymech.co.uk/Useful_Tables/Matter/Costs_Plastics.html
PEEK, Aluminium, Copper	25.63	26.91	24.30	Average Price	
Plastics	1.33	1.64	1.00	Average Price	
Platinum	46,018.67	62,434.96	31,448.53		Bloomberg[216]
Polybenzimidazol (PBI)	195.00	195.00	195.00		cordis.europa.eu/result/rcn/56073_de.html
Polyester	1.50	1.50	1.50		Matteson[215]
Polyethylene	1.60	1.96	1.22		Bloomberg[216]
Polyethyleneterephthalate	1.35	1.75	1.00		Bloomberg[216]
Polypropylene	1.40	1.65	1.04		Bloomberg[216]
Polytetrafluoroethylene	13.56	13.56	13.56	US$ 4bn market for 295 kT	https://globenewswire.com
Polyvinylchloride	0.99	1.19	0.75		Bloomberg[216]
Potassium hydroxide	0.50	0.50	0.50		www.alibaba.com/showroom/potassium-hydroxide-price.html
Ruthenium	5,977	21,517	1,481		Bloomberg[216]
Sand	0.01	0.01	0.01		Bloomberg[216]
Sb, Sn, As	10.00	10.00	10.00		Matteson[215]
Silica	8.80	8.80	8.80		Lubin, G. Handbook of Composites. Van Nostrand Reinhold Company.
Silicon	1.94	2.29	1.22		Bloomberg[216]
Silicon Carbonate	36.00	36.00	36.00	1999	http://ocw.mit.edu/courses/materials-science-and-engineering/3-11-mechanics-of-materials-fall-1999/modules/props.pdf
Sodium	0.45	0.65	0.31		Bloomberg[216]
Stainless Steel	2.25	2.97	1.35		Bloomberg[216]
Steel	0.72	1.06	0.52		Bloomberg[216]
Steel and copper	3.62	5.33	1.80	Average Price	
Sulphur	0.11	0.14	0.08		Bloomberg[216]
Sulphuric Acid	0.11	0.31	0.05		Bloomberg[216]
Thermal insulation	12.50	12.50	12.50		www.gunnarmusan.de/Material/ZEBRA%20Battery%20-%20Material%20Cost,%20Availability%20and%20Recycling.pdf
Tin	18.16	26.90	10.70		Bloomberg[216]
Titanium	6.54	15.05	3.20		Bloomberg[216]
Vanadium	27.38	40.00	13.60		Bloomberg[216]
Vanadium pentoxide	12.62	16.60	5.25		Bloomberg[216]
Water	-	-	-		

Wood	0.24	0.25	0.24		Bloomberg[216]
YBCO	1,333	1,333	1,333		High Temperature Superconducters (HTS) for energy applications, Ziad Melhem, 2011, Woodhead Publishing.
Yttrium	45.78	70.00	34.00		Bloomberg[216]
Zinc	2.26	4.23	1.21		Bloomberg[216]
Zirconium	1.18	2.50	0.70		Bloomberg[216]

A.4 Growth projection for solar photovoltaics

Table A.4 – Market growth projection, key parameters and underlying assumptions for solar photovoltaics.



Key parameters:

- Growth rate: 0.328
- Standard error: 0.013

- Min growth rate = 0.252
- Max growth rate = 0.452

Assumptions:

- Initial capacity: 1 GW p.a. (2004[252])
- Saturation: 200GWh p.a. (2050[373])
- Literature estimates[252,373–375]

Comment: Total PV new capacity installed each year peaks at 200 GW by 2025[373]

A.5 Parameters for levelised cost analyses

Table A.5 – Parameters and references used for levelised cost analyses.

	ICEV Fuel tank	EV Lithium-ion battery pack	Installed residential Lithium-ion system
Investment cost	US$ 180[376]	US$ 9,900 (2016)*	1,883 US$/kWh (2016)
Capacity (distance)	17 gallons (510 mi)[377]	30 kWh (107 mi)[280]	-
Experience rate	0%[378]	16% ± 4%	12% ± 4%
Growth Rate**	-	0.348 (0.306, 0.436)	0.500 (0.466, 0.656)
Residual Value	0% (of capital cost)[379]	30%[380] (of capital cost)	0% (of capital cost)[89]
Warranted lifetime	100,000 miles/ 8 years	100,000 miles/ 8 years[280]	2,500 cycles/ 10 years[89]
Fuel Price	2.36 US$/gallon[221]	0.12 US$/kWh[381]	LCOE of residential solar PV****
Round-trip efficiency	100%	90%[382]	92%[89]
Depth-of-discharge	100%	80%[382]	80%[282]
Fuel efficiency	30 miles/gallon[377]	4.46 miles/kWh***	-
Annual degradation	0% (of capacity)	5%[383] (of capacity)	0.5% (of capacity)[114]
Discount rate	5%	5%	5%
Power-to-Energy (1/h)	-	3[280]	0.33[353,354]
O&M cost	-	-	0% (of capital cost)[89]
Retail power price	-	-	0.36 US$/$kWh_e$[384] (2016)

*Capacity x Price = 30 kWh x 330 US$/kWh (reduces over time as function of ER)
**r parameter from equation (9) (Table 4.2.)
***Distance per capacity / (Capacity * Depth of discharge) = 107 miles / (30kWh * 80%)
****See Figure A.5 in Appendix A.8 and Table A.4 in Appendix A.4

A.6 Historic prices and deployment of hydropower

Historic price[87,345,346,385] and cumulative deployment[386,387] data are analysed for hydropower generation plants. This is done in light of the potential applicability of additional insights to pumped hydro storage due to the similarity of both technologies.

Project price data of hydropower plants from 1956 to 2015 reveal an overall negative experience rate of -11±8% (N=204, R^2=0.033, p=0.010, σ=0.056). Separating into small (<50 MW) and large projects (>50 MW) shows that prices of small hydropower plants tend to increase less at a negative ER of -1±12% (N=59, R^2=0.001, p=0.839, σ=0.089) compared to large hydropower plants at -3±9% (N=145, R^2=0.003, p=0.509, σ=0.067). The increased construction of small hydropower plants compared to large ones drives the overall, highly negative experience rate.

Potential reasons for the observed price increases have been named as[385]:

- Higher cost of more difficult and remote sites
- Increased development time required due to required public hearings and licensing
- Increased cost of environmental mitigation
- Increased cost escalation and interest during construction

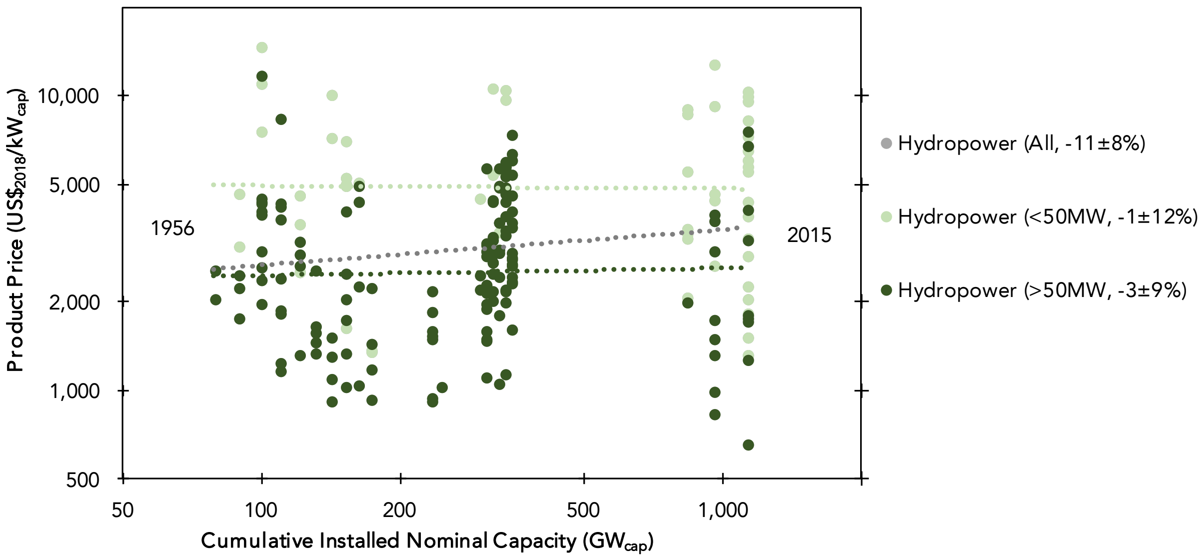


Figure A.1 – Historic price and cumulative installation data for hydropower plants. Results shown for product prices per nominal power capacity. Dotted lines represent the resulting experience curves based on linear regression of the data for small (<50 MW), large (>50 MW) and all hydropower systems. Experience rate uncertainty is quantified as its 95% standard error confidence interval. Experience rate for all hydropower stations is higher than for small or large individually, because of increasing deployment of more expensive small hydropower stations in recent years.

Due to the similarity between hydropower generation and pumped hydro storage technology, it is conceivable that these factors are also applicable to pumped hydro projects and equally drive the project prices.

The cost indices in Figure A.2. refer to hydropower plant prices in Norway[388]. Project costs are disaggregated into three categories: civil, mechanical and electro-technical works, and adjusted for inflation.

The analysis reveals that increasing prices are most likely driven by the costs of the civil works. This confirms the reasons for the price increases outlined in Figure A.1., since civil works (dam construction, reservoir preparation) are affected by sites that are more difficult to access, environmental mitigation measures and cost escalations during the construction period. It is conceivable that this effect is less pronounced for small compared to large hydropower installations, given that the former benefit from the use of simpler civil structures due to low water flows and low associated risks[385], leading to smaller relative cost proportion of civil works.

Regardless of size, the parallel that can be drawn from the comparison to hydropower is that investment cost for pumped hydro installations appear to increase due to the increase in civil works costs. This can be a result of more difficult and remote sites, increased development time due to public hearings and licensing and increased environmental protection requirements.

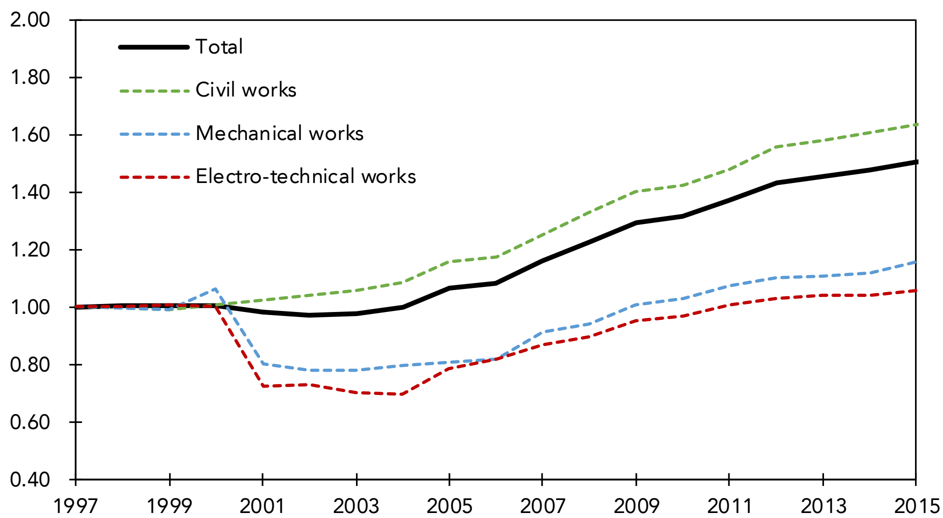


Figure A.2 – Hydropower cost indices for different cost components (Norway) . Cost indices show a significant increase of costs for civil works, the largest cost component for hydropower stations.[219]

A.7 Raw material cost of electricity storage technologies

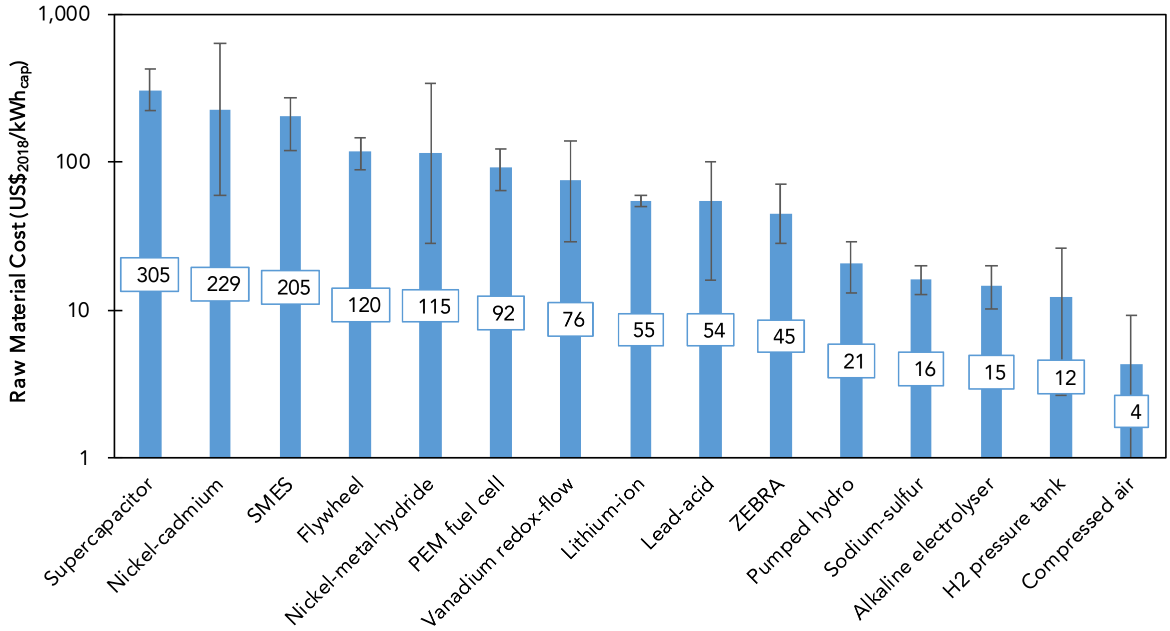


Figure A.3 – Cost analysis of raw material inputs for EES technologies. ZEBRA – sodium-nickel chloride battery. For more details about the raw material cost ranges and breakdown by individual material cost contributions, see Table A.4.

Wadia et. all explore the raw material cost of the active materials of five of the technologies investigated in this study (vanadium redox-flow, lithium-ion (LMO), lead-acid, sodium-nickel-chloride (ZEBRA), sodium-sulphur)[263]. Their finding of 90 $US/kWh for vanadium redox-flow matches our range of 29 – 140 US$/kWh, because in this technology the active materials comprise ~90% of overall raw material costs.

Regarding lithium-ion with an LMO cathode, active materials make up 75% of the total raw material cost of a battery pack. The difference to the findings of this study (75% of 50 - 59 US$/kWh vs. 1 US$/kWh[263]) mainly results from the consideration of spherical graphite and battery-grade lithium carbonate needed for battery electrode manufacturing as opposed to flake graphite and extraction-grade lithium carbonate. For lead-acid, the active material also accounts for 75% of the total raw material cost of a battery pack. The difference to the findings in this study (75% of 16 – 100 US$/kWh vs. 10 US$/kWh[263]) are subject to significant variations in lead prices. Active material costs for sodium-nickel-chloride (ZEBRA) battery packs are determined by nickel, comprising between 50% and 60%. Here, the difference (50% of 28 – 71 US$/kWh vs. 10 US$/kWh[263]) could be the result of differing assumptions on the nickel requirements per kWh_{cap}. Finally, for sodium-sulphur battery packs, findings on active material costs are within similar ranges, however, raw material costs of the complete battery pack (13 – 20 US$/kWh vs. 0.1 US$/kWh) are significantly higher due to the low relative cost proportion comprised by the active materials (<1%).

Additional costs for other factors of production: direct labour, overhead, sales, R&D, depreciation, profit and warranty, are below 20% of final system price for electrochemical technologies at high annual production volumes[217,218]. For mechanical storage such as pumped hydro, costs for planning, civil works, infrastructure and logistics dominate total costs at 50 - 80%[219]. Adding these cost contributions to the raw material cost for nickel-metal hydride and pumped hydro, the electrochemical and mechanical technologies with highest material costs, yields 138 US$/kWh (range: 35 – 407 US$/kWh) and 101 US$/kWh (range: 65 – 160 US$/kWh) respectively. This is below the price ranges we forecast at 1 TWh cumulative installed capacity. Therefore, the experience-curve based price projections are not infeasible.

Lithium ion is a family of technologies with different cathode chemistries being considered for electric vehicle battery packs. Figure A.4 shows an analysis of the raw material costs for lithium-ion battery packs with different cathode chemistries. Nickel and Cobalt based chemistries exhibit the highest average raw material costs compared to Li-manganese or Li-phosphate. Shifting the Nickel-Cobalt ratio towards increased Nickel contents reduces material costs.

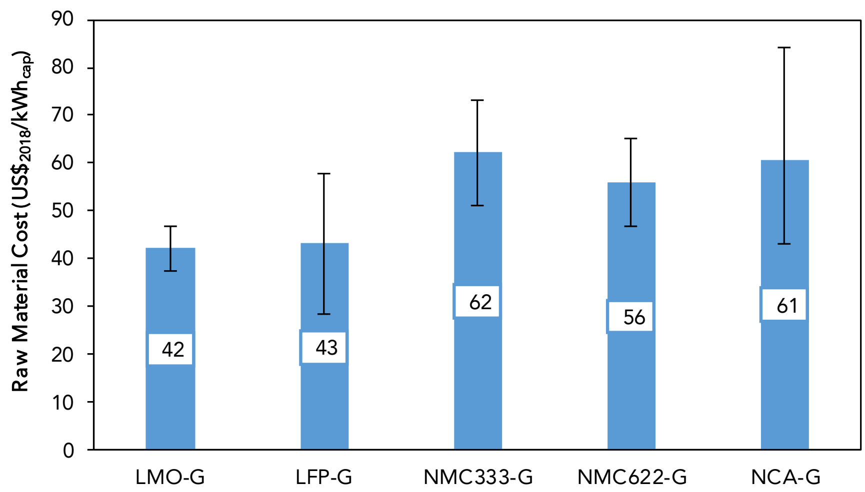


Figure A.4 – Blue bars show the raw material cost of lithium-ion battery packs with different cathode chemistries (LMO, LFP, NMC, NCA) and graphite anodes (G). The error bars account for variations in each technology's material inventory and commodity prices over the past 10 years. LMO: Lithium Manganese Oxide, LFP: Lithium Iron Phosphate, NMC: Lithium Nickel Manganese Cobalt Oxide, NCA: Lithium Nickel Cobalt Aluminium Oxide. NMCxxx denotes molar fraction of respective elements. More details in Table A.5.

Table A.6 – Breakdown of raw material cost contribution per material for each EES technology.

Supercapacitor[210]		**US$/kWh**	
Material	*min*	*mid*	*max*
Ammonium Salts	88	99	111
Aluminium	56	116	214
Activated Carbon	75	82	88
Plastics	4	9	16
Total	**223**	**305**	**428**

Nickel-Cadmium[210,211]		**US$/kWh**	
Material	*min*	*mid*	*max*
Nickel Compounds	43	173	478
Cobalt	6	13	26
Cadmium	4	22	89
Copper	2	9	19
Chromium	2	6	13
Lithium Hydroxide	1	2	2
Carbon Steel	1	2	3
Plastics	0	1	2
Potassium hydroxide	0	1	1
Nickel	59	229	634
Lithium	43	173	478
Total	**6**	**13**	**26**

SMES[210]		**US$/kWh**	
Material	*min*	*mid*	*max*
Copper	44	95	139
Carbon Steel	60	88	101
Yttrium	9	12	19
Barium	7	7	7
Copper	2	4	5
Sulphuric Acid	0	0	0
Total	**122**	**205**	**271**

Flywheels[210]		**US$/kWh**	
Material	*min*	*mid*	*max*
Carbon	47	47	47
Carbon Steel	22	33	38
Copper	12	25	37
Plastics	8	15	25
Yttrium	0	2	6
Barium	1	1	2
Copper	0	1	2
Total	**88**	**120**	**146**

Nickel-metal hydride[210,211]		**US$/kWh**	
Material	*min*	*mid*	*max*
Nickel Compounds	22	88	244
Cerium Metal	4	19	83
Carbon Steel	2	6	11
Plastics	1	0	0
Potassium Hydroxide	0	0	0
Total	**29**	**115**	**339**

PEM fuel cell[213]		**US$/kWh**	
Material	*min*	*mid*	*max*
Platinum	56	82	112
Graphite	5	7	8
Nafion	2	2	2
Polytetrafluoroeth.	0	0	0
Carbon	0	0	0
Plastics	0	0	0
Copper	0	0	0
Iron	0	0	0
Steel	0	0	0
Plastics	0	0	0
Total	**64**	**92**	**122**

Vanadium redox-flow[210]	US$/kWh		
Material	*min*	*mid*	*max*
Vanadium	23	64	119
Carbon Steel	2	3	5
Copper	1	2	4
Plastics	1	2	3
Graphite	1	2	3
Carbon Black	1	1	2
Sulphuric Acid	0	1	4
Total	**29**	**76**	**140**

Lead-acid[210,211]	US$/kWh		
Material	*min*	*mid*	*max*
Lead oxides	7	26	48
Lead	5	19	34
Plastics	2	5	9
Antimony	1	3	7
Sulphuric Acid	0	0	2
Copper	0	1	2
Glass	0	0	0
Total	**16**	**54**	**100**

Pumped Hydro[210]	US$/kWh		
Material	*min*	*mid*	*max*
Concrete	11	17	23
Iron	1	2	2
Wood	0	1	1
Chromium	0	0	1
Molybdenum	0	0	1
Plastics	0	0	0
Aluminium	0	0	0
Copper	0	0	0
Zinc	0	0	0
Lead	0	0	0
Total	**13**	**20**	**32**

Lithium-ion (LMO)[389]	US$/kWh		
Material	*min*	*mid*	*max*
Lithium mang. ox.	26	26	26
Carbon, graphite	13	13	13
Copper	3	6	8
Aluminium	2	3	4
Binder PVDF	2	2	2
Lithium hexafluoroph.	1	2	2
Dimethyl carbonate	1	1	1
Ethylene carbonate	0	0	0
Copper	0	1	1
Thermal insulation	0	0	0
Stainless Steel	0	0	0
Polypropylene	0	0	0
Polyethyleneterepht.	0	0	0
Glycol	0	0	0
Polyethylene	0	0	0
Total	**50**	**55**	**59**

ZEBRA[214]	US$/kWh		
Material	*min*	*mid*	*max*
Nickel	14	29	53
Thermal insulation	5	5	5
Beta-alumina	5	5	5
Stainless Steel	1	2	3
Halide salts	2	2	2
Copper	1	2	3
Iron	1	1	1
Steel	0	0	0
Total	**28**	**45**	**71**

Sodium-sulphur[210,211]	US$/kWh		
Material	*min*	*mid*	*max*
Alpha-alumina	3	3	3
Aluminium	3	4	6
Beta-alumina	3	3	3
Stainless steel	2	3	4
Copper	1	2	3
Sodium	0	0	1
Sulphur	0	0	0
Glass	0	0	0
Sand	0	0	0
Total	**13**	**16**	**20**

Alkaline electrolyser[212]	US$/kWh		
Material	*min*	*mid*	*max*
Polybenzimidazol (PBI)	5	5	5
Stainless Steel	3	5	6
Nickel	2	5	9
Copper	0	0	0
Graphite	0	0	0
Potassium hydroxide	0	0	0
Aramid fibres	0	0	0
Polytetrafluoroeth.	0	0	0
Aluminium	0	0	0
Iron	0	0	0
ABS	0	0	0
Total	**10**	**15**	**20**

Compressed Air[210]	US$/kWh		
Material	*min*	*mid*	*max*
High Alloy Steel	0	3	6
Concrete	0	1	2
Carbon Steel	0	0	0
Iron	0	0	0
Manganese	0	0	0
Copper	0	0	0
Plastics	0	0	0
Vanadium	0	0	0
Silicon	0	0	0
Molybdenum	0	0	0
Chromium	0	0	0
Total	**1**	**4**	**9**

H2 pressure tank[261,262]	US$/kWh		
Material	*min*	*mid*	*max*
Stainless Steel, Steel, Concrete Vessel	**4**		
Steel/Concrete Composite Vessel		**12**	
Stainless Steel			**26**

Table A.7 – Breakdown of material cost for different chemistry lithium-ion battery packs[217], including battery components.

Lithium-ion	LFP-G	US$/kWh		
		Min	*Mid*	*Max*
Lithium hydroxide	Cathode	4	4	4
Phosphoric acid	Cathode	1	1	1
Iron sulfate	Cathode	0	0	0
Graphite	Anode	13	17	20
Carbon	Anode	1	1	1
Binder PVDF	Binder	2	2	2
Copper	Negative foil, interconnectors	2	5	7
Aluminium	Positive foil, bus bars, connectors	3	4	6
Lithium hexafluorophosphate	Electrolyte	2	3	3
Ethylene carbonate	Electrolyte	1	1	1
Dimethyl carbonate	Electrolyte	1	1	1
Plastics	Separator, Spacers, Housing	0	0	0
Steel	Module compression plates	0	0	0
Thermal insulation	Thermal insulation	2	2	2
Glycol	Coolant	0	1	1
Copper	Electronic Parts (Terminals, Regulators)	**1**	**3**	**4**
Total		**34**	**43**	**52**

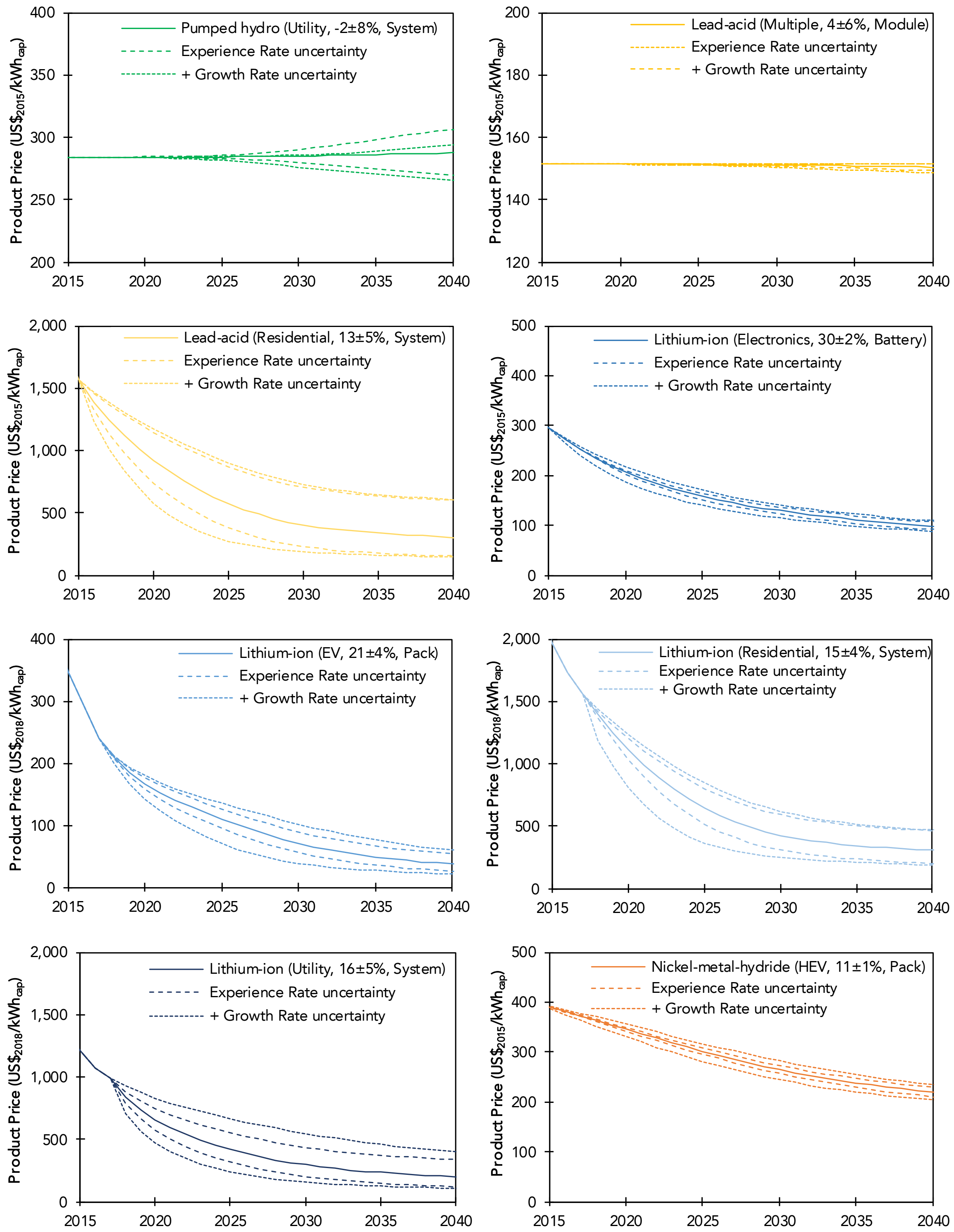
Lithium-ion	NMC333-G	US$/kWh		
		Min	*Mid*	*Max*
Nickel	Cathode	6	13	25
Cobalt	Cathode	9	11	14
Manganese	Cathode	1	2	2
Lithium hydroxide	Cathode	3	3	3
Graphite	Anode	13	16	19
Carbon	Anode	1	1	1
Binder PVDF	Binder	2	2	2
Copper	Negative foil, interconnectors	2	4	7
Aluminium	Positive foil, bus bars, connectors	3	4	5
Lithium hexafluorophosphate	Electrolyte	1	2	2
Ethylene carbonate	Electrolyte	0	0	0
Dimethyl carbonate	Electrolyte	1	1	1
Plastics	Separator, Spacers, Housing	0	0	0
Steel	Module compression plates	0	0	0
Thermal insulation	Thermal insulation	1	1	1
Glycol	Coolant	0	1	1
Copper	Electronic Parts (Terminals, Regulators)	1	2	4
Total		**45**	**62**	**86**

Lithium-ion	NMC622-G	US$/kWh		
		Min	*Mid*	*Max*
Nickel	Cathode	5	11	21
Cobalt	Cathode	7	9	12
Manganese	Cathode	1	1	2
Lithium hydroxide	Cathode	3	3	3
Graphite	Anode	12	15	18
Carbon	Anode	1	1	1
Binder PVDF	Binder	1	1	1
Copper	Negative foil, interconnectors	2	4	6
Aluminium	Positive foil, bus bars, connectors	3	3	5
Lithium hexafluorophosphate	Electrolyte	1	1	2
Ethylene carbonate	Electrolyte	0	0	0
Dimethyl carbonate	Electrolyte	1	1	1
Plastics	Separator, Spacers, Housing	0	0	0
Steel	Module compression plates	0	0	0
Thermal insulation	Thermal insulation	1	1	1
Glycol	Coolant	0	1	1
Copper	Electronic Parts (Terminals, Regulators)	1	2	4
Total		**40**	**56**	**77**

Lithium-ion	LMO-G	US$/kWh		
		Min	*Mid*	*Max*
Manganese	Cathode	4	6	8
Lithium carbonate	Cathode	2	3	4
Graphite	Anode	11	14	17
Carbon	Anode	1	1	1
Binder PVDF	Binder	2	2	2
Copper	Negative foil, interconnectors	2	5	8
Aluminium	Positive foil, bus bars, connectors	3	4	5
Lithium hexafluorophosphate	Electrolyte	1	2	2
Ethylene carbonate	Electrolyte	0	0	0
Dimethyl carbonate	Electrolyte	1	1	1
Plastics	Separator, Spacers, Housing	0	0	0
Steel	Module compression plates	0	0	0
Thermal insulation	Thermal insulation	1	1	1
Glycol	Coolant	0	0	1
Copper	Electronic Parts (Terminals, Regulators)	1	3	4
Total		**31**	**42**	**53**

Lithium-ion	LMO-G	US$/kWh		
		Min	*Mid*	*Max*
Nickel	Cathode	10	21	38
Cobalt	Cathode	5	6	8
Aluminium	Cathode	0	0	0
Lithium hydroxide	Cathode	2	2	2
Graphite	Anode	13	16	19
Carbon	Anode	1	1	1
Binder PVDF	Binder	1	1	1
Copper	Negative foil, interconnectors	2	4	6
Aluminium	Positive foil, bus bars, connectors	2	3	5
Lithium hexafluorophosphate	Electrolyte	1	1	2
Ethylene carbonate	Electrolyte	0	0	0
Dimethyl carbonate	Electrolyte	1	1	1
Plastics	Separator, Spacers, Housing	0	0	0
Steel	Module compression plates	0	0	0
Thermal insulation	Thermal insulation	1	1	1
Glycol	Coolant	0	0	1
Copper	Electronic Parts (Terminals, Regulators)	1	2	3
Total		**41**	**61**	**88**

A.8 Individual investment cost projections



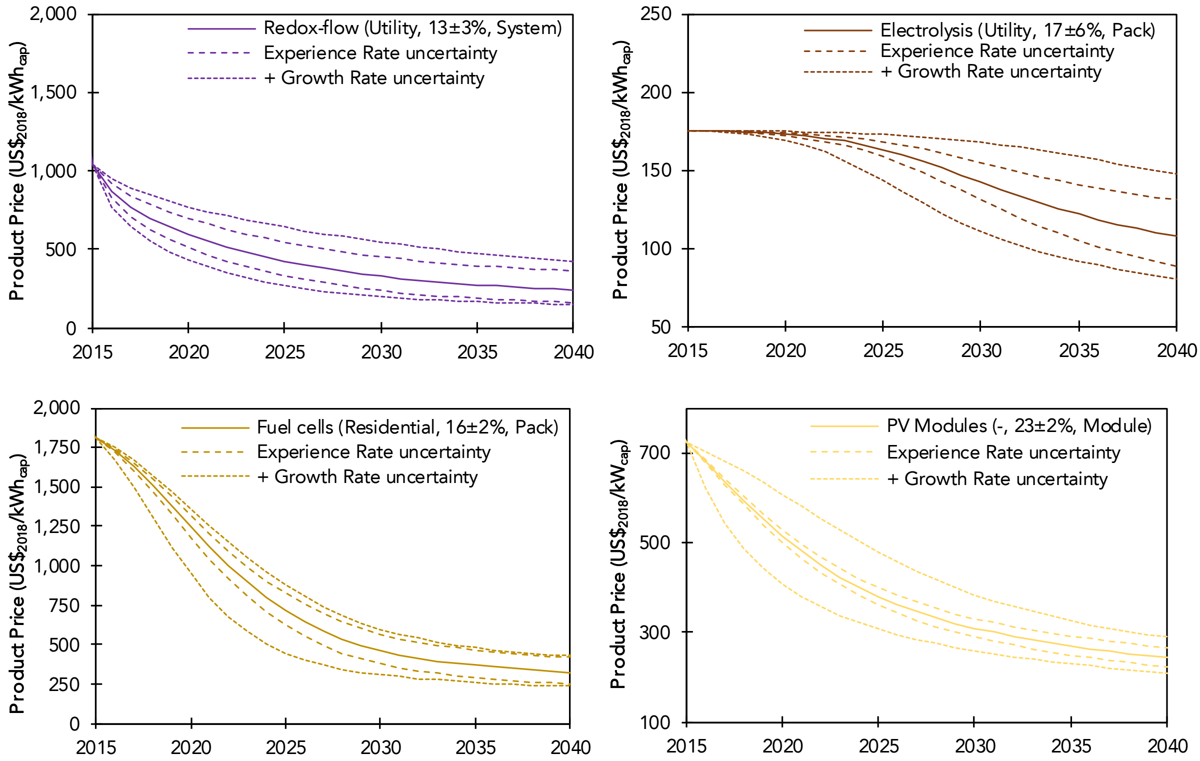


Figure A.5 – Technology-specific investment cost projections with experience and growth rate uncertainty.

A.9 Cumulative investment sensitivity to ER uncertainty

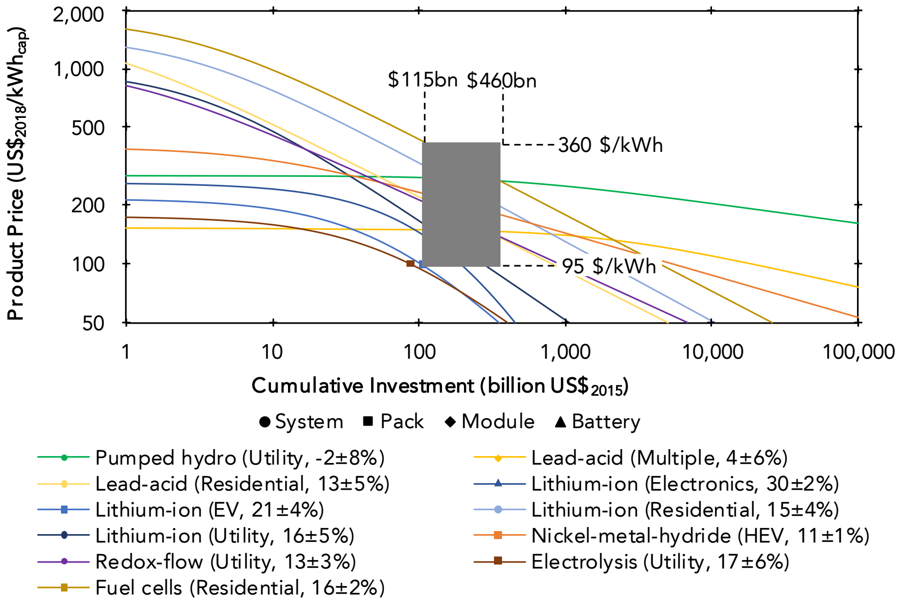


Figure A.6 – Impact of cumulative investment in EES deployment on future cost of EES (high experience rate). Graph shows investment in storage deployment required to "pull" technologies along their high individual experience curves. This investment could be consumer capital, industry capital, government subsidy or a mix of all. Shaded rectangle indicates investment required to reach prices of 95 – 360 US$/kWh. Symbols mark the amount of investment required to deploy 1 TWh cumulative capacity for each technology. No symbol means 1 TWh cumulative capacity is already deployed (pumped hydro, lead-acid modules). Legend denotes technology (including application and experience rate with uncertainty). Fuel cell and electrolysis must be considered in combination to form an EES technology. kWh_{cap} - nominal storage capacity. Symbols: circle – system, square – pack, diamond – module, triangle – battery.

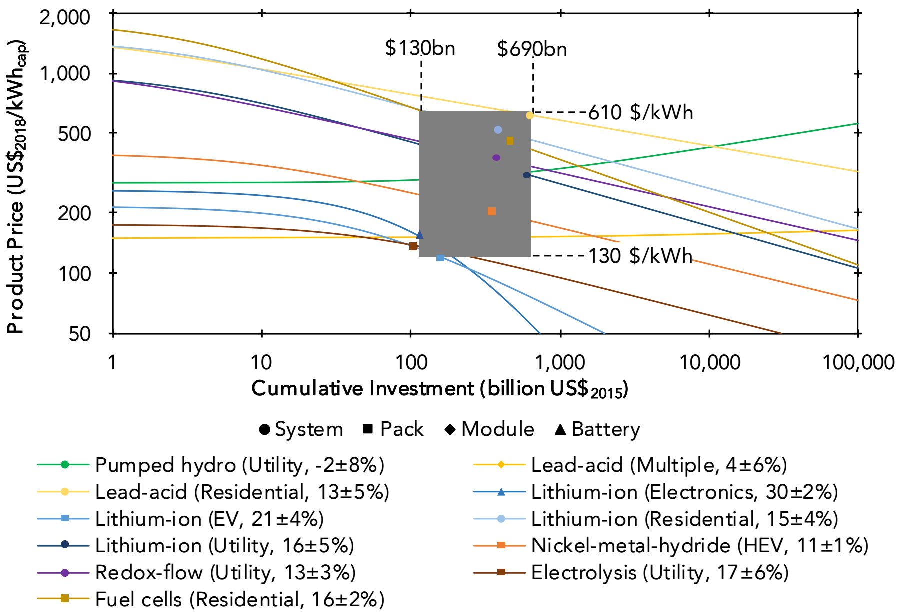


Figure A.7 – Impact of cumulative investment in EES deployment on future cost of EES (low experience rate). Graph shows investment in storage deployment required to "pull" technologies along their low individual experience curves. This investment could be consumer capital, industry capital, government subsidy or a mix of all. Shaded rectangle indicates investment required to reach prices of 130 – 610 US$/kWh. Symbols mark the amount of investment required to deploy 1 TWh cumulative capacity for each technology. No symbol means 1 TWh cumulative capacity is already deployed (pumped hydro, lead-acid modules). Legend denotes technology (including application and experience rate with uncertainty). Fuel cell and electrolysis must be considered in combination to form an EES technology. kWh_{cap} - nominal storage capacity. Symbols: circle – system, square – pack, diamond – module, triangle – battery.

B. Appendix to Chapter 5

B.1 Expert estimates for investment cost

Table B.1 — Expert estimates for water electrolyser investment cost.

Technology/ Percentile			2020 capital cost range (US$/kW)						2030 capital cost range (US$/kW)					
			R&D			RD&D			R&D			RD&D		
			1x	2x	10x	1x	2x	10x	1x	2x	10x	1x	2x	10x
AEC	90th	Max	2026	2026	1592	1953	1953	1302	1447	1447	1302	1157	1157	1085
		Min	1447	1302	1230	1302	1302	1157	1447	1447	1302	1157	1157	1085
	50th	Max	1881	1809	1302	1881	1809	1085	1085	1085	1013	796	796	723
		Min	1157	1157	1049	868	868	796	1085	1085	1013	796	796	723
	10th	Max	1736	1664	1157	1736	1664	1013	1013	1013	940	579	579	506
		Min	1013	1013	868	651	651	579	1013	1013	940	579	579	506
PEMEC	90th	Max	2170	2170	2151	1936	1936	1936	2170	2026	1881	1809	1809	1736
		Min	1881	1809	1447	1592	1519	1375	1447	1302	1157	1375	1230	1085
	50th	Max	1882	1882	1721	1694	1694	1549	1881	1614	1398	1375	1291	1119
		Min	1447	1375	1230	1157	1085	1013	1230	1085	868	796	723	579
	10th	Max	1614	1614	1291	1452	1452	1162	1592	1230	1076	1230	1013	861
		Min	1157	1085	1013	940	868	796	1013	868	723	506	506	362
SOEC	90th	Max	11575	11575	11575	5787	5643	5353	9839	9839	9839	5643	5498	5064
		Min	5787	5787	5787	5787	4630	3617	1809	1736	1157	1447	1302	1085
	50th	Max	7234	6511	6511	4341	3979	3617	6149	5534	5534	3617	3617	3183
		Min	4341	3979	3617	2894	2315	2026	1519	1447	940	1013	868	796
	10th	Max	5064	4341	4341	2894	2894	2749	4304	3689	3689	2749	2749	2170
		Min	3617	2894	2749	1736	1736	1447	1085	1085	723	723	579	434

Table B.2 — Expert estimates for lithium-ion battery pack investment cost.

Technology/ Percentile		2020 capital cost range (US$/kW)						2030 capital cost range (US$/kW)					
		R&D			RD&D			R&D			RD&D		
		1x	2x	10x	1x	2x	10x	1x	2x	10x	1x	2x	10x
90th	Max	696	636	636	696	583	572	542	480	449	480	449	371
	Min	212	212	191	212	191	138	159	117	85	159	106	85
50th	Max	650	542	495	619	433	433	464	402	371	402	371	325
	Min	175	175	148	175	143	101	106	90	58	106	80	53
10th	Max	542	464	418	542	356	356	387	325	294	325	294	248
	Min	106	106	85	106	85	53	53	42	21	53	32	21

B.2 Expert estimates for cycle lifetime

Table B.3 – Expert estimates for water electrolyser lifetime (hours).

Technology/ Percentile			Lifetime (hours) 2020 1x	2020 2x	2020 10x	2030 1x	2030 2x	2030 10x
AEC	10th	Max	110,000	115,000	120,000	80,000	80,000	82,500
		Min	80,000	80,000	80,000	80,000	80,000	82,500
	50th	Max	90,000	90,000	100,000	62,250	72,500	82,500
		Min	41,000	50,000	62,000	62,250	72,500	82,500
	90th	Max	80,000	80,000	80,000	40,000	40,000	40,000
		Min	40,000	40,000	40,000	40,000	40,000	40,000
PEMEC	10th	Max	85,000	90,000	90,000	100,000	100,000	110,000
		Min	80,000	80,000	80,000	80,000	80,000	82,500
	50th	Max	60,000	70,000	70,000	80,000	80,000	90,000
		Min	41,000	50,000	62,000	62,250	72,500	80,000
	90th	Max	45,000	50,000	55,000	65,000	65,000	65,000
		Min	40,000	40,000	40,000	40,000	40,000	40,000
SOEC	10th	Max	100,000	115,000	130,000	120,000	125,000	150,000
		Min	15,000	15,000	20,000	40,000	40,000	50,000
	50th	Max	70,000	85,000	95,000	90,000	105,000	115,000
		Min	9,000	10,000	11,000	30,000	35,000	35,000
	90th	Max	50,000	60,000	70,000	70,000	80,000	100,000
		Min	6,000	6,000	8,000	10,000	10,000	10,000

Table B.4 – Expert estimates for lithium-ion battery pack lifetime (charge-discharge cycles).

Technology/ Percentile		Lifetime (cycles) 2020 1x	2020 2x	2020 10x	2030 1x	2030 2x	2030 10x
10th	Max	20,000	20,000	20,000	40,000	50,000	1,000,000
	Min	2,000	2,500	3,000	3,000	3,000	4,500
50th	Max	15,000	15,000	15,000	25,000	25,000	30,000
	Min	1,500	2,000	2,000	2,000	2,400	3,250
90th	Max	7,500	8,000	10,000	15,000	17,500	20,000
	Min	1,000	1,000	1,000	1,000	1,600	2,000

B.3 Innovations for water electrolysers

Table B.5 – AEC system innovations as a result of R&D (innovations in bold were mentioned by multiple experts).

Impact	Area	Component	Innovation	Comment
Reduced capital cost	Cells		Increased current density	Up to 0.5 or 0.6 A/cm^2 by 2020
		Catalysts	**Better materials**	Mixed metal oxides,e.g., RuOx, IrOx; leads to increased current density due to higher reaction rates
		Electrodes	More stable electrode materials	
		Electrolyte	Electrolytes for high temperature operation	e.g., molten salts; by 2030
		Separator	New membrane	e.g., ion-solvating; ion-exchange; effect is higher current density (due to lower internal resistance)
	Stack		High pressure operation	effect is higher current density; by 2020
			Larger stack sizes	e.g., 200kW; by 2020
	System	Balance-of-Plant	Aq. KOH lye circulation loop	- improved system dynamics - lower cost
			Thermal management	
			Water purification	
		New set-up / chemistries	Zero-gap configuration	i.e., non-porous membrane, porous electrodes; effect is increased current density (due to lower internal resistance)
Longer lifetime	Cells	Electrodes	More stable electrodes	e.g., better materials, design, catalyst coating
	System		**Incremental improvements**	
		Balance-of-Plant	Improved water purification	Effect is less impurities (e.g., trace metals) in feed-water that plate onto electrodes and deactivate them
		New set-up / chemistries	Higher durability materials for zero-gap cells	
			New system configurations	Avoidance of impurity penetration (e.g., valves set-up)
Higher efficiency	Cells	Electrode	Improved design	optimise transport processes (e.g., electrons, ions, water, bubbles)
		Separator	Ion Exchange Membrane	e.g., Alkaline PEM
	System	Balance-of-plant	Lye circulation	
			Thermal management	
			Water purification	e.g., 3-5% system efficiency;
			Hydrogen drying	
			Rectification	e.g., 2-3% system efficiency with more expensive diodes
		Operation	Start/Stop procedure	Optimised depending on operation strategy
		New set-up / chemistries	Higher operating temperature	e.g., 200°C, by 2030
			Zero-gap configuration with state-of-the-art membrane/diaphragm	By 2030

Table B.6 – AEC system innovations as a result of production scale-up (innovations in bold were mentioned by multiple experts).

Impact	Area	Category	Innovation	Comment
Reduced capital cost	Manufacturing	Automation	From batch to roll-to-roll production	
			Robot assembly	
		Method	**Electrode coating process**	e.g., plasma method
		Scale	**Increased production rates**	Economies of scale with reduced overhead costs
			Larger unit sizes	less engineering work per kW and BoP scale effects
			Larger plant sizes	Reduced overhead costs
		Experience	Learning in manufacturing	Incremental improvements
	Supply chain	Volume	Volume purchasing agreements	e.g., materials, components, balance-of-plant
Longer lifetime	Manufacturing	Method	Manufacturing in clean rooms	Avoid impurity penetration

Table B.7 – PEMEC system innovations as a result of R&D (innovations in bold were mentioned by multiple experts).

Impact	Area	Component	Innovation	Comment
Reduced capital cost	Cell		**Increased current density**	Up to 3A/cm^2 by 2020
			Size scale up	scale effects in cell, stack and system components
		Catalyst	**Lower loading of Platinum-group metal catalysts**	Incremental reduction, up to -50% by 2020, e.g., due to more stable support (Ir/Ru not as blacks)
			New/Improved catalysts	e.g., Telluride, nano-catalysts
		Electrode	Structural improvements	Incremental up to 2030, enabling more efficient use of catalyst particles
			Improved coating	
		Membrane	Thinner	Incremental up to 2030
			Novel Chemistries	e.g., non-fluorinated/organic alternatives to Nafion
	Stack		Electrochemical pressurisation	Up to 100bar by 2030
			Differential pressure operation	
			Increased stack size	Reduces overall system footprint and costs
		Bipolar Plates	Reduction of titanium use	High conductivity coating on low-cost substrate e.g., steel instead of titanium; 10-20% cost reduction by 2020, up to 100% by 2030
			Optimised diffusor set-up	To enable mass transport at increased current densities
	System		**Combination and scale-up of system components due to operational de-risking/ increased operational confidence**	Safe operation with >200cells, e.g., combined and scaled cooling and water circulation
		Balance-of-Plant	More efficient water purification	
			Improved component integration	"good engineering", e.g., pumps, cooling
		Operation	**Optimised operation set points**	
		New set-up/ chemistries	Alkaline Polymer Systems	
			Novel stack designs	e.g., rotating systems
			Design for high pressure operation	new stack concepts
Longer lifetime	Cell	Catalyst	Improved durability	
		Electrode	Structural improvements	Electrode design and/or coating reduces movement/deactivation of active catalyst particles
		Membrane	**Higher physical stability**	Incremental
			Higher impurity tolerance	
	Stack	Bipolar Plates	Slower H2 embrittlement through more suitable coating	
	System	Balance-of-Plant	Improved water purification	
		New set-up/ chemistries	Avoidance of impurity penetration	e.g., valves set-up
Higher efficiency	Cell	Membrane	Thinner	
	Stack		Higher operating temperatures	~120°C in pressurised systems leading to 15 – 20% increase in stack efficiency and increase in cooling efficiency
	System	Balance-of-Plant	More efficient rectification through more expensive diodes	e.g., 2-3 % increase
			More efficient hydrogen purification	e.g., 3-5% increase

Table B.8 – PEMEC system innovations as a result of production scale-up (innovations in bold mentioned by multiple experts).

Impact	Area	Category	Innovation	Comment
Reduced capital cost	Manufacturing	Automation	**From batch to roll-to-roll production**	e.g., membrane electrode assembly (MEA)
			Improved process integration	
			Robot assembly	
		Method	Water/ laser cutting	e.g., sheets
			Stamping	e.g., bipolar plates

			Hydroforming	e.g., bipolar plates
			Layer-by-layer wielding	e.g., stack
			Plastic injection moulding	
		Scale	**Increased production rates**	Economies of scale with reduced overhead costs, in particular effect for MEA
			Larger unit sizes	less engineering work per kW and BoP scale effects
			Larger plant sizes	Reduced overhead costs
		Design	Design for manufacture and low costs	
			Bespoke BoP components	
			Component standardisation	Standards/codes between suppliers
		Experience	Learning in manufacturing	Incremental improvements
	Supply chain	Volume	Volume purchasing agreements	
		Competition	**Stronger supplier competition**	e.g., membrane electrode assembly (MEA)
Longer lifetime	Manufacturing	Method	Manufacturing in clean rooms	Avoid impurity penetration

Table B.9 – SOEC system innovations as a result of R&D (innovations in bold were mentioned by multiple experts).

Impact	Area	Component	Innovation	Comment
Reduced capital cost	Cell		Higher power density	Due to thinner materials as result of better material processing methods (e.g., vapour deposition)
			Material-Microstructure combination / integration	optimise triple phase boundary network optimise oxygen transport
			Size scale-up	Larger cell area
		Catalyst	Alternatives for Nickel and Cobalt	
		Electrodes	Reduce polarisation resistance	Enable lower operating temperatures (~450°C); positive effects on lifetime
			Replace Ni-YSZ with stainless steel	
		Membrane	Proton conducting materials	
	System		**Leaner system engineering**	Result of field experience
			Improved system integration	
			Pressurised system	e.g., up to 40bar
		Balance-of-Plant	Optimised components and system integration	Result of lower operating temperature
		New set-up / chemistries	Proton conducting cell design	to produce dry H2 at high operating temperatures
			Reversible systems (electrolysis, fuel cell operation)	
Longer lifetime	Cell		More robust materials	As result of better material processing methods (e.g., vapour deposition)
			Material-Microstructure combination / integration	optimise triple phase boundary network optimise oxygen transport
		Electrodes	Reduce polarisation resistance	Enable lower operating temperatures (~450°C); positive effects on lifetime
	System	Operation	Optimised operation scheme	
			Methods for accelerated testing	
			Methods for in-situ monitoring	
Higher efficiency	Cell		Material-Microstructure combination / integration	optimise triple phase boundary network optimise oxygen transport
	System		Pressurised system	e.g., up to 40bar
			Leaner system engineering	Result of field experience
			Improved system integration	
		Balance-of-Plant	Optimised components and system integration	Result of lower operating temperature

Table B.10 – SOEC system innovations as a result of production scale-up (innovations in bold mentioned by multiple experts).

Impact	Area	Category	Innovation	Comment
Reduced capital cost	Manufacturing	Automation	From batch to roll-to-roll production	
		Method	Vapour deposition	High investment manufacturing technologies for low cost production (i.e., additive manufacturing)
			Laser printing	
			Typecasting	
			Screen printing	
			3D-printing	
			Thin-film technologies	
		Scale	**Increased production rates**	Economies of scale with reduced overhead costs
			Mass produced balance-of-system components	
	Supply chain	Volume	Volume purchasing agreements	e.g., materials, components, balance-of-plant
		Competition	More suppliers	
Longer lifetime	Manufacturing	Method	Improved material processing (e.g., vapour deposition)	

B.4 Innovations for lithium-ion batteries

Table B.11 – Lithium-ion battery innovations as a result of R&D (innovations in bold were mentioned by multiple experts).

Impact	Area	Component	Innovation	Comment
Reduced capital cost	Cell	Electrode	**Incremental chemistry change**	Optimise ratio of active species in electrodes for material cost and cathode voltage
			Cost-effective materials	Reduce content of expensive metals like cobalt; reduce cost of battery-grade graphite; Lithium-sulphur, lithium-air batteries (post-2030)
			Higher cathode voltage	High voltage means high energy density; Nickel-content leads to higher cathode voltage
			Add silicon to graphite anode	Silicon has higher energy density than graphite, e.g., can storage more lithium ions per mass
		Electrolyte	Aqueous electrolyte	Low-cost saline solution electrolyte
			Solid electrolyte	Polymer or ceramic electrolyte resisting high discharge voltage leading to high energy density
			New additives	Support electrolyte to resist higher discharge voltages
		Binder	Lower cost materials	-
		Separator	Thinner materials	e.g., cellulose
		-	New cell format	Higher energy density and material efficiency through improved cell format
			Increasing cell size	Higher material efficiency
	Module	Battery Management System	**Standardization**	Standardised systems are more cost-effective than individually designed
		-	**Improved packaging**	-
	System	-	Improved sizing	Operational experience leading to improved sizing of energy capacity and thermal mgmt
Longer lifetime	Cell	Electrode	Higher stability materials	Materials enabling high voltage discharge while being stable
		Electrolyte	New additives	Support electrolyte to resist higher discharge voltages
			Solid electrolyte	Polymer or ceramic less susceptible to degradation and more resistant to high discharge voltages
		-	**New cell format**	Larger cells are less susceptible to mechanical degradation arising from volume changes during charge-discharge operation
	Module	Thermal Management	Water cooling	More efficient cooling process reduces heat development and degradation
			Improved cooling efficiency	See above
		Battery Management System	**Improved operation pattern**	Based on better understanding of how usage patterns affect degradation (e.g., discharge rate; state-of-charge, depth-of-discharge, temperature)
	System	-	More integrated design	-

Table B.12 – SOEC system innovations as a result of production scale-up (innovations in bold mentioned by multiple experts).

Impact	Area	Category	Innovation	Comment
Reduced capital cost	Manufacturing	Automation	**Increased automation**	-
		Method	Spray deposition	e.g., spray coating of anodes
			Higher speed	-
		Experience	**Learning-by-doing**	Incremental efficiency improvements
			Scale	Larger factories
		Design	**Standardisation**	Standardised chemistries and geometries
	Supply-chain	Volume	Cheaper logistics	Lower relative cost for transport
			Cheaper suppliers	Bulk discount

C. Appendix to Chapter 6

C.1 Optimal depth-of-discharge values

Table C.1 – Optimal depth-of-discharge in various applications and years for lithium-ion systems.

Lithium ion	2015	2020	2025	2030	2035	2040	2045	2050
Bill Management	77%	77%	77%	77%	80%	80%	80%	80%
Black Start	100%	100%	100%	100%	100%	100%	100%	100%
Congestion Management	92%	92%	92%	92%	92%	92%	92%	92%
Energy Arbitrage	92%	92%	92%	92%	92%	92%	92%	92%
Peaker Replacement	100%	100%	100%	100%	100%	100%	100%	100%
Power Quality	100%	100%	100%	100%	100%	100%	100%	100%
Power Reliability	100%	100%	100%	100%	100%	100%	100%	100%
Primary Response	45%	45%	45%	45%	45%	45%	45%	45%
Seasonal Storage	100%	100%	100%	100%	100%	100%	100%	100%
Secondary Response	57%	57%	57%	63%	67%	67%	67%	67%
T&D Investment Deferral	92%	92%	92%	92%	92%	92%	92%	92%
Tertiary Response	100%	100%	100%	100%	100%	100%	100%	100%

Table C.2 – Optimal depth-of-discharge in various applications and years for sodium-sulphur systems.

Sodium sulphur	2015	2020	2025	2030	2035	2040	2045	2050
Bill Management	100%	100%	100%	100%	100%	100%	100%	100%
Black Start	100%	100%	100%	100%	100%	100%	100%	100%
Congestion Management	100%	100%	100%	100%	100%	100%	100%	100%
Energy Arbitrage	96%	96%	100%	100%	100%	100%	100%	100%
Peaker Replacement	100%	100%	100%	100%	100%	100%	100%	100%
Power Quality	100%	100%	100%	100%	100%	100%	100%	100%
Power Reliability	100%	100%	100%	100%	100%	100%	100%	100%
Primary Response	64%	64%	64%	64%	64%	64%	64%	64%
Seasonal Storage	100%	100%	100%	100%	100%	100%	100%	100%
Secondary Response	100%	100%	100%	100%	100%	100%	100%	100%
T&D Investment Deferral	96%	96%	96%	96%	96%	100%	100%	100%
Tertiary Response	100%	100%	100%	100%	100%	100%	100%	100%

Table C.3 – Optimal depth-of-discharge in various applications and years for lead-acid systems.

Lead-acid	2015	2020	2025	2030	2035	2040	2045	2050
Bill Management	80%	80%	80%	80%	80%	80%	80%	80%
Black Start	100%	100%	100%	100%	100%	100%	100%	100%
Congestion Management	96%	96%	96%	96%	96%	96%	96%	96%
Energy Arbitrage	96%	96%	96%	96%	96%	96%	96%	96%
Peaker Replacement	100%	100%	100%	100%	100%	100%	100%	100%
Power Quality	100%	100%	100%	100%	100%	100%	100%	100%
Power Reliability	100%	100%	100%	100%	100%	100%	100%	100%
Primary Response	100%	100%	100%	100%	100%	100%	100%	100%
Seasonal Storage	100%	100%	100%	100%	100%	100%	100%	100%
Secondary Response	61%	61%	61%	61%	61%	61%	61%	61%
T&D Investment Deferral	96%	96%	96%	96%	96%	96%	96%	96%
Tertiary Response	100%	100%	100%	100%	100%	100%	100%	100%

C.2 Cycle life relative to depth-of-discharge

Table C.4 – Technology cycle life relative to depth-of-discharge (DoD).

Depth-of-Discharge	Pumped hydro	Compres-sed air	Flywheel	Lithium-ion	Sodium-sulphur	Lead-acid	Vanadium redox-flow	Hydrogen	Super-capacitor
100%	33,250	16,250	143,402	3,250	4,098	1,225	8,272	20,000	300,000
90%	33,250	16,250	143,402	4,875	4,131	1,336	8,272	20,000	300,000
80%	33,250	16,250	143,402	6,297	4,193	1,501	8,272	20,000	300,000
70%	33,250	16,250	143,402	8,531	4,592	1,763	8,272	20,000	300,000
60%	33,250	16,250	143,402	10,766	5,299	2,074	8,272	20,000	300,000
50%	33,250	16,250	143,402	14,219	6,006	2,598	8,272	20,000	300,000
40%	33,250	16,250	143,402	18,586	7,050	3,194	8,272	20,000	300,000
30%	33,250	16,250	143,402	24,984	8,516	4,211	8,272	20,000	300,000
20%	33,250	16,250	143,402	35,953	10,654	6,316	8,272	20,000	300,000
10%	33,250	16,250	143,402	60,734	21,325	13,183	8,272	20,000	300,000
Source				[390]	[391]	[76]			

C.3 Electricity storage services overview

Table C.5 – Review of 27 unique-purpose electricity storage services. Display of alternative names and allocation to core services based on similar technical requirements.

Application	Description	Alternative name	Core application
Wholesale arbitrage	Purchase power in low-price periods and sell in high price periods on the energy wholesale market[65]	Electric Energy Time-shift	Energy arbitrage
Retail arbitrage	Purchase power in low-price periods and sell in high price periods on the energy retail market[65]	End-consumer arbitrage	Energy arbitrage
Regulating reserve	Automatically correct the continuous, fast, frequent changes in load or generation within the shortest applicable market interval[164]	Frequency regulation, Frequency control	Primary response
Primary reserve	Automatically stabilise frequency after rare, sudden change in load or generation[164]	Primary contingency reserve, Frequency response	Primary response
Following reserve	Manually correct anticipated imbalances between load and generation[164]	Load following, Balancing reserve	Secondary response
Secondary reserve – spinning	Automatically return frequency to nominal with operating generator[73] after rare, sudden change in load or generation	Spinning reserve	Secondary response
Secondary reserve – non-spinning	Automatically return frequency to nominal after rare, sudden change in load or generation with non-operating generator[73]	Secondary contingency reserve, Non-spinning reserve	Secondary response
Ramping reserve	Manually correct for unexpected, severe, infrequent and non-instantaneous[164] changes in load or generation	-	Secondary response
Renewables smoothing	Change output from variable supply resources when generation is out of line with forecasts[392]	Correct for forecasting inaccuracy	Secondary response
Tertiary reserve	Automatically replace primary and secondary contingency reserve[164]	Tertiary contingency reserve, Supplemental / Replacement reserve	Tertiary response
Peaker replacement	Ensure availability of sufficient generation capacity at all times[65]	Capacity mechanism, Electric supply/System capacity, Microgrid	Peaker replacement
Black start	Restore power plant operations after network outage without external power supply[65]	-	Black start
Seasonal storage	Compensate longer-term supply disruption or seasonal variability in supply and demand[24]		Seasonal storage
Transmission upgrade deferral	Defer transmission infrastructure upgrades required when peak power flows exceed existing capacity[65]	Transmission support, Network efficiency	T&D deferral
Distribution upgrade deferral	Defer distribution infrastructure upgrades required when peak power flows exceed existing capacity[65]	Distribution substation, Network efficiency	T&D deferral
Congestion relief	Avoid risk of overloading existing infrastructure that could lead to re-dispatch and local price differences[65]	Transmission support, Network efficiency	Congestion management
Bill management	Purchase power in low-price periods and use during high-price periods[65]	Energy management, Retail ToU charges	Bill management
Demand charge reduction - R	Reduce demand supplied by the network during periods of highest retail network charges[65]	Peak reduction, Retail demand charges	Bill management
Demand charge reduction - D	Reduce demand supplied by the network during periods of highest distribution network cost[392]	Peak reduction, Red zone management	Bill management
Demand charge reduction - T	Reducing demand supplied by the network during periods of highest transmission network cost[392]	Peak reduction, Triads, Transmission access charges	Bill management
Renewable energy self-consumption	Minimise export of renewable electricity and increase self-consumption to maximise financial benefits[27]		Bill management
Power quality	Protect on-site load against short-duration power loss or variations in voltage or frequency[65]		Power quality
Power reliability	Fill gap between variable resource and demand[24]	Off-grid, On-site power	Power reliability
Backup power	Provide sustained power during total loss of power from source utility[65]	Home backup, Emergency supply, Resiliency	Power reliability
Renewables firming	Change and optimise output from variable supply resources to mitigate output changes and match supply with demand[24]	Off-peak storage, Variable resource integration, On-site generation shifting	Power reliability
Voltage support	Maintain voltage levels across networks via reactive power supply/reduction[65]	-	-
VAR support	Maintain voltage levels across transmission network via reactive power supply/reduction[73]	-	-

C.4 Relative investment cost projections

Table C.6 – Investment cost projections relative to 2015 with forecast uncertainty.

	2015	2020	2025	2030	2035	2040	2045	2050	Comment
Pumped hydro	100% (0%)	100% (0%)	100% (1%)	100% (3%)	101% (6%)	101% (8%)	102% (10%)	102% (12%)	Original
Compressed air	100% (0%)	100% (0%)	100% (1%)	100% (3%)	101% (6%)	101% (8%)	102% (10%)	102% (12%)	Same as pumped hydro
Flywheel	100% (0%)	84% (3%)	66% (6%)	53% (8%)	44% (10%)	39% (11%)	36% (10%)	33% (10%)	Same as hydrogen
Lithium-ion	100% (0%)	55% (12%)	34% (14%)	23% (13%)	18% (12%)	16% (10%)	15% (10%)	14% (9%)	Original
Sodium-sulphur	100% (0%)	84% (3%)	66% (6%)	53% (8%)	44% (10%)	39% (11%)	36% (10%)	33% (10%)	Same as hydrogen
Lead-acid	100% (0%)	80% (5%)	68% (6%)	63% (5%)	61% (5%)	59% (4%)	59% (4%)	58% (5%)	Original
Vanadium redox-flow	100% (0%)	49% (15%)	34% (16%)	26% (14%)	21% (12%)	19% (11%)	18% (10%)	17% (9%)	Original
Hydrogen	100% (0%)	84% (3%)	66% (6%)	53% (8%)	44% (10%)	39% (11%)	36% (10%)	33% (10%)	Original
Supercapacitor	100% (0%)	84% (3%)	66% (6%)	53% (8%)	44% (10%)	39% (11%)	36% (10%)	33% (10%)	Same as hydrogen

C.5 Standard deviations for investment cost

Table C.7 – Combined standard deviations for investment cost parameters.

Investment cost - Power	2015	2020	2025	2030	2035	2040	2045	2050
Pumped hydro	45%	45%	45%	45%	45%	45%	46%	46%
Compressed air	35%	35%	35%	35%	35%	36%	36%	36%
Flywheel	17%	17%	19%	23%	29%	32%	33%	34%
Lithium-ion	17%	28%	45%	59%	65%	67%	67%	68%
Sodium-sulphur	27%	28%	29%	32%	36%	39%	40%	41%
Lead-acid	23%	24%	24%	24%	24%	24%	24%	24%
Vanadium redox-flow	21%	37%	51%	59%	61%	60%	58%	57%
Hydrogen	48%	48%	49%	51%	53%	55%	56%	57%
Supercapacitor	31%	31%	32%	35%	39%	41%	42%	43%
Investment cost - Energy								
Pumped hydro	63%	63%	63%	63%	63%	63%	64%	64%
Compressed air	58%	58%	58%	58%	59%	59%	59%	59%
Flywheel	67%	67%	67%	69%	71%	72%	73%	73%
Lithium-ion	24%	33%	48%	61%	67%	69%	70%	70%
Sodium-sulphur	12%	13%	15%	20%	26%	30%	31%	32%
Lead-acid	38%	38%	39%	38%	38%	38%	38%	38%
Vanadium redox-flow	17%	35%	49%	58%	60%	58%	57%	56%
Hydrogen	60%	60%	60%	62%	64%	66%	66%	67%
Supercapacitor	19%	19%	20%	24%	30%	33%	34%	35%

D. Appendix to Chapter 7

D.1 75th and 25th percentile market values

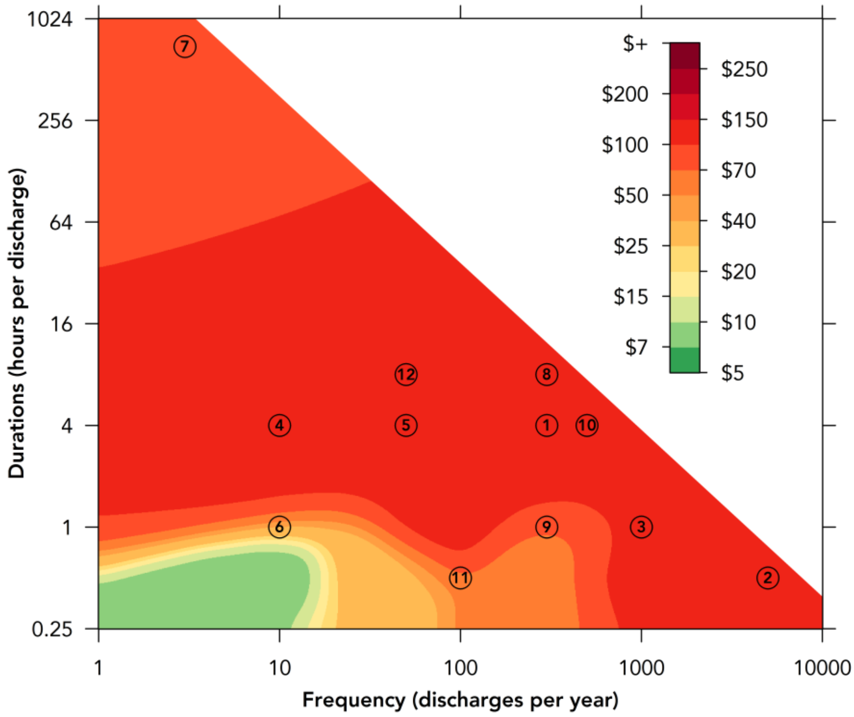


Figure D.1– Highest 75th percentile of economic market value for electricity storage power capacity in US$/$kW_{year}$ in applications with various discharge duration and cycle frequency combinations.

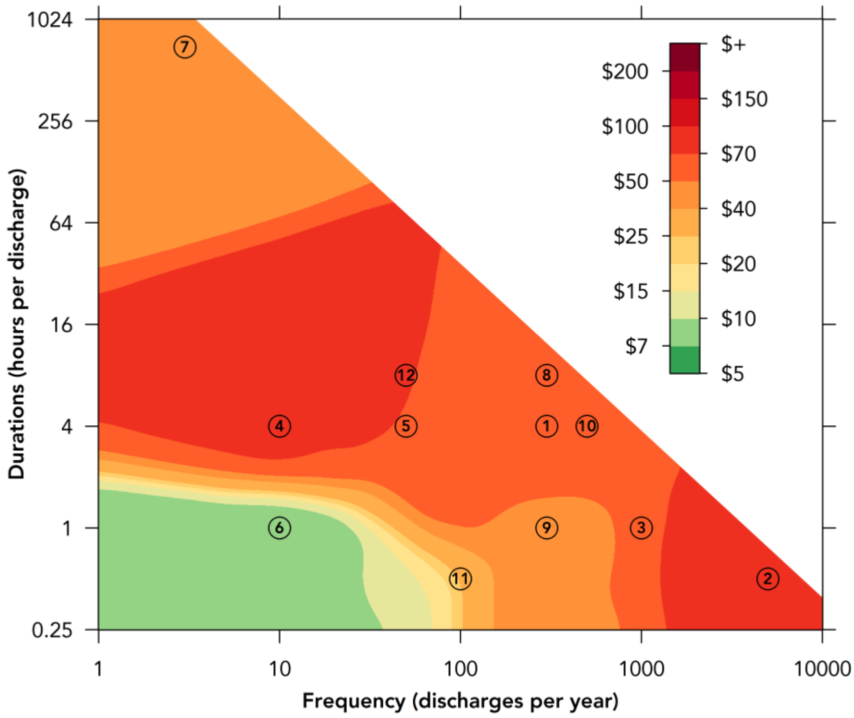


Figure D.2 – Lowest 25th percentile of economic market value for electricity storage power capacity in US$/$kW_{year}$ in applications with various discharge duration and cycle frequency combinations.

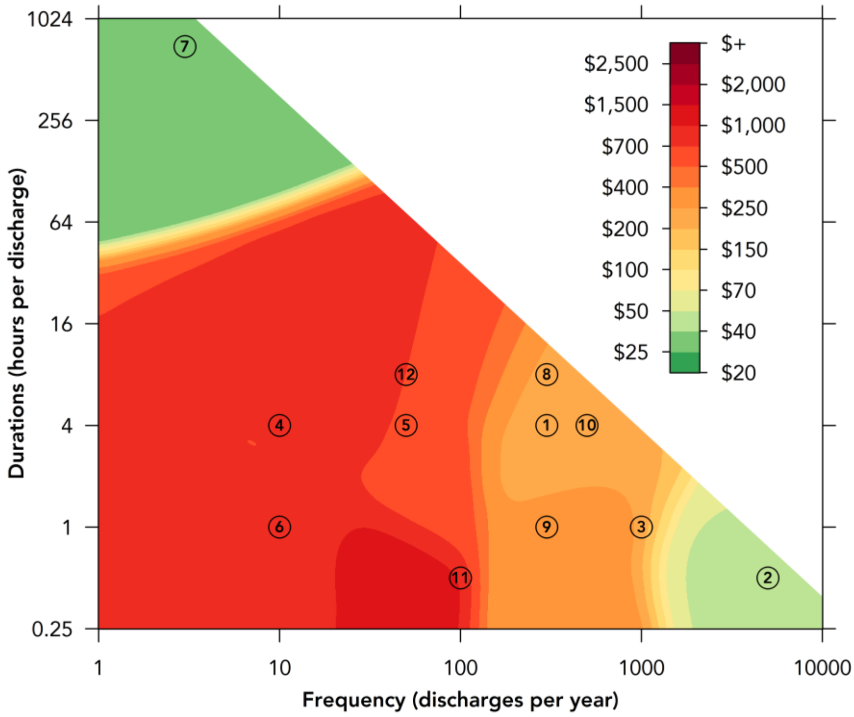


Figure D.3 – Highest 75th percentile of economic market value for electricity storage energy capacity in US$/MWh in applications with various discharge duration and cycle frequency combinations.

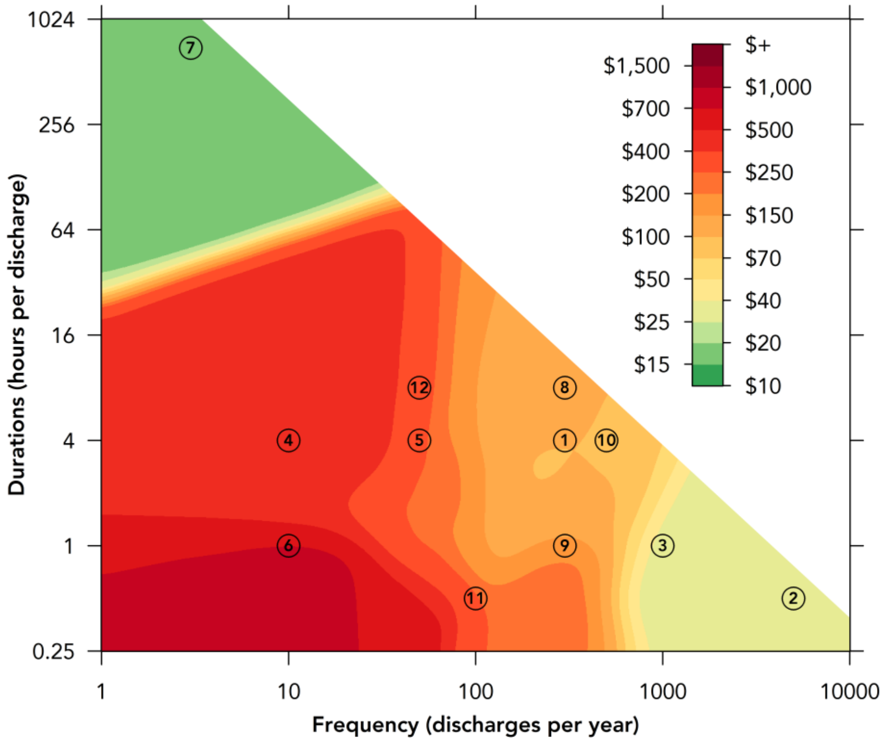


Figure D.4 – Lowest 25th percentile of economic market value for electricity storage energy capacity in US$/MWh in applications with various discharge duration and cycle frequency combinations.

D.2 Alternative approach for market value assessment

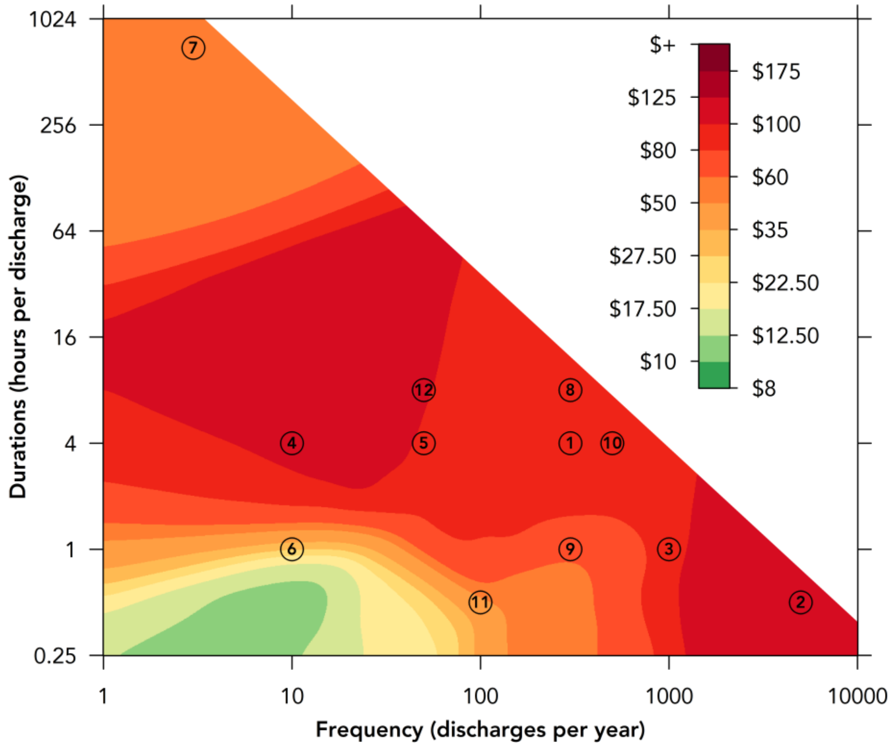


Figure D.5 – Economic market value for electricity storage power capacity based on Monte-Carlo simulation with random distribution of values between 25th and 75th percentiles of given market values.

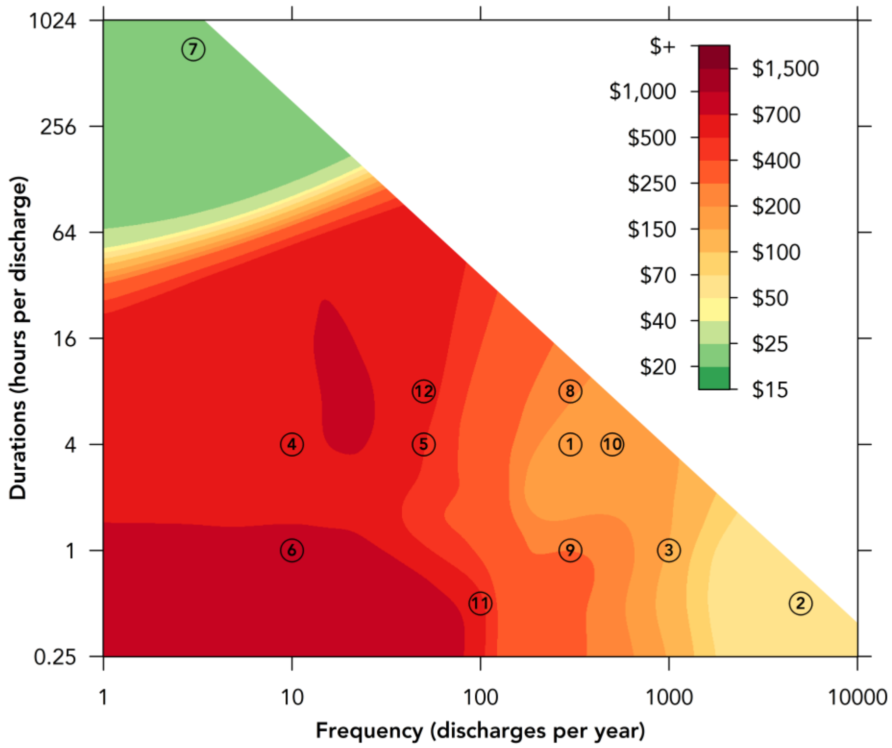


Figure D.6 – Economic market value for electricity storage power capacity based on Monte-Carlo simulation with random distribution of values between 25th and 75th percentiles of given market values.

D.3 Modelled market values for core applications

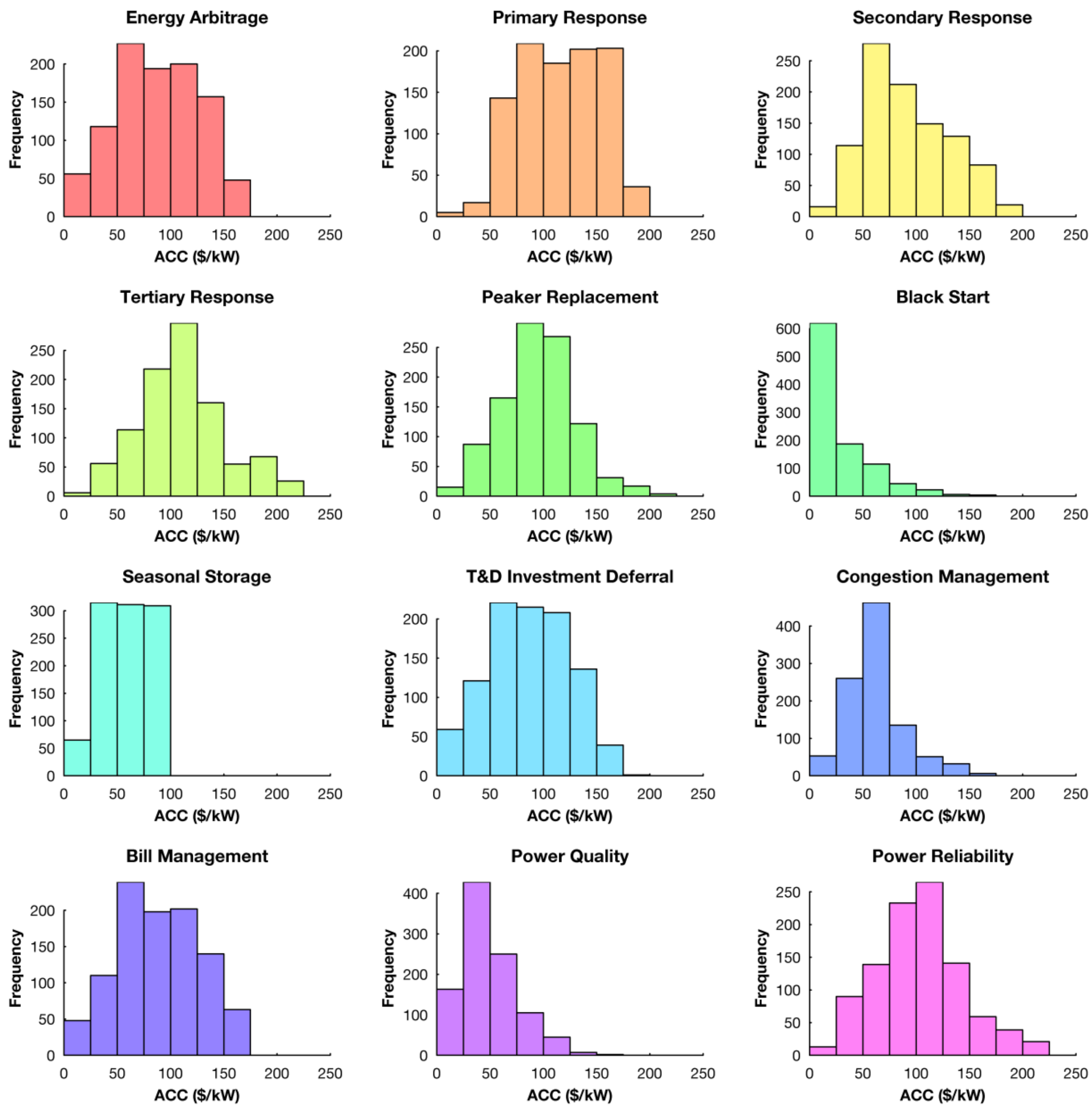


Figure D.7 – Distribution of market values for power provision (US$/kW$_{year}$) for 12 core services in 1,000 trial Monte Carlo simulation.

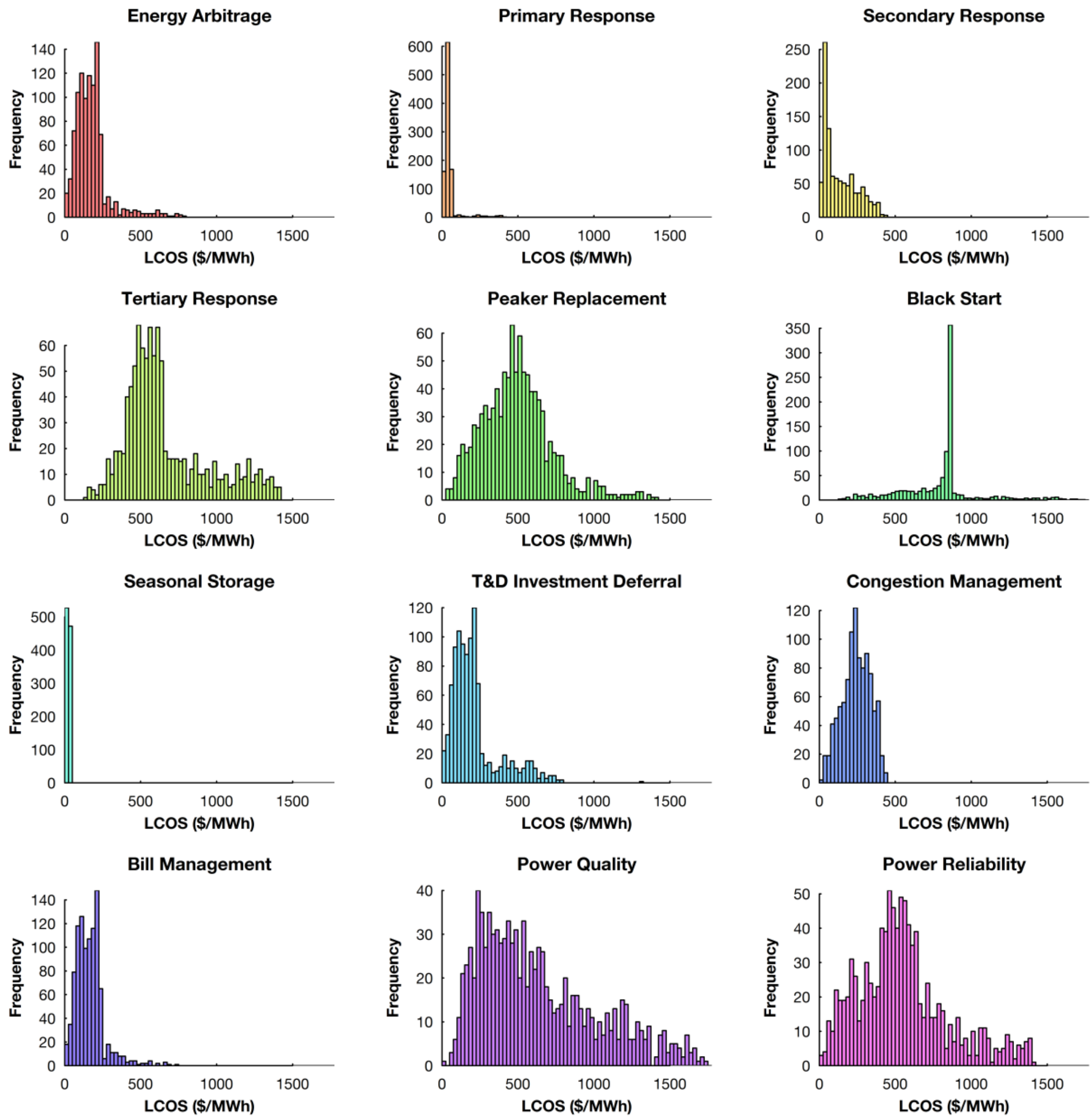


Figure D.8 – Distribution of market values for discharged energy (US$/MWh) for 12 core services in 1,000 trial Monte Carlo simulation.

D.4 Dispatchable capacity margin

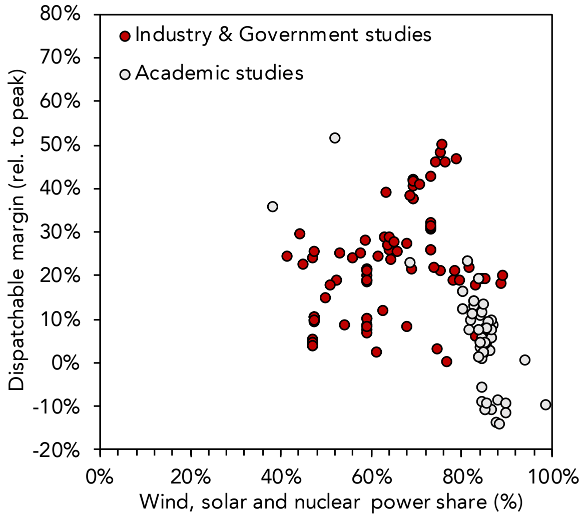


Figure D.9 – Dispatchable capacity margin relative to peak demand as a function of wind, solar and nuclear power penetration. Dispatchable refers to all generation capacity except wind and solar. Data differentiated along commissioning institution. Industry & Government: BEIS, BNEF, CCC, Carbon Trust, National Grid. Academia: Heuberger et al., Edmunds et al., Pfenninger et al., Price et al., Zeyringer et al.

D.5 Total capacity relative to wind and solar capacity

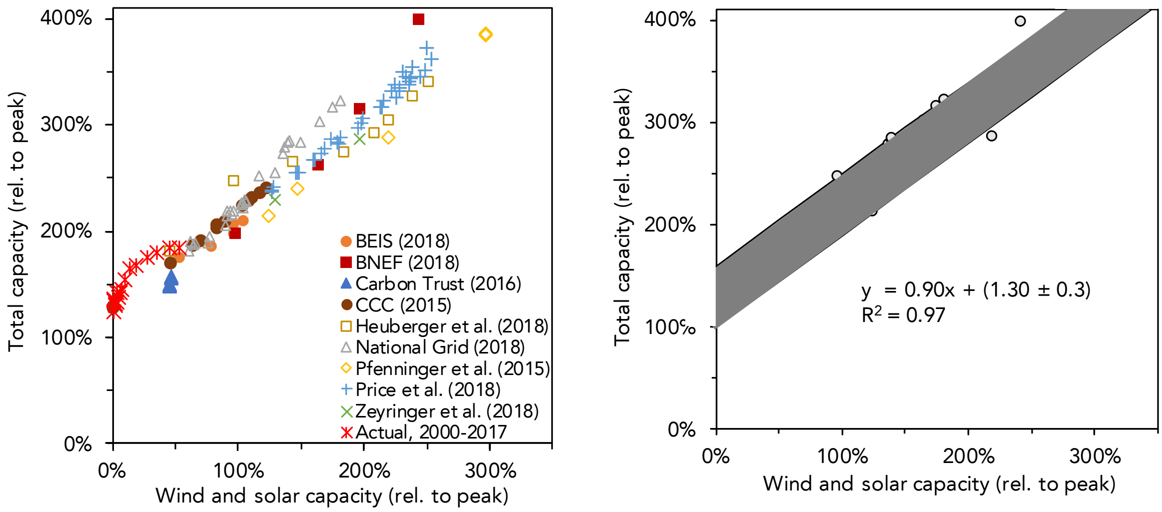
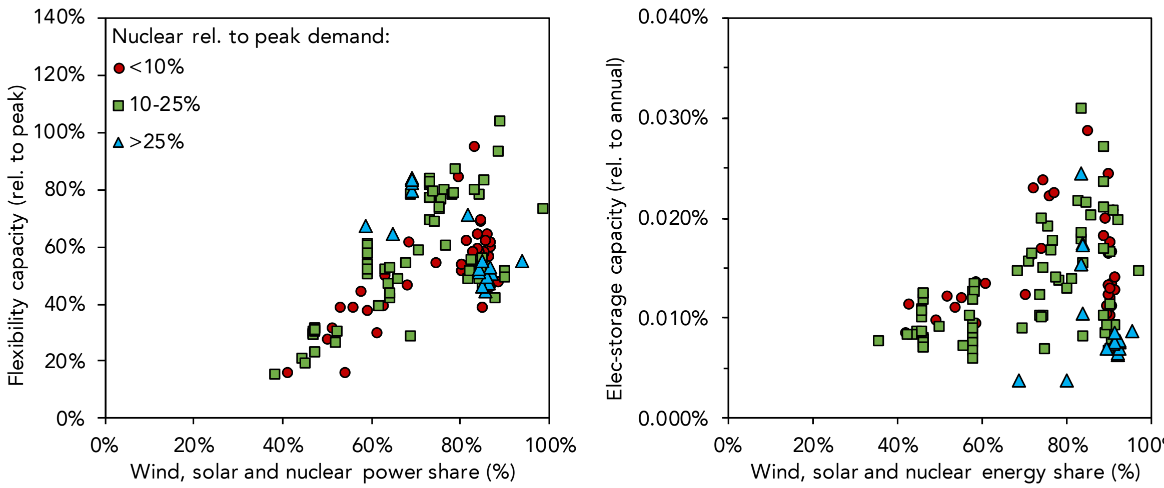


Figure D.10 – Total installed power capacity as a function of wind and solar capacity. Left: Individual GB power system studies. Right: Combined data for analysis. Shaded area represents linear fit to data set with uncertainty.

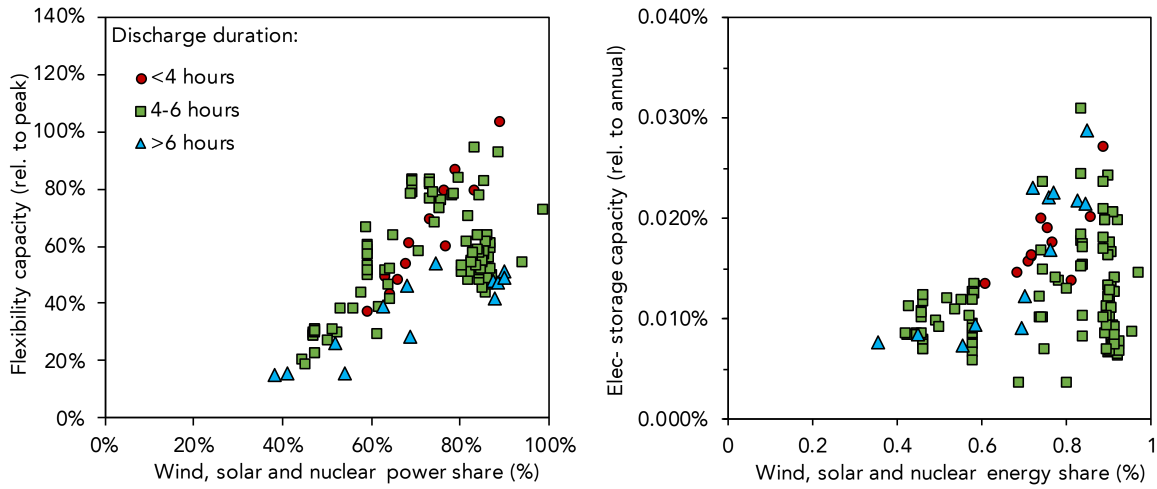
D.6 Impact of system portfolio on flexibility requirements

Table D.1 – Impact of power system and technology characteristics on flexibility capacity requirements. Analysed variables are nuclear share in power portfolio, electricity storage discharge duration and wind / solar ratio.

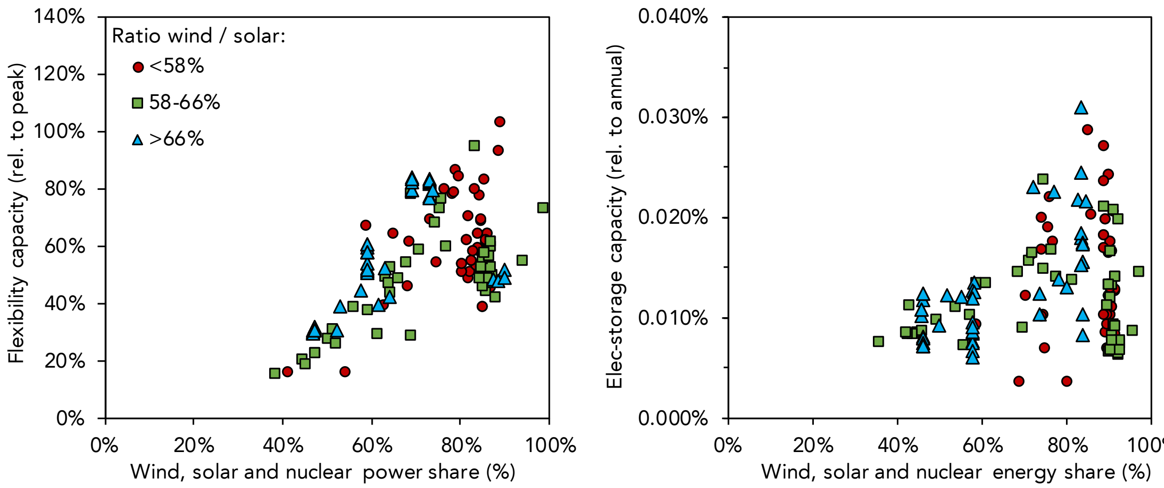
Share of nuclear power



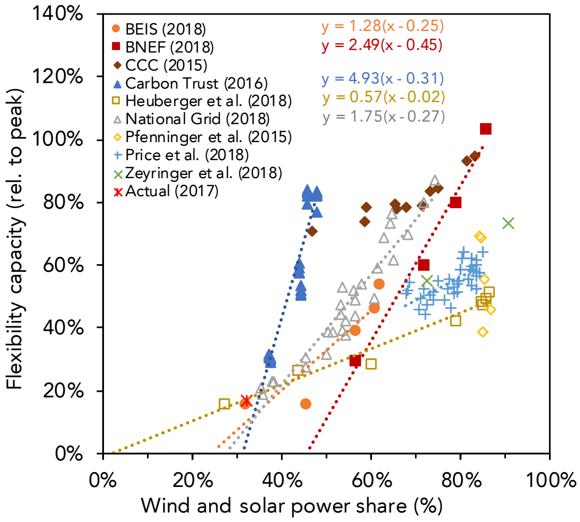
Electricity storage discharge duration



Type of renewable energy technology



D.7 Flexibility capacity relative to wind and solar share



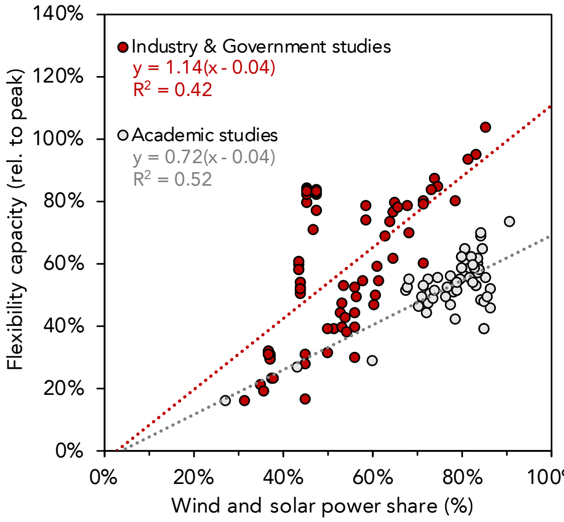


Figure D.11 – Analysis of flexibility capacity requirements relative to peak demand and as a function of wind and solar power penetration for the GB power system. Left: Results from individual studies. Right: Differentiation of studies along commissioning institution. Trendlines in left panel displayed for data series with more than two data points and coefficient of determination of $R^2 \geq 0.85$. Trendline formulae in both panels displayed in respective colour code. Negative term in bracket denotes trendline intersection with x-axis. Trendline coefficients of determination (R^2) shown in right panel only. Two data points of the CCC (2015)[189] study at 0% wind and solar power share are removed. Industry & Government: BEIS (2018)[187], BNEF (2018)[188], Carbon Trust (2016)[20], CCC (2015)[189], National Grid (2018)[192]. Academia: Edmunds et al. (2014)[190], Heuberger et al. (2018)[191], Pfenninger et al. (2015)[193], Price et al. (2018)[194], Zeyringer et al. (2018)[195].

Permission table

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18	Figure	Figure 1.1	Core Writing Team, R.K. Pachauri & L.A. Meyer (eds.). Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. (IPCC, 2014).	© Intergovernmental Panel on Climate Change, 2015	-	yes	"Short extracts from this publication may be reproduced without authorization provided that complete source is clearly indicated."
29	Figure	Figure 2.3	Hajforoush, M., Madandoust, R. & Kazemi, M. Effects of simultaneous utilization of natural zeolite and magnetic water on engineering properties of self-compacting concrete. Asian J. Civ. Eng. 20, 289–300 (2019).	© Springer Nature Switzerland AG 2018	06.05.2019	yes	License Number: 4583230306116 via Copyright Clearance Center, Inc.
34	Figure	Figure 2.9	Bosch batteries for leisure and lighting. Available at: http://br.bosch-automotive.com/en/internet/parts/parts_and_accessories_2/specials_1/leisure/batteries_6/batteries_leisure_special_parts.html. (Accessed: 27th February 2019)	© Robert Bosch Ltda. 2019	06.05.2019	yes	Confirmation e-mail by Francesca Herdahl Thorsing from Bosch on 24.09.2019 Ticket#2019050693012553231
35	Figure	Figure 2.10	Liu, C., Neale, Z. G. & Cao, G. Understanding electrochemical potentials of cathode materials in rechargeable batteries. Mater. Today 19, 109–123 (2016).	© 2015 The Authors. Published by Elsevier Ltd.	-	yes	Attribution-NonCommercial-NoDerivatives 4.0 International (CC BY-NC-ND 4.0)
36	Figure	Figure 2.12	Hannan, M. A., Hoque, M. M., Mohamed, A. & Ayob, A. Review of energy storage systems for electric vehicle applications: Issues and challenges. Renew. Sustain. Energy Rev. 69, 771–789 (2017).	© 2016 Elsevier Ltd. All rights reserved.	06.05.2019	yes	License Number: 4583240815014 via Copyright Clearance Center, Inc.
37	Figure	Figure 2.13	Li, L., Kim, S., Wang, W., Vijayakumar, M., et al. A New Vanadium Redox Flow Battery Using Mixed Acid Electrolytes US DOE Energy Storage Systems (ESS) Program Review Washington DC. (2010).	© Pacific Northwest National Laboratory	06.05.2019	yes	Confirmation e-mail of Peter C. Christensen, Deputy Director for Licensing at PNNL on 06.05.2019 at 11:15pm (BST)
38	Figure	Figure 2.14	Guerra, M. Can Supercapacitors Surpass Batteries for Energy Storage? | Electronic Design. 2016 Available at: https://www.electronicdesign.com/power/can-supercapacitors-surpass-batteries-energy-storage. (Accessed: 27th February 2019)	© 2016 IntechOpen Limited	-	yes	Attribution 3.0 Unported (CC BY 3.0)