The positives and negatives of stationary battery life cycle assessments

Recommendations for modelling the use phase in stationary battery LCA studies from a critical review of current approaches in LCA studies and an LCA of an emerging organic lignin based redox flow battery

GUDO WISSELO

MASTER'S THESIS

August 2023

MSc Industrial Ecology
Leiden University & Delft University of Technology

The positives and negatives of stationary battery life cycle assessments

Recommendations for modelling the use phase in stationary battery LCA studies from a critical review of current approaches in LCA studies and an LCA of an emerging organic lignin based redox flow battery

in partial fulfilment of the requirements for the degree of

Master of Science in Industrial Ecology

by

Gudo Wisselo

August 2023

G. (Gudo) Wisselo

Student number Leiden University: 2389029
Student number Delft University of Technology: 4984862

Academic supervisors: Dr. C.F. Blanco Rocha
Institute for Environmental Sciences (CML), Leiden University

Prof. dr. ir. J.B. Guinée
Institute for Environmental Sciences (CML), Leiden University

Prof. dr.ir. W.J.G.M. Peijnenburg
Institute for Environmental Sciences (CML), Leiden University

Cover image from Doets Reizen (2023)

Preface

Before writing this thesis I was not an expert in battery technologies, which gave me doubts. I am still not an expert in this field, but this thesis gave me the opportunity to learn a lot about battery technologies, battery terminology and the complexity of this field. Getting acquainted with the different applications of stationary battery systems alone was very insightful for me. I came a long way, working on different projects to end with an extensive critical review of current approaches regarding modelling the use phase of stationary batteries in environmental assessments. The process of writing this thesis held up a mirror to me which made me learn a lot about myself. An important thing I learned is that you don't need to be able to do something to do it. This thesis has been written to obtain the master Industrial Ecology at the University of Leiden and Delft University of Technology. This research is mainly written for life cycle assessment practitioners who are tasked with performing lifecycle assessments of stationary battery systems.

I would like to thank some people who have supported me during writing this thesis, without whom it would have been impossible. First and foremost I would like to thank Petra. Without your help, listening, motivation and your insights about life, this thesis would not have been here. I would also like to thank Jeroen Guinée for his commitment to my work and support throughout the process I went through, his patience, thorough feedback and quick responses. He always kept me believing in myself. Furthermore, I would to thank Carlos Felipe Blanco Rocha for his feedback and our sometimes almost philosophical meetings. Even though his answers sometimes provoked even more questions, it made me look very critical at my own work and he gave me confidence in my own writings. I would also thank Willie Peijnenburg for his role as second supervisor. And last, but not least, I would like to thank my mother for her emotional support and for keeping believing in me during the whole process.

Gudo Wisselo

Veenendaal, August 2th, 2023

"Certainty is the enemy of growth. Nothing is for certain until it has already happened – and even then, it is still debatable."
– Mark Manson

Abstract

Introduction
Over 80% of worldwide electricity demand is expected to be supplied by renewables In 2050, of which wind energy and photovoltaics account for more than half. The mismatch between supply and demand resulting from these intermittent energy sources and the physical limits of the existing electrical grids are challenges in this transition, for which energy storage, particularly batteries, is part of the solution. Batteries serve other applications than storing renewable electricity as well. This results in a renewed interest to develop advanced and environmentally sound batteries, which requires assessing their environmental impacts by means of life cycle assessment (LCA). The environmental impacts of the production of batteries is increasingly assessed, however, the use phase, which is oftentimes excluded, and EOL phase are insufficiently addressed. Moreover, it is needed to incorporate the utilisation of a battery for multiple applications simultaneously, i.e., value stacking, in LCAs since this is emerging as a practical and economically beneficial operational strategy. The aim of this research is to gain insight into current approaches of modelling the use phase in LCAs of stationary battery systems in order to provide recommendations, improved approaches and focus areas. The research question is: *What are important considerations and how can these be included when modelling the use phase of a stationary battery system in a life cycle assessment?*

Methodology
A literature review is performed in which current approaches of modelling the use phase in stationary battery LCAs are analysed. This included 26 papers, Regulation (EU) No 2019/1020 Annex II and the PEFCRs for High Specific Rechargeable Batteries for Mobile Applications, hereinafter referred to as PEFCRs. Papers were reviewed on: application(s), FU, compared alternatives; use process modelling; and value stacking. Moreover, implications of incorporating value stacking in modelling the use phase are discussed in a qualitative way. Next, the relative effect on a battery's life cycle impact assessment (LCIA) scores of four issues identified in the literature review is analysed in an illustrative case study about an organic redox flow battery (ORFB).

Results
Key differences where found in the functional unit (FU) and system boundaries. FUs vary between studies and some do not include any discussion of a FU. Energy storage capacity is sometimes used in the FU, even though the function of a battery is delivering electricity. Several ambiguities are identified which relate to system boundaries: including electricity input or not; including electricity throughput or electricity losses; whether or not inverters are included and thus which battery efficiency is used; which application is served and whether or not impacts of displaced electricity are included. Value stacking is assessed in one study, but the results are ambiguous.

Relevant operational parameters and application characteristics to model the electricity and battery system inputs of the use process are the battery's nominal energy capacity, depth of discharge (DoD), round-trip efficiency, lifetime and annual cycle frequency for the application. Increased utilisation due to value stacking results in accelerated battery degradation which potentially reduces battery lifetime. When incorporating value stacking, the product system becomes multifunctional as applications are closely connected to the function, for which allocation and system expansion are identified as solutions. Moreover, modelling the use process is affected in four ways. Determining the nominal

energy capacity is questionable; it can be based on the sum of required energy capacities for distinct applications or on the required capacity for the primary application. The DoD might become higher, which could imply installing a higher energy capacity to reduce the DoD and increase the lifetime. An important question is how the energy (Wh) and power (W) capacities of the battery system are allocated to applications which depends on the technical compatibility of the battery and operational compatibility of applications and generally results from an optimisation algorithm. The cycle frequency increases, but is lower than the sum of cycle frequencies for individual applications, which should be corrected for when comparing systems. Finally, the lifetime might decrease; this only applies when the cycle lifetime becomes shorter than the calendar lifetime due to the increased cycle frequency.

ORFB LCIA scores for freshwater ecotoxicity, human toxicity and ozone layer depletion impact categories reduce considerably when the required cycle frequency of an application is increased. A reduction of battery lifetime results in higher LCIA scores for freshwater ecotoxicity, human toxicity and ozone layer depletion, but climate change and acidification impacts are not considerably affected because cradle-to-gate and end-of-life impacts contribute less to these categories. Altering the round-trip efficiency by 1% leads to a decrease of 1-3% of the five impact categories. Using an ORFB for multiple applications results in lower impact scores, but the reduction is smallest for the climate change and acidification categories. The reduction in climate change impact scores is similar when using a lithium-ion battery for multiple applications, in contrast to a valve regulated lead acid battery which does not result in environmental benefits due to its low cycle life. Storing renewable electricity in an ORFB and providing frequency regulation simultaneously considerably decreases impact scores in the climate change, freshwater ecotoxicity and acidification categories compared to using batteries for the distinct applications.

Conclusions and discussion

Many studies do not provide clear information on how the FU is specified, which application(s) the battery is utilised for, application characteristics, modelling assumptions including the electricity and battery inputs or complete LCI data. Overall, the degree of transparency of many battery LCA studies is mediocre which complicates judging the usefulness of results and should be improved to improve comparability and reproducibility for which recommendations are provided. Moreover, LCA practitioners should focus on harmonising system boundaries with the LCI phase. The interaction of battery parameters and application characteristics is captured in proposed modelling guidelines. Value stacking results in environmental benefits, particularly when the battery is used to store renewable electricity which is used to serve another application simultaneously. It seems only interesting for battery technologies with high cycle lives such as RFBs and some lithium-ion batteries because these have the ability to increase battery utilisation without considerably decreasing the battery's lifetime.

To reach sustainability ambitions, battery applications leading to a reduction in environmental impacts should be promoted for which a general incentive policy for all batteries is not appropriate. Such policy stimulates all battery applications, which could lead to small or even negative contributions to environmental impact reduction compared to the current situation. Even though this is a temporary transition problem it could lead to an undesirable interim increase of environmental impacts during the transition. To this end, performing comparative assessments of applications that are expected to be served by batteries in the future, requiring the involvement of transmission network operators, and how these are served in the current situation are highly useful.

Recommendations

- Electricity delivery of a battery in Wh is the metric that should always be used in the FU and not the battery energy storage capacity in Wh.
- Proposed FUs for two subgroups of battery applications.
  For storage applications: *delivering one MWh electricity of the total electricity delivered over the battery's lifetime from a battery used for [specify application*].
  For power applications: *delivering one MWh of electricity of the total electricity delivered over the battery's lifetime in order to provide X MW of power capacity from a battery used for [specify application].*
- Consider the battery as part of the bigger electricity system in which it serves (a) specific application(s). This defines the required power and energy storage capacity, operation which is reflected by the cycle frequency and electricity source.
- Specify the characteristics of the battery's application(s) that is/are assessed including the required battery power, discharge duration, battery energy capacity and the cycle frequency in a table after the FU.
- The FU in Regulation (EU) No 2019/1020 Annex II and the PEFCRs is recommended to be adapted to the FUs as defined above. The reference flow in these guidelines is recommended to be adapted to be an output of the use process instead of an input and results from the combination of the FU and the alternative (Guinée et al., 2002).
- Transparently report the electricity and battery system inputs of the use process and which battery efficiency is used by including calculations, or at least equations.
- Include the required cycle frequency for the application(s) and the round-trip efficiency as range combined with uncertainty analysis, or at least sensitivity analyses, to evaluate the effect of these characteristics on LCIA scores.
- Future work should focus on developing cycle life models including DoD, charge/discharge rate, average SoC and operating temperature for different battery technologies. The outcomes of such models should be used in LCA models in order to refine the battery lifetime estimation.
- To reflect the possibility of replacing components of battery systems, future battery LCA studies could define the total battery system's economic lifetime and consider which and how often components have to be replaced during this lifetime instead of using the battery's calendar lifetime.

Modelling guidelines for electricity and battery system inputs of the use process

Electricity input

$$Electricity\ lost\ due\ to\ efficiency\ losses\ = \frac{100}{\eta} - 1 \qquad [MWh/MWh_{delivered}]$$

Electricity consumption for the operation of the battery system is recommended to be modelled as a separate input, which should be obtained from the battery manufacturer.

Battery system input

$$\frac{1}{C_{bat}\ [MWh]\ \cdot\ DoD\ [\%]\ \cdot\ annual\ cycle\ frequency\ [number]\ \cdot\ \eta^{0,5}\ [\%]\ \cdot\ \text{battery lifetime [y]}}$$

Contents

List of Figures

List of Tables

Abbreviations

aFRR	automatic frequency restoration reserve
ALCA	attributional life cycle assessment
BMS	battery management system
BRP	balancing responsible party
C2G	cradle-to-gate
CLCA	consequential life cycle assessment
CO_2	carbon dioxide
DoD	depth of discharge
DAM	day-ahead market
EASE	European Association for Storage of Energy
EC	European Commission
EFC	equivalent full cycle
EMS	energy management system
ENTSO-E	European Network of Transmission System Operators for Electricity
EOL	end-of-life
ESS	energy storage system
EU	European Union
FCR	frequency containment reserve
FR	frequency regulation
FU	functional unit
ILCD	International Reference Life Cycle Data system
IRENA	International Renewable Energy Agency
ISO	International Organization for Standardization
kt CO_2-eq.	kilotons of carbon dioxide equivalents
LCA	life cycle assessment
LCI	life cycle inventory
LCIA	life cycle impact assessment
LFP	lithium iron phosphate (lithium-ion battery)
LIB	lithium-ion battery
mFRR	manual frequency restoration reserve
ORFB	organic redox flow battery
PEF	Product Environmental Footprint
PEFCRs	Product Environmental Footprint Category Rules
PS	peak shaving
PV	photovoltaics
RET	renewable energy technology
RFB	redox flow battery
RR	replacement reserve
SMT	spot market trading
SoC	state of charge
T&D	transmission and distribution
TSO	transmission system operator
VRFB	vanadium redox flow battery
VRLA	valve regulated lead acid (battery)
WA	wholesale arbitrage

1

Introduction

1.1. Background

1.1.1. Renewable energy sources

In the past decades, there is growing concern about climate change due to greenhouse gas emissions from anthropogenic activities (Intergovernmental Panel on Climate Change, 2014). A transition towards renewable energy sources is ongoing, not only driven by the concern about climate change, but also by other environmental concerns such as loss of biodiversity and resource scarcity (Solomon & Krishna, 2011). Worldwide, the electricity sector shows a growing share of renewable energy technologies (RETs) (Gallo et al., 2016), largely due to the steep learning curve of photovoltaics (PV) and wind energy turbines, resulting in a much faster decline of prices than predicted (International Energy Agency, 2020a; Roser, 2020).

Despite the discussion about the development of new renewable energy technologies, to combat climate change it is required to scale up existing technologies, primarily photovoltaics, i.e., solar energy, and wind energy (International Energy Agency, 2019), right at this time, since these are the greatest endowments. Besides, deep decarbonisation is directly connected to electrification meaning that electricity demand will even increase (Hopkins et al., 2018). It is expected that electricity demand will rise by 0,8% per year until 2030 already due to the electrification of mobility and heat generation, which is set to be one of the primary technological pathways to realise a carbon neutral society. (European Commission, 2019a; International Energy Agency, 2020b). In the European Union (EU), the share of electricity in final energy demand is expected to double to 53% by 2050. Additionally, in developing countries and emerging economies, a strong growth in electricity demand is forecasted due to an increase in the ownership of household appliances and air conditioners and an increasing level of consumption of goods and services (International Energy Agency, 2020b).

Worldwide, renewable sources of electricity are forecasted to experience a strong growth, increasing by about 60% between 2020 and 2030 according to the Stated Policies Scenario (International Energy Agency, 2020b). Renewables are expected to meet 80% of the increase in global electricity demand in the next decade and to overtake coal as the primary energy source. By 2030 renewable electricity generation sources are proposed to provide roughly 40% of electricity supply. According to the International Energy Agency (Wanner & Cozzi, 2020), the world enters a new era in which solar PV is the king of electricity supply. PV generation expands in the coming two decades more than coal-fired plants increased during the past two decades. Electricity generation by PV and wind energy together is set to double from 9% in 2020 towards 20% in 2030, which is a global phenomenon. In the EU, electricity generation increases up to 2,5 times of today's levels in order to reach net-zero greenhouse gas emissions in 2050 (European Commission, 2018a). More than 80% of this electricity generation is expected to be generated by renewable energy sources by 2050 (European Commission, 2018a). A combined electricity generation share of 35% by wind and PV is envisaged for 2050 (European Commission, 2016). Worldwide, over 80% of the world's electricity demand is expected to be derived from renewable sources in 2050, of which PV and wind power account for 52% (International Renewable Energy Agency [IRENA], 2017).

1.1.2. Energy storage

A challenge emerging from this high supply of electricity by renewables is the mismatch between supply and demand. Our energy system is designed so that electricity must be utilised immediately, while wind and solar energy are intermittent and variable in nature (Eindhoven University of Technology, 2021). Moreover, the expected growth of this transient and distributed electricity generation may lead to reaching the physical limits of the existing electrical grid due to for example, voltage rise during feed-in and power peaks (Bucher, 2014; Faessler et al., 2017; Lopes et al., 2007). This requires increasing flexibility from the energy infrastructure, which is also described as the cornerstone of electricity security in power systems (Wanner & Cozzi, 2020). Flexibility is referred to here as a variety of services and possibilities to cover mismatches in the order of hours, days and seasons to support the quality and reliability of electricity supply. A lot could be achieved by expanding the grid, i.e., improved interconnections and building *smart grids*, but also by demand-side management and more flexible conventional energy generation (European Association for Storage of Energy [EASE], 2018; European Commission, 2019a; Gallo et al., 2016). An explanation of these concepts is provided below.

Grid expansion improves the regional exchange of electricity, or in other words, there is always a location where the sun is shining or the wind is blowing. Even though there is no universal definition of what a *smart grid* entails exactly, the overall principle is to increase the intelligence of the electricity network components in order to better match supply and demand. The definition provided by the European Union Commission Task Force for Smart Grids is "an electricity network that can cost efficiently integrate the behaviour and actions of all users connected to it – generators, consumers and those that do both – in order to ensure economically efficient, sustainable power system with low losses and high levels of quality and security of supply and safety" (European Commission, 2011, p. 2) Demand-side management refers to end-consumers modifying their energy demand as a result of over- or undersupply. The line between demand-side management and energy storage might not always be completely transparent however. For example, energy storage in order to reach a self-sufficient house could be considered as demand-side management. Finally, flexible conventional energy generation is the ability of thermal electricity generation plants (e.g., natural gas and coal) to vary the electricity generation corresponding to the volatile generation of renewable energy sources to balance supply and demand. The extent to which these four options are established defines the total required amount of energy storage that is still required to match demand and supply in a future with a high share of renewable energy generation (EASE, 2018).

This indicates that energy storage is part of the puzzle with options that allow the integration of an increasing amount of renewable variable electricity sources. A share of 20% renewables might already be sufficient to destabilize the grid due to its intermittent nature (National Research Council, 2008). Energy storage systems (ESSs) will play a vital role in smart grids to facilitate the integration of renewable energy sources (Bradbury et al., 2014; Denholm et al., 2010) and counteract their intermittent electricity generation (Guney & Tepe, 2017; Telaretti & Dusonchet, 2017). ESSs help balancing load by their flexible dispatch of stored electricity (Bradbury et al., 2014) and help optimise grid operations (de Sisternes et al., 2016). The bloom of renewable energy requires energy storage to effectively integrate sustainably generated electrical energy (European Commission, 2019a), which is also reflected by the ambitious goals on energy storage development set in the recent Green Deal published by the European Commission (2019b).

The European Commission set some scenarios in which annual electricity storage increases tenfold from 2015 to 2050 (European Commission, 2019a). The European Association for Storage of Energy assessed the technical required energy storage by 2050 (EASE, 2018). This is the *technical need for storage* which means that it does not reflect a *future market estimation for storage* which would require addressing economic aspects and exploring the viability of such large scale storage. They analysed studies made for EU Member States and derived a required electricity storage power of 70-220 GW and electricity storage energy capacity of 1500-5500 GWh for the EU in 2050. The former is not about energy storage (Wh) for later use, but about offering a certain power capacity (W) availability to the grid. Instead of storing electricity for later use, some ESSs can also be used as an extra capacity that is available to provide electric power to the grid when required.

1.1.3. Energy storage systems

ESSs can be classified based on their form of storage or on their functions. Five types of ESSs could be distinguished in terms of the form of storage: mechanical (e.g., pumped hydro, compressed air and flywheel); chemical (e.g., hydrogen); electrochemical (e.g., lithium-ion and redox flow batteries); electrical (e.g., supercapacitors); and thermal (e.g., phase change materials) (Aneke & Wang, 2016; Eller & Gauntlett, 2017; Guney & Tepe, 2017). Among these, a sub-category of the electrochemical technologies are batteries. Within the range of ESSs, particularly batteries are envisaged to play an important and promising role for storage in power grids in future highly renewable energy scenarios for two reasons (Behrens, 2020; Dunn et al., 2011; Eindhoven University of Technology, 2021; European Commission, 2019a; Longson, 2021; Mooney, 2015). First, batteries can either be centrally positioned or distributed, depending on their ability of on- and off-grid application (Battke et al., 2013). Second, generally batteries have a fast response time to changes in electricity demand and good scalability opportunities, resulting in the ability to serve both energy storage and power (e.g., frequency balancing) applications (Battke et al., 2013; Eindhoven University of Technology, 2021). Besides storing electricity for later use, i.e., energy storage, some ESSs could provide ancillary services that stabilise the grid. The penetration of renewable energy sources negatively influences the control power that secures normal and reliable power system network functioning, e.g., maintaining supply to all users, but also maintaining a constant voltage and frequency. Without the ability to control this, there is a risk of imbalances and even electricity blackouts (IRENA, 2017). Although some of the previously mentioned ESSs could provide grid balancing services, they may not necessarily be suitable alternatives for conventional electricity generators that currently provide these services due to technical limitations and economic considerations. Batteries, however, show various advantages based on technical characteristics such as fast response time, high efficiency and a low self discharge (Hesse et al., 2017), which makes them one of the most promising alternatives for providing ancillary services.

Therefore, there is a renewed interest within the industry, R&D institutions and the scientific community to develop advanced and environmentally sound batteries for stationary applications (Hiremath et al., 2015). The number of scientific publications regarding batteries strongly exceeds any other type of electrical ESS (Weitzel & Glock, 2018). Despite battery storage currently represents only a minor share of actual energy storage around the world, it is already pushing towards 9 GW power and 17 GWh energy capacity, while this was only several hundred MW a few years ago (BloombergNEF, 2019). Stationary battery storage power is foreseen to reach 14 GW in terms of power already by 2023 (Robson & Bonomi, 2020). Exceptionally high growth rates are expected resulting in a rise to 100-167 GWh in 2030 (IRENA, 2017), while BloombergNEF (2019) even envisages an exponential growth to 1095 GW and 2850 GWh in 2040.

1.2. Problem statement, research aim and research questions

Since the industry, R&D institutions and the scientific community are increasingly interested in developing advanced and environmentally sound batteries for stationary applications it is required to assess the environmental performance of these battery systems. The trade-offs in life cycles, the complexity of the life cycle of batteries and of the impacts they have on the environment requires a comprehensive assessment method in order to evaluate the environmental burdens. Life cycle assessment (LCA) is an appropriate and widely used methodology to assess and provide an interpretation of the environmental burden of a product system throughout the whole life cycle (Guinée et al., 2002). Moreover, it is also used to examine environmental trade-offs between different product systems that provide a comparable function.

The environmental impacts of a battery, or any product system, result from the cradle-to-gate (C2G) and end-of-life (EOL) phase complemented by the use phase. Pellow et al. (2020) state that comprehensive LCA studies of stationary batteries have not received sufficient scientific inquiry. Moreover, even though a substantial and growing amount of literature assesses the environmental impacts of the production of batteries, in particular lithium-ion batteries (LIBs), the subsequent use phase and EOL phase of the storage system are addressed insufficiently (Pellow et al., 2020; Rahman et al., 2021). The use phase of a stationary battery is oftentimes excluded in LCA studies for reasons of complexity of modelling battery behaviour and lacking performance data from real-world battery applications (Porzio & Scown, 2021). However, Pellow et al. (2020) state that the use phase of stationary battery systems is a major, or even dominant, contributor to the overall environmental impacts. This implies that it is important to include the use phase in LCAs and to model it in an appropriate way. This also applies to comparative LCA studies in order to assess which battery technology performs better in terms of environmental impact scores when the use phase is considered as well. Moreover, it enables LCA practitioners to assess the effect on the overall impacts of the battery over its lifetime resulting from particular adjustments in the battery design that influence the use phase. This supports battery developers to focus on the elements that are paramount to reduce the environmental impacts of a battery technology. However, there is no previous research specifically on how the use phase is modelled in stationary battery LCA studies and, resulting from that, recommendations for future LCA studies. Furthermore, there is no consensus in the field of LCA on how the use phase of batteries should be modelled in LCA studies of stationary batteries.

Although, in the preceding sections, the impression may be conveyed that stationary batteries are only utilised for storing excess electricity from renewable energy sources, this is not the case. Batteries are applied to serve a multitude of applications for which they are also charged with fossil-based electricity and not necessarily renewable electricty. A battery has the capability to be leveraged to provide several applications, even at the same time. This results in a use case which is a technically feasible and monetizable combination of applications that is provided by a single ESS. This phenomenon is also called value stacking for which there is an increasing interest for reasons of increasing the financial viability of stationary batteries through capturing several revenue streams (Englberger et al., 2020; Malhotra et al., 2016; Pellow et al., 2020). Therefore, the importance of value stacking is expected to increase if future market rules allow additional compensation mechanisms for serving multiple applications with batteries (Pellow et al., 2020). Although value stacking is shown to result in profitable battery operation, the effect of value stacking on environmental impacts is yet unclear. The need to incorporate value stacking in LCA studies of stationary batteries is also raised by Pellow et al. (2020), but at the same time it is not clear yet how value stacking could be included in modelling the use phase in an LCA of a battery system.

The current study aims to gain insight into current approaches of modelling the use phase in LCA and footprinting studies and related methodological guidelines of stationary battery systems by means of a critical literature review. Furthermore, an illustrative case study is performed in which some of the issues identified in the literature review discussion are put in an illustrative context to illustrate the relative effect of these issues on a battery's environmental impacts scores. Based on both, best practices are suggested and recommendations are provided to provide guidance for LCA practitioners for the execution of stationary battery LCA studies. This is of importance for the assessment of battery technologies in future research as well as the assessment of new battery technologies to support battery development. Moreover, it is also required to be able to perform adequate LCAs of battery systems in order to provide information that is required to select battery technologies with the least overall environemtal impacts to policy makers. This enables policy makers to stimulate battery technologies that have the lowest environmental impacts in order to reach the set energy storage capacity goals with regard to the energy transition that is required to realise the ambition set by the EC to become climate neutral by 2050. Addittionally, this research also provides basic battery terminology which can be useful for LCA practitioners without any knowledge of batteries. The target audience of this study is LCA practitioners interested or involved in performing LCA studies of stationary battery systems. The main research question addressed by this study is: *What are important considerations and how can these be included when modelling the use phase of a stationary battery system in a life cycle assessment?*

To answer the main research question, the following sub-questions have been formulated:

1. *How is the use phase modelled for different applications in existing life cycle assessment and footprinting studies and related methodological guidelines of stationary battery systems, what are their key characteristics and methodological principles and which challenges can be identified?*
2. *How could the use phase be modelled in life cycle assessments of stationary battery systems, which operational parameters and application characteristics are relevant and how do they interact when performing an application?*
3. *What is the effect of incorporating alternative use cases consisting of multiple applications on the modelling of the use phase in a life cycle assessment of a stationary battery system, which challenges arise and which solutions can be identified to deal with these challenges?*
4. *What implications do the issues identified in the literature review have on the environmental impact scores of a battery system?*

1.3. Reading guide

Chapter 2 provides a short explanation of the working principle of a battery and battery terminology and applications and describes the principle of value stacking. Chapter 3 describes the research approach of the research in this study including the literature review method for the critical review of current approaches in battery LCA studies and related methodological guidelines. Moreover, it provides a justification for the selected illustrative case study. In chapter 4 the results of the literature review are presented followed by a discussion of the review results. The effect of value stacking on the operation of a battery system is discussed in chapter 5. Moreover, it is discussed how value stacking can be incorporated in battery LCA studies and which difficulties and challenges occur for which solutions are proposed in a qualitative way. Chapter 6 presents a concise description of the illustrative case study including a justification for the included issues from the literature review and technical information of the performed simplified LCA of an organic redox flow battery using electrolytes synthesised from lignin. Finally, in chapter 7 findings are discussed and topics for further research are presented and in chapter 8 conclusions are drawn and recommendations for future battery LCA studies are provided.

2

Theoretical background

The focus of this research is the use phase of battery systems in LCA. LCA is a comprehensive assessment method to provide an interpretation of the environmental burden of a product throughout the whole life cycle of a product system is life cycle assessment (LCA). Since this research considers LCA practitioners as target audience it is assumed that readers are familiar with the LCA method. Appendix A provides a short explanation of LCA for readers that are not familiar with this method. In order to understand how batteries are modelled in an LCA it is required to have some more knowledge on battery terminology and battery applications. In order to provide background information for LCA practitioners without knowledge of batteries, section 2.1 provides a basic description of the working principle of a battery and discusses battery terminology and the different applications for which stationary batteries are used. Since the concept of value stacking might not be clear for LCA practitioners, section 2.2 provides a description of the principle of value stacking and the rationale

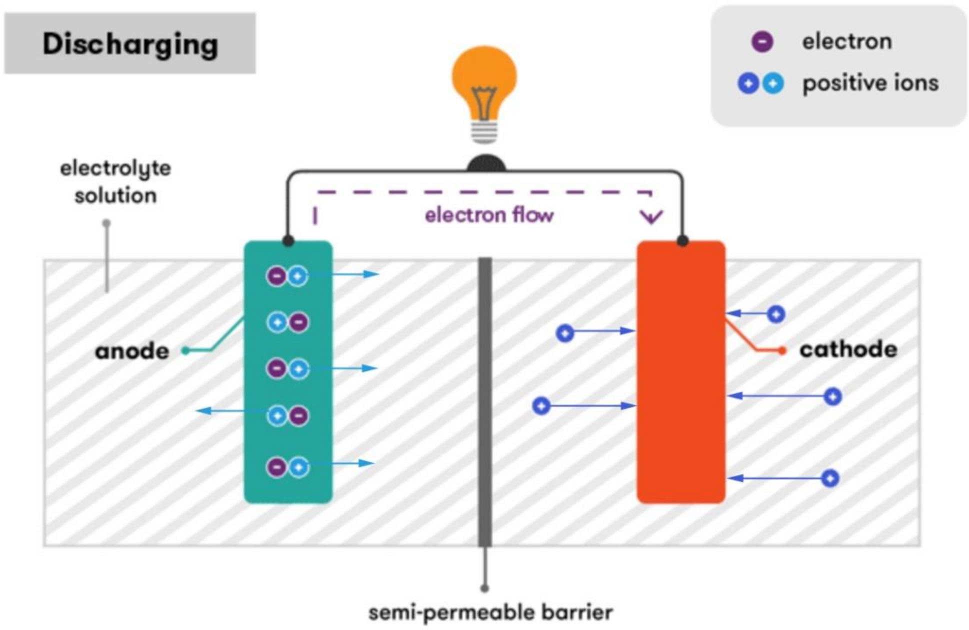
2.1. Battery working principle and terminology

A battery is a device that converts chemical energy in electrical energy and the other way around, as depicted in Figure 1. During discharging a chemical reaction occurs at the anode (the negative electrode) that produces electrons which flow from the anode through the external wire to the cathode (the positive electrode) (Bhatt et al., 2016). To maintain a neutral charge balance on the anode, the same amount of positively charged ions is produced at the same time. These ions are released in the electrolyte solution, which provides a medium through which the positive ions can flow. At the same time, the cathode attracts positively charged ions to balance the negative charge of the electrons that it receives. During discharge the energy of the electrons that flow thought the external wire can be harnessed and used to power an electrical device. During charging the exact opposite happens. Electrons flow back to the anode, positive ions are released from the cathode into the electrolyte and are attracted by the anode to keep a neutral charge balance on the electrodes. When the external circuit is open, the flow of electrons is halted and the chemical reactions at the electrodes will stop. The semi-permeable barrier, or membrane, prevents the electrolyte solutions from mixing while it allows ions to transfer.

Different types of batteries exist and several classifications can be made. However, an important distinction to be made in this research is the one between a redox flow battery (RFB) and other types of batteries. Different battery types use different metals for the anode and cathode and different electrolytes which leads to different electrochemical properties. An RFB, however, uses two electrolytes; a negative electrolyte which is the anolyte and a positive electrolyte which is the catholyte (Park et al., 2016). Below the basic concepts specific for batteries are provided and the variables used to characterise battery operating conditions are defined.

Figure 1

Schematic diagram of the working principle of a battery cell



Note. Adapted from *How a battery works*, A. Bhatt, M. Forsyth, G. Wang, and R. Withers, 2016, Australian Academy of Science (https://www.science.org.au/curious/technology-future/batteries).

- **Anolyte** is the negative electrolyte of a battery, sometimes also called the negolyte.
- **Battery lifetime** is the amount of time that a battery can provide charging and discharging before its energy storage capacity degrades to a specified EOL condition (Bowen et al., 2019; T. S. Schmidt et al., 2019). It depends on battery degradation, which is a function of how the battery is cycled and utilised during the use phase, but also how it degrades over time independent of its use (Ryan et al., 2018). Therefore, a battery has a certain calendar lifetime and cycle lifetime.
- **Battery management system (BMS)** is the system that gathers the sensor measurements and is tasked with monitoring the battery so that it does not operate outside its safe operating area, monitoring the state which consists of items such as voltage, temperature and current and controlling the recharging of the battery.
- **Calendar degradation** is the decreasing performance of a battery over time in terms of power, energy capacity and efficiency independent of charge-discharge cycling as a result of ageing processes causing degradation of a battery cell, (Keil et al., 2016). This is also called calendar ageing.
- **Calendar lifetime** is the lifetime of a battery expressed in years before the battery degrades to a specified condition, also called the EOL energy capacity criterion, which is a specific percentage of the nominal battery energy capacity. The calendar lifetime is determined by calendar degradation (Hiremath et al., 2015; T. S. Schmidt et al., 2019). Calendar lifetime is also referred to as shelf life.
- **Catholyte** is the positive electrolyte of a battery, sometimes also called the posolyte.
- **Charge and discharge power** refers to how quickly a battery takes energy from, or provides energy to, the grid measured in watts (W).

- **C-rate or charge-discharge rate** is a measure of the rate at which a bare battery cell is (dis)charged relative to its maximum energy capacity (MIT Electric Vehicle Team, 2008). A 1C rate means that the discharge current will discharge the entire battery in 1 hour. For a battery with a capacity of 100 Ah, this equates to a discharge current of 100 A. This can be converted to the E-rate by multiplying by the voltage at which the battery operates, e.g., 100 Ah · 12 V = 1200 Wh. The 1E rate is the discharge power to discharge the battery in 1 hour, which is 1200 W.
- **Cycle degradation** is the decreasing performance of a battery in terms of power, energy capacity and efficiency as a result of each charge-discharge cycle. This is also called cycle ageing.
- **Cycle frequency** refers to how often a battery is charged and discharged on average, e.g., multiple times a day or once a week (Pellow et al., 2020). The number of cycles that the battery encounters during its operation depends on the application for which the battery is utilised. Stationary battery applications are discussed in section 2.1.1. The application requires a certain power (W) during a certain discharge duration (hours) for a certain number of times per day, which determines the operational profile (charge-discharge behaviour) of the battery.
- **Cycle life** is the number of cycles the battery can perform under specific conditions before its energy storage capacity degrades to a specified condition, also called the EOL energy capacity criterion, which is a specific percentage of the nominal battery energy capacity (Hiremath et al., 2015; T. S. Schmidt et al., 2019).
- **Cycle lifetime** is the lifetime of a battery expressed in years based on the cycle life. The cycle life can be converted to cycle lifetime expressed in years by dividing the cycle life by the required number of cycles per year (e.g., 5000 cycles / 300 cycles per year = 17 years).
- **Cycle** refers to one time charging and discharging the battery. This is also called a charge-discharge cycle.
- **Deep cycling** are charge-discharge cycles at a high DoD.
- **Depth of discharge (DoD)** refers to the usable range of a battery's installed energy capacity that is dispatched before recharging, expressed as percentage of the nominal battery energy capacity (Pellow et al., 2020).
- **Efficiency degradation** is the rate of increase in energy losses incurred from charging-discharging the battery.
- **Electrolyte** is a medium that contains ions and is electrically conducting through the movement of those ions, but does not conduct electrons (Muelaner, 2021). The electrolyte allows electrical current in the form of ions to flow between the anode and the cathode of a battery.
- **Energy management system (EMS)** is the system that monitors and controls the energy flows within the battery system (Solovev & Petrova, 2021). It coordinates the work of a BMS and other components of a battery system in order to efficiently manage the power resources of the system.
- **Equivalent full cycle (EFC)** is a charge-discharge cycle that does not use the full nominal battery energy capacity converted to the amount of cycle at full energy capacity.
- **Nominal battery energy capacity** is the nominal installed battery energy capacity expressed as the power of the battery (W) as a function of time (h) (i.e., watt-hour (Wh)), that is required to ensure the application specifications over the battery’s lifetime (T. S. Schmidt et al., 2019).

- **Operational energy** is the electricity that can be required for the operation of the battery, for some batteries even when it is on standby (da Silva Lima et al., 2021). Depending on the battery technology, operational energy use consists of energy for the battery and energy management system, cooling of the battery and pumping the fluid in case of an RFB.
- **Ramp rate** is the speed at which a battery can increase or decrease (dis)charge (Solovev & Petrova, 2021).
- **Rated charge and discharge power** is the maximum rate of (dis)charge in watts (W) at which a battery takes energy from, or provides energy to, the grid (Bowen et al., 2019; Pellow et al., 2020).
- **Round-trip efficiency** is the ratio as a percentage of electricity charged into the battery system to the electricity discharged from the battery (Bowen et al., 2019). Round-trip efficiency in this research refers to the AC-AC round-trip efficiency which includes efficiency losses of the inverters.
- **Self-discharge** arises when the amount of stored electricity available for discharge reduces without electricity being discharged from the battery to perform work, for example due to internal chemical reactions (Bowen et al., 2019). This is expressed as a percentage of stored energy lost over a certain period.
- **Shallow cycling** are charge-discharge cycles at a low DoD.
- **State of charge (SoC)** is a measurement of a battery's present level of charge, expressed as a percentage of the nominal battery energy capacity (Bowen et al., 2019). It influences the ability of the battery to provide electricity at any given time.
- **Storage duration** is the amount of time a battery can discharge at its rated power before the energy capacity is depleted. For example, a battery with a rated discharge power of 1 MW and 4 MWh energy capacity results in 4 hours storage duration (Bowen et al., 2019).

2.1.1. Stationary battery applications

Basically, the function of each stationary battery is to charge it with electricity in order to discharge it at a later point in time, i.e. storing electricity. Even though the function of a battery always is to store and deliver electricity, it can be utilised at different locations in the electricity supply chain and for different functions, also known as services or applications. The applications lead to different profiles with regard to the frequency and the duration of charging and discharging (Jones et al., 2019). In the past two decennia, several publications have been written on different applications of electricity storage. However, applications are classified along different parameters such as the technical requirements (e.g., discharge duration or power versus energy capacity), its location in the electricity supply chain, or the source of value creation (Battke & Schmidt, 2015). There seems to be no consensus regarding the nomenclature of electricity storage applications (Malhotra et al., 2016). Malhotra et al. (2016) performed an extensive literature review of different application classification schemes and studies reviewing energy storage applications with the aim to arrive at an exhaustive classification. They identified the scheme by Battke and Schmidt (2015), as depicted in Figure 2, as a mutually exclusive and collectively exhaustive scheme. Therefore, this scheme is followed in the current research as a basis to distinguish the different battery applications. It should be noted, though, that other classifications have been introduced at a later stage and that no classification scheme is right or wrong. The number of distinguished applications varies and overlap of applications or grouped applications exists between different application classification schemes. Some examples of other schemes and the discrepancies between them are provided in Appendix B.

In the scheme by Battke and Schmidt (2015), applications are classified along two dimensions: source of economic value and location in the electricity supply chain. Stationary batteries can be located in different parts of the energy supply chain: in the transmission network; in the distribution network near load centres; co-located with (renewable energy) generators or at the end-customer (Bowen et al., 2019). Figure 3 gives an impression of the different locations in an electricity network. The x-axis in Figure 2 represents the location in the electricity supply chain which is divided into the *generation source, transmission and distribution* and the *end-consumer*. Depending on the location, different applications can be served. The y-axis in Figure 2 represents the source of economic value that the storage creates. *Power quality* refers to the compensation of disturbances and anomalies to keep the electricity system's performance at its optimal level in terms of voltage and frequency. These applications ensure power supply without deviations from the optimal frequency and voltage level which is financially compensated. *Power reliability* on the other hand concerns the guarantee of electricity in case of an interrupted supply. Applications in the category of *increased utilization of existing assets* create economic value by improving the use and value of existing generation or transmission capacity and therefore avoiding or deferring additional investments. Finally, *arbitrage* applications concern the trade in electricity. Price differentials over time are used by storage operators to create economic value. 14 applications across the value chain emerge from the four sources of value creation.

The application of batteries that probably comes to mind first is the utilisation of batteries to store excess electricity generated by intermittent renewable energy sources at times when supply exceeds demand. This is used at a later time and therefore it increases the dispatchability of renewable energy. This is called renewable energy technology (RET) firming in Figure 2. In contrast, in case of RET arbitrage renewable energy is stored as well, however in this case the aim is to sell it at times when electricity prices are high for economic reasons. Finally, a battery can also be connected to RETs in order to reduce voltage sags or frequency distortions of RET electricity output.

When a battery is utilised in the distribution and transmission network, i.e., the grid, it can take part in different markets to generate revenue (Jongsma et al., 2021). All further information in the next sections is based on Jongsma et al. (2021). The electricity market generally refers to the day-ahead market (DAM) or also called EPEX SPOT or APX. The DAM determines the price for electricity that will be supplied and demanded the next day, which works via the merit order mechanism, as visualised in Figure 12. This implies that the price in a specific hour is equal to the highest production price that is required in order to meet the electricity demand. The price more or less equals the marginal costs of the electricity generator when there is sufficient electricity supply. A day in advance, electricity providers and consumers make bids for each hour of the next day based on what they expect to generate or consume. These bids are recorded in a so called e-program by the transmission system operator (TSO). The DAM defines the electricity price for all regular providers and consumers. Applying a battery to store electricity that is bought on these markets when electricity prices are low (typically during night time) to sell it when prices are high is called wholesale arbitrage.

Electricity providers and some of the large electricity generators and consumers, also called balancing responsible parties (BRPs), also have a balancing responsibility. They have to contribute to matching supply and demand in the electricity system. Imbalance occurs when the actual demand or supply of electricity deviates from the e-program. This imbalance is resolved by the TSO, but the BRPs are charged for this. Therefore, it is oftentimes advantageous for BRPs to (partly) reduce their imbalance. This can be done via the intraday market up until 15 minutes before supply. For example, if it less sunny than expected, the electricity supply of a solar park will be less than expected. The operator of the solar park can purchase extra electricity on the intraday market in order to prevent supplying less electricity than indicated on the DAM. However, even after trade on the intraday market some imbalance will still occur. This remaining imbalance is fixed by the TSO by controlling parties directly based on deviations from the grid frequency, which is called frequency regulation. There are three products to resolve frequency imbalance: frequency containment reserve (FCR), automatic and manual frequency restoration reserve (aFRR and mFRR) and replacement reserve (RR), which are further explained in Appendix C.

A battery can also be utilised to supply these products. The battery can be used to immediately charge or discharge reactive power within a couple of seconds to maintain the grid frequency within permissible limits, which is called area and frequency regulation in Figure 2. When the battery is used for support of voltage regulation the same principle applies but this time to maintain the local voltage level in an acceptable range. Applying a battery to balance long-term imbalances in demand and supply is called reserve capacity.

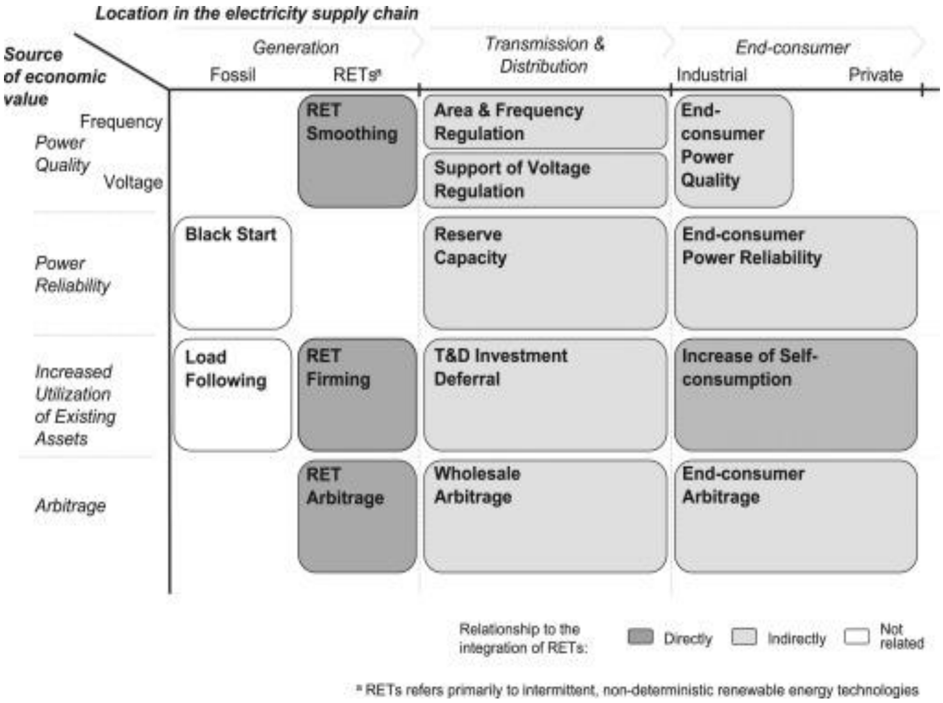
Finally, a congestion market exists. Congestion occurs when the total energy demand or supply exceeds the capacity of (a part of) the transmission or distribution system. With congestion management, the electricity network operator asks the consumers and suppliers to temporarily increase or decrease demand or supply. Batteries can also be used to defer, reduce or avoid investments to expand the grid to meet demand growth by storing electricity when demand is low and discharging locally when demand is high. This application is called transmission and distribution investment deferral.

Batteries can also be co-located to fossil electricity generators. For example to restart the generator in case of a grid outage, which is called black start. They can also be used to compensate for the difference between day-ahead scheduled generator output, actual generator output and actual demand in order to maintain the balance between electricity supply and demand. This can defer or reduce the need for new electricity generators. This application is called load following.

Finally, a battery can be used behind the end-consumer electricity meter for different reasons. It can be used to maintain the frequency and voltage within permissible limits at the end-consumer location in case the frequency or voltage of electricity from the grid is outside the permissible limits. This application is called end-consumer power quality. It can also be used to provide backup power in case of power outages, which is called end-consumer power reliability. A battery utilised in this location could also be used to maximise the use of electricity generated by the consumer’s own non-dispatchable electricity generation such as solar energy, which is called increase of self-consumption. Finally, an end-consumer can use a battery to reduce electricity bills by storing electricity when the retail electricity price is low and using it when the price is high. This application is called end-consumer arbitrage, which is different from wholesale arbitrage since the consumer does not participate in the electricity market. A description of all applications is included in Table 1.

Figure 2

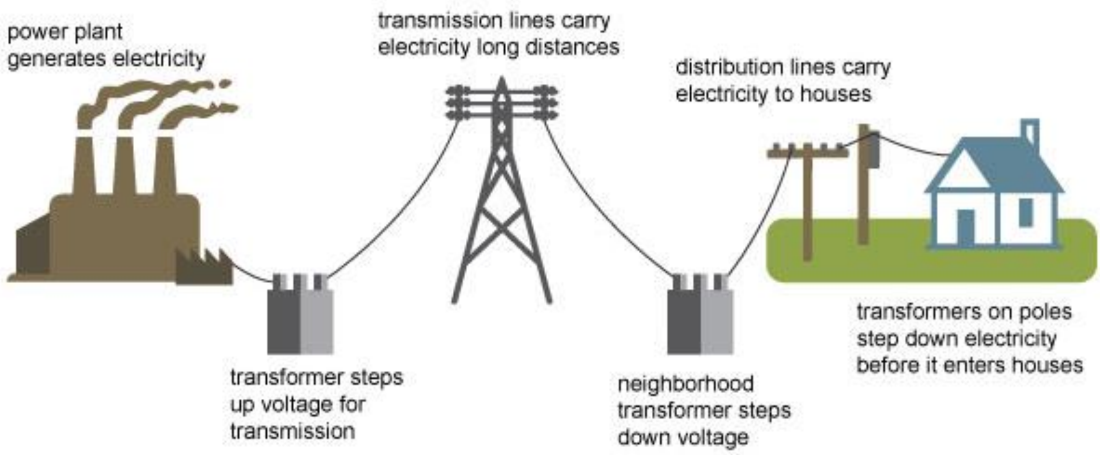
Classification of stationary electric storage applications



Note. Classification scheme of energy storage system applications based on their position in the electricity supply chain (X-axis) and how this application translates into economic value (Y-axis). From "Cost-efficient demand-pull policies for multi-purpose technologies," by B. Battke and T. S. Schmidt, 2015, *Applied Energy, 155*, p. 42.

Figure 3

Electricity generation, transmission, distribution and consumption



Note. The figure shows poles for the local distribution which is common for electricity grids in the United States, but less common in Europe where these lines are oftentimes underground. From *Electricity explained How electricity is delivered to consumers*, by U.S. Energy Information Administration, n.d., (https://www.eia.gov/energyexplained/electricity/delivery-to-consumers.php).

Table 1

Description of energy storage applications

Source of economic value creation	Application	Description	Function as basis for FU
Power quality: These applications create economic value by keeping frequency and voltage levels within permissible limits.	RET smoothing	Reducing voltage sags or harmonic distortions of RET electricity output.	Providing X MW of power capacity to regulate frequency or voltage distortions.
	Area and frequency regulation	Maintain grid frequency within permissible limits by immediate charging and discharging reactive power within seconds. This avoids system-level frequency spikes or dips caused, for example, by the intermittent nature of renewable energy sources (Rebours et al., 2007).	Providing X MW of power capacity to regulate the grid frequency.
	Support of voltage regulation	Maintaining the local voltage within an acceptable range by charging and discharging reactive power.	Providing X MW of power capacity to regulate the local voltage.
	End-consumer power quality	Maintain the frequency and voltage within permissible limits at the end-consumer location.	Providing X MW of power capacity to regulate the frequency and voltage at the end-consumer location.
Power reliability: These applications create economic value by providing a source of back-up power in case of interruptions in power supply.	Black start	Restarting a generation unit without relying on the grid in case of a grid outage.	Delivering X MWh of electricity to restart an electricity generation unit.
	Reserve capacity	Balancing long-term imbalances in demand and supply, which is also known as spinning and non-spinning reserve. Spinning reserve is the energy capacity that is online and able to serve demand immediately in response to an unexpected event, such as an electricity generation outage. Non-spinning reserve is the energy capacity that can respond to unforeseen events for a short period, generally less than ten minutes, but is not available immediately (Fitzgerald et al., 2015).	Delivering X MWh of electricity to support balancing electricity demand and supply.
	End-consumer power reliability	Providing backup power in case of power outages.	Delivering X MWh of electricity at the end-consumer location in case of a power outage.
Increased utilization of existing assets: These applications create economic	Load following	Managing the difference between day-ahead scheduled generator output, actual generator output and actual demand in order to maintain the balance between electricity	Delivering X MWh of electricity to balance demand and supply in order to reduce the need

value by optimizing the use of existing assets in the power system.		supply and demand, while allowing conventional generation units to operate at peak capacity. Electricity storage can defer or reduce the need for new generation capacity.	for new generation capacity.
	RET firming	Storing excess RET electricity generation to be dispatched during high electricity demand and therefore increasing RET dispatchability.	Delivering X MWh of stored excess renewable electricity in order to maximise RET dispatchability.
	T&D investment deferral	Deferral, reduction or avoidance of conventional grid investments, which would be necessary to meet projected electricity demand growth on specific regions, by taking over technical functions in the electrical grid (Fitzgerald et al., 2015).	Delivering X MWh of electricity to reduce peak grid demand in order to reduce grid investments.
	Increase of self-consumption	Maximising the self-consumption of energy produced by consumer's own non-dispatchable distributed generation (e.g. photovoltaic).	Delivering X MWh of stored excess renewable electricity in order to maximise self-consumption.
Arbitrage: These applications create economic value by using price differentials over time, storing energy when prices are low and discharging when they are high.	RET arbitrage	Storing electricity produced by variable RET generators in order to sell it when electricity prices are high.	Delivering X MWh of stored excess renewable electricity in order to maximise profit.
	Wholesale arbitrage	Buying and storing electricity from the wholesale market when electricity prices are low (typically during night time) to sell it when prices are high.	Delivering X MWh of stored low price electricity in order to maximise profit.
	End-consumer arbitrage	Making use of time-based pricing to reduce electric bills by storing electricity when the retail electricity price is low and using it when the price is high. Another option is to reduce peak demand from the grid by supplying peak demand with electricity from the storage.	Delivering X MWh of stored electricity to reduce high price electricity consumption and/or peak demand.

Note. The functions as basis for the FU are not obtained from existing work but are suggested in the current research, which is discussed in section 4.2.1.1. Adapted from "Use cases for stationary battery technologies: A review of the literature and existing projects," by A. Malhotra, B. Battke, M. Beuse, S. Annegret, and T. Schmidt, 2016, *Renewable and Sustainable Energy Reviews, 56*, p. 718.

2.2. Value stacking principle

Regardless of falling costs of battery systems, high investment costs are still the primary barrier to large scale energy storage utilisation (Battke & Schmidt, 2015; Bhatnagar et al., 2013; Braff et al., 2016). Batteries will be applied on a large scale only if they become economically feasible or even profitable. Economic analyses of battery systems are oftentimes focused on the cost side, concluding that single applications do not result in necessary financial margin to operate economically (Klausen et al., 2016). Demand policies might increase deployment and drive battery technology costs down

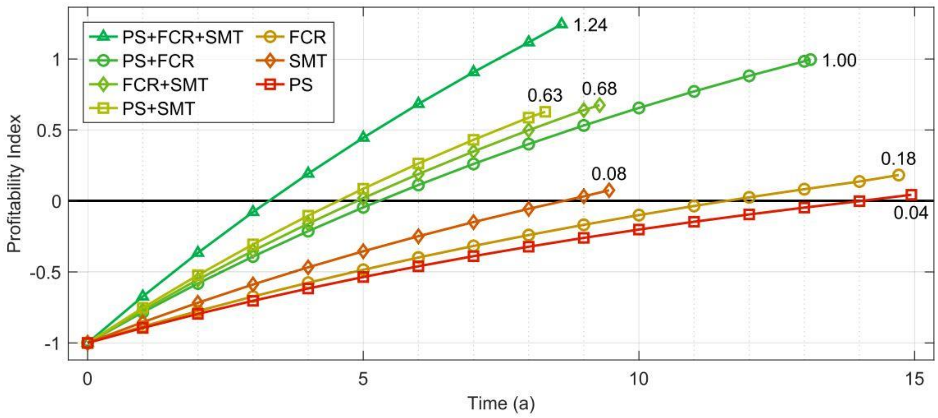
(Battke & Schmidt, 2015; Nykvist & Nilsson, 2015; O. Schmidt et al., 2017), however, an alternative to increase the attractiveness of investing in batteries is to focus on the revenue side. Batteries are multi-application technologies; they can serve multiple applications at a time. While serving a single application only, a battery system is often idle or underused (Fitzgerald et al., 2015; Lombardi & Schwabe, 2017) and struggles to obtain profitability (Olk et al., 2019; Stephan et al., 2016). During battery idle times, when no application is actively served, but battery calendar degradation is still ongoing. Since the capacity of a battery is not utilised the entire time, the idle capacities can be employed for additional applications. The stacking of applications, also referred to as value stacking, multi-use or multi-purpose applications, is now emerging as a practical operational strategy for ESSs and is a currently hotly debated topic (Bowen et al., 2019; Brogan et al., 2020; Englberger et al., 2019; Hesse et al., 2017; Namor et al., 2019; Truong et al., 2018). Serving multiple applications results in a use case which is a technically feasible and monetizable combination of applications that is provided by a single ESS at a particular location (Akhil et al., 2015; Malhotra et al., 2016). Because some applications are rarely called for or are required infrequently, serving multiple applications enables higher battery utilisation (Bowen et al., 2019). A single battery system could for example be used as electricity storage for intermittent renewable energy generation, i.e., RET firming, while it could also increase grid power quality utilising a part of the battery to provide frequency regulation.

Stacking compatible applications by utilising a multi-use operation strategy can maximise the revenue generation and thus improve the financial viability of batteries. This is concluded by Stephan et al. (2016) and Jongsma et al. (2021), who show increased profitability for stationary battery storage systems that combine applications. Moreover, in a recent study by Englberger et al. (2020), the techno-economic performance of single-use and multi-use operation of a stationary lithium-ion battery system that is utilised by a commercial consumer in Germany is analysed. As depicted in Figure 4, the results show that, despite accelerated battery cycle degradation and therefore a decreased battery lifetime, the battery is profitable under a multi-use operation strategy, in contrast to single-use operations.

Value stacking is described as a practice that is definitely gaining attention in the industry. Battery vendors are trying to develop systems that can be applied for several applications (Mai, 2019). Furthermore, battery software developers are already responding to this development by developing software that balances battery degradation and revenue because they anticipate that the need to recognise and reward multiple applications will presumably grow with an increasing penetration of renewable energy (Colthorpe, 2021). Value stacking is already being operationalised in practice to a certain extent. Examples are the Hornsdale Power Reserve, providing both energy arbitrage and frequency regulation, and the Green Mountain Power project in Vermont, CA, providing RET firming and demand charge reductions (i.e., end-consumer arbitrage in Table 1) (Bowen et al., 2019). However, these real-world examples are about batteries still providing only two applications.

Figure 4

Investment attractiveness of single-use and multi-use scenarios



Note. The y-axis represents the profitability index which is the net present value normalised to the initial investment. Different combinations of applications are evaluated where PS = peak shaving, FCR = frequency containment reserve and SMT = spot-market trading, which correspond to T&D investment deferral, frequency regulation and wholesale arbitrage respectively in Table 1. From "Unlocking the Potential of Battery Storage with the Dynamic Stacking of Multiple Applications," by S. Englberger, A. Jossen and H. Hesse, 2020, *Cell Reports Physical Science, 1*(11), p. 4.

Which combination of applications can be served depends on numerous factors such as energy capacity and power of the battery, discharging time, aim of the operator, centralised or decentralised location in the grid, financial compensation, regulatory constraints, etc. For example, in Germany, the unbundling law prohibits capturing value from different stages of the electricity supply chain simultaneously such as generation and transmission (Stephan et al., 2016). For this reason, the storage system should be separated into different virtual partitions which can capture value from different origins in the value chain. Moreover, in the Netherlands, for example, an energy supplier had to pay electricity taxes when it sells electricity to a battery operator (Van Gastel & De Jonge Baas, 2019). When the electricity from the battery is fed back into the electricity network again and sold to an energy supplier, the energy supplier is charged with electricity taxes again when it sells to the consumer. Overall, this results in double taxation, which puts the utilisation of batteries in the grid and serving multiple applications in an unfavourable situation. However, this is abolished as per 2021 in order to improve the storage of electricity (Van Gastel & De Jonge Baas, 2019). In conclusion, the importance of value stacking is likely to increase if future market rules clarify additional compensation mechanisms for multiple applications (Pellow et al., 2020) and therefore it is highly likely the way to go for future battery operationalisation.

Currently, the most common applications served by stationary battery systems are arbitrage at the consumer, grid and generation level, frequency regulation and RET smoothing (Malhotra et al., 2016). According to the US Energy Information Administration (2021), in 2019, 73% of battery storage in the United States provided a frequency regulation application. On the short-term it is likely to continue to be the same, but it is likely to change in the future. At a growing percentage of renewable energy systems, other applications that increase the utilisation of existing generation assets and therefore defer or avoid investments seem to provide more economic value (Mallapragada et al., 2020). However, high penetration of photovoltaics and wind energy to the network also introduces frequency regulation, voltage regulation harmonics and reverse power flow problems (Quan et al., 2019; Shafiul Alam et al., 2020). Ideally, electricity supply has a perfect sinusoidal waveform at a constant frequency with a specified constant voltage. Harmonics are currents or voltages whose frequency is an integer multiple of the fundamental frequency, which is 50 Hz in the EU (Shah, 2005). E.g., the first fundamental frequency is 50 Hz, then the second is 100 Hz and he third is 150 Hz. Harmonics distort the waveform shape of the voltage and current of electricity supply. Reverse power flows are generally caused when electricity generation from intermittent sources exceeds demand causing power to flow in the opposite direction than normal (Holguin & Ramos, 2020). Batteries could facilitate renewable energy penetration by increasing operating reserve (i.e., reserve capacity in Table 1), frequency regulation, enhancement of power transmission capacity of transmission lines (i.e., T&D investment deferral in Table 1), support of voltage fluctuations regulation and improving reliability (Krishan & Suhag, 2019). The Energy Information Administration (2021) expects that future battery storage will increasingly be used for renewable energy storage, since most planned projects in the upcoming three years are co-located with renewable energy generation, in particular solar energy. However, which (combination of) applications will result in optimal economic value and therefore will be served by battery system operators is uncertain since it concerns the distant future.

3

Methodology

3.1. Research approach

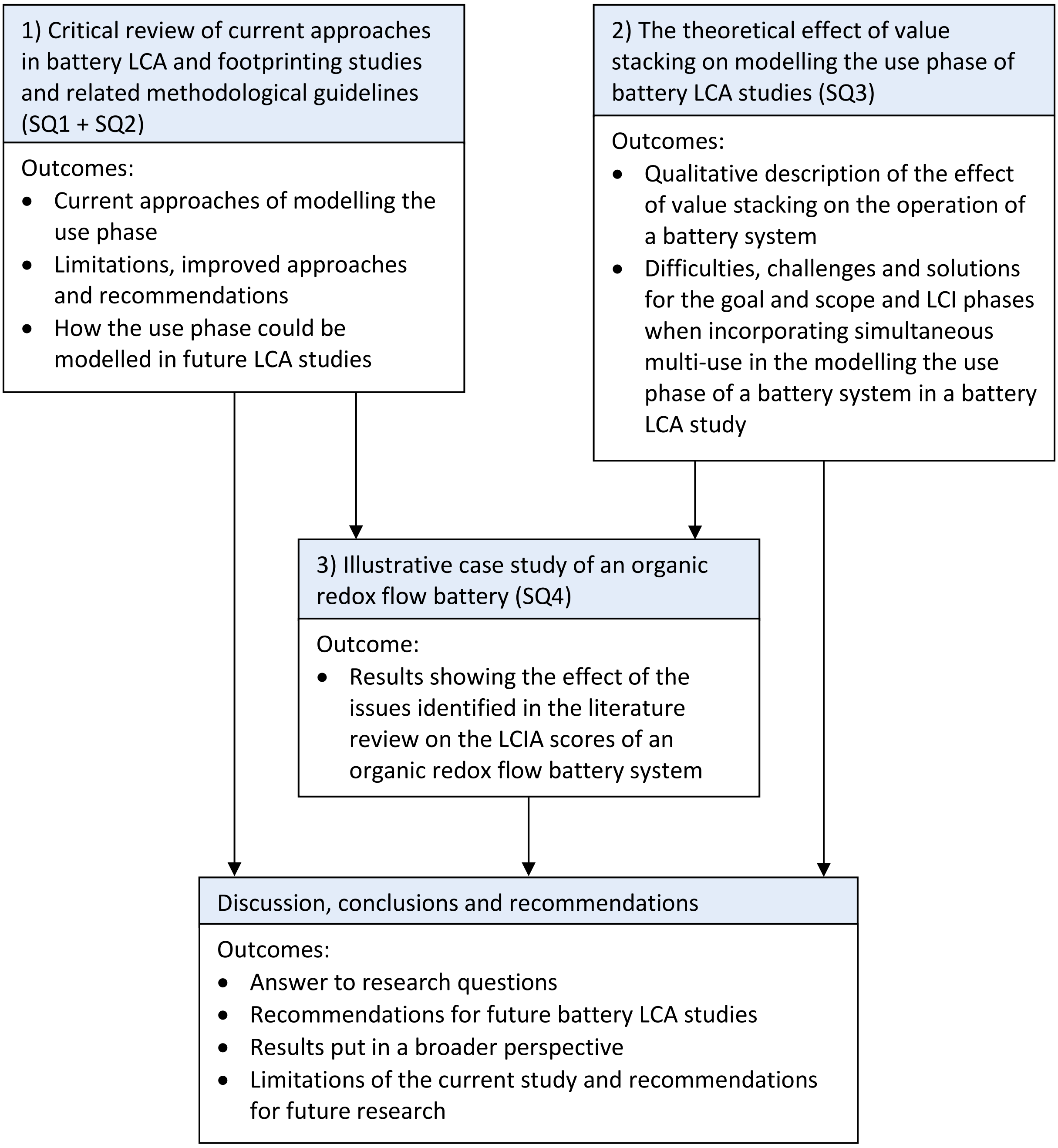
To answer the sub-research questions formulated in section 1.2**,** this thesis followed a 3-step research approach as depicted in Figure 5. The study focuses on how the use phase of stationary battery systems is modelled in current approaches in life cycle assessments and footprinting studies and related methodological guidelines of stationary battery systems and intends to draw recommendations for the execution of future stationary battery LCA studies. Therefore, qualitative research is performed to study how the use phase is incorporated in current LCA studies and related guidelines of stationary battery systems by means of a literature review. The literature review results are discussed during which issues are identified, but also improved approaches and recommendations are provided. Moreover, it is identified which operational parameters and application characteristics are relevant and how they interact based on which recommendations are provided about how the use phase could be modelled in future research. A discussion follows concerning difficulties regarding these parameters and characteristics, how these are theoretically reflected in the modelling of the use phase and from that which aspects require attention in future battery LCA studies. Finally, a discussion is included about the modelling of value stacking in current LCA studies. The effect of value stacking on the operation of a battery system is described in a qualitative way. Based on this, the difficulties and challenges for the goal and scope and LCI phases when incorporating value stacking simultaneously in modelling the use phase of a battery system of a battery LCA study are identified and solutions are proposed in a qualitative way.

Next, the effect of some of the issues identified in the literature review are put in an illustrative context by means of an illustrative case study about an organic redox flow battery (ORFB) to illustrate the relative effect of these aspects on a battery's environmental impact scores and to get a first impression of the impact of value stacking on the environmental impact scores of a battery system. This case study is mainly qualitative in its character; even though numbers are included, it is not aimed at providing absolute results or drawing conclusions about the battery technology itself.

Based on these two steps, recommendations and improved approaches are provided, but also focus areas for future battery LCA studies are discussed. The details about the literature review method to identify relevant literature are described in section 3.1.1 and a description of the illustrative case study is provided in section 3.1.2.

Figure 5

Schematic representation of the research approach



3.1.1. Literature review method

Section 4.1 reviews the environmental assessment of stationary batteries in current LCAs. A literature search was conducted in *Web of Science* (Clarivate Analytics, n.d.) using the following keywords: “life cycle assessment” AND “stationary batter*” OR "LCA" AND "stationary battery" OR "life cycle assessment" AND "stationary energy storage" OR "LCA" AND "stationary energy storage" OR “life cycle assessment” AND "batter*" AND "stationary" OR “LCA” AND "batter*" AND "stationary" OR "life cycle assessment" AND "battery storage" OR "LCA" AND "battery storage" OR "life cycle assessment" AND "battery" AND "grid application*" OR "LCA” AND "battery" AND "grid application*" OR “life cycle assessment” AND "battery energy storage" AND "grid" OR “LCA” AND "battery energy storage" AND "grid".

This resulted in 109 hits. The selection of papers took place after screening titles and abstracts on the question if an actual LCA was performed. After this, the abstracts of these papers were analysed in more detail to see if the paper would assess a stationary battery system and the papers were screened to ascertain if the use phase is included. Finally, 26 papers were included, which are listed in Table E1, according to the following inclusion criteria:

- Original peer reviewed article
- An actual LCA study is performed of a stationary battery system
- Includes a use process

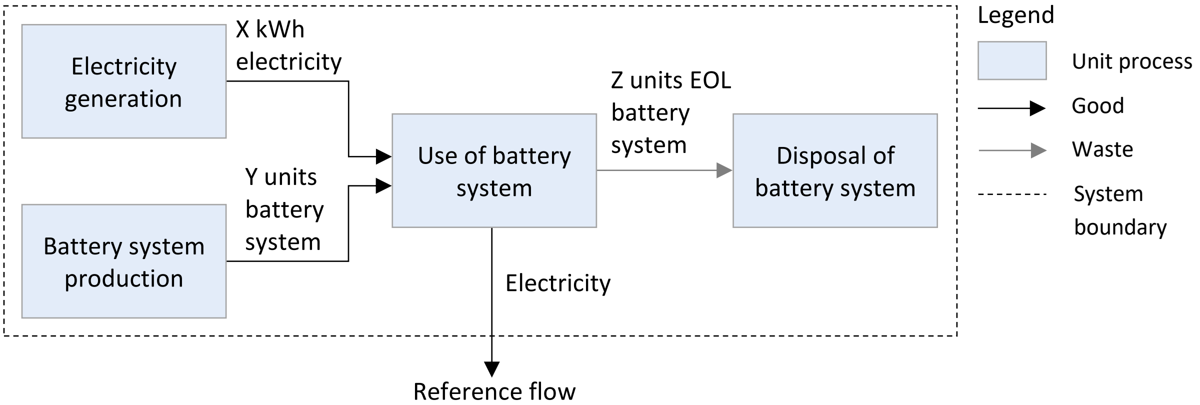
The author is confident that this selection of papers provides the most relevant studies in the field for the current research in which the goal is to review what different LCA studies did at the level of modelling the use phase. The goal was not to provide a complete literature review of all LCA studies or LCA related studies of stationary batteries. For example, meta-analysis studies or studies that use LCA results and couple this to another modelling tool where not included.

The environmental impacts of a battery system result from the C2G and EOL phase complemented by the use phase, as depicted in Figure 6. This figure shows the conceptual structure and the constituents of the product system of a battery system in an LCA that includes the use phase. This structure with constituents will be used throughout the research. Since a battery does not cause direct emissions during its use, the environmental impacts associated with the use of a stationary battery basically relate to the upstream environmental impacts which are determined by the quantity and type of electricity that is used to utilise the battery for a specific application (Hiremath et al., 2015).

In case of a battery, electricity is the product that is obtained from the battery during the use phase, which is the reference flow. The reference flow in Figure 6 is drawn according to the LCA-Handbook definition by Guinée et al. (2002) which means that the reference flow is a measure of the outputs from the processes in the product system to fulfil the function. Here, the combination of the FU and the alternative results in the reference flow which is the output of the use process that is required to fulfil the FU.

Figure 6

Constituents of the product system of a stationary battery system including the use phase



The current study focuses on the goal and scope and LCI phases of an LCA of a battery system. The goal and scope phase was analysed since this phase includes the definition of the function, FU and reference flow (s). Electricity delivery from the battery system is the reference flow, which is directly linked to the FU, since it follows from the function and FU. The definition of the function and FU is fundamental in LCA since it defines what will be modelled in the total LCA study and is decisive for all subsequent steps within the assessment since it determines all upstream and downstream processes, which indicates the importance of analysing these. Subsequently, it is relevant to analyse how the use unit process is modelled in the LCI phase.

Therefore, the selected studies were analysed on the level of the use phase. The studies were reviewed on which application(s) is/are assessed, how the FU is defined and how the use process is modelled in terms of electricity in- and output and battery system input. Moreover, the included alternatives were reviewed to get insight in which systems were actually compared, e.g., battery versus battery or electricity system with battery versus electricity system without battery. Finally, the studies were checked on the presence of value stacking and if this was the case, the modelling method was reviewed.

Next to the LCA studies, the proposed calculation rules to define the carbon footprint of batteries in Annex II of the proposed Regulation (EU) No 2019/1020 were considered to be relevant to review as well. The next section shortly describes this regulation and why it is relevant.

Carbon footprint rules in Regulation (EU) No 2019/1020

On 10 December 2020, the European Commission (EC) presented a proposal for Regulation (EU) No 2019/1020 concerning batteries and waste batteries (European Commission, 2020b) in order to modernise the current batteries directive (Directive 2006/66/EC). The aim of this regulation is to ensure that batteries placed in the EU market are sustainable and safe over their entire life cycle. Article 7 in Chapter 2, together with Annex II, of this proposal lays down harmonised calculation rules on the carbon footprint of electric vehicle batteries and rechargeable industrial batteries with internal storage and an energy capacity above 2 kWh. An industrial battery is defined as “any battery designed for industrial uses and any other battery excluding portable batteries, electric vehicle batteries and automotive batteries" (European Commission, 2020b, p. 46). Stationary battery systems above 2 kWh are therefore part of this definition.

Annex II provides essential elements that the carbon footprint calculation should be build on. But it is noted in the Annex that the calculation should also be in compliance with the latest version of the Product Environmental Footprint (PEF) method (European Commission, 2013) and relevant Product Environmental Footprint Category Rules (PEFCRs) (European Commission, 2017). The EC developed the PEF methodology as an attempt to standardise the assessment of the environmental performance of products and is supposed to increase comparability (European Commission, 2013). The PEF is proposed by the EC as "a common way of measuring environmental performance" (European Commission, 2021, sec. Background).

It is intended to provide guidance to companies to calculate the environmental performance of their products based on reliable, verifiable and comparable information. PEFCRs provide guidelines on how to implement selected specific steps of LCA for a specific product category. Communication of the environmental footprint of products is intended to influence consumer choices. Therefore, it is important to critically evaluate the modelling guidance for batteries in Annex II of Regulation (EU) No 2019/1020 and the category-specific methodological requirements which are included in the PEFCRs. However, a number of batteries under the scope of the new regulation, among which stationary batteries, do not have established PEFCRs. At this moment, only PEFCRs for High Specific Rechargeable Batteries for Mobile Applications (European Commission, 2018b) are available. Therefore, these PEFCRs are considered in the review. Moreover, these PEFCRs are currently undergoing a major revision to provide the industry and the EC with high-quality tools to assist in implementing the new requirements in the proposed regulation (Eurometaux, 2021), which makes a review even more relevant.

3.1.2. Illustrative case description justification

To illustrate the relative effect of some of the issues identified in the literature review discussion on a battery's life cycle impact assessment (LCIA) score, an illustrative case study is conducted. The battery market is currently dominated by lithium-ion batteries due to its impressive energy density and rapidly declining battery pack costs (Choi & Aurbach, 2016; Nykvist & Nilsson, 2015; Puiu, 2020). However, redox flow batteries are a versatile means of storing electricity as they have an attractive characteristic that makes them a promising candidate for stationary large-scale storage (Soloveichik, 2015). The electrolyte (storage) and electrode (cell stack) are separated which enables scaling the energy storage capacity (Wh) independent from the power output (W) of the battery (Noack et al., 2015; Park et al., 2016). The working principle of an RFB is explained in Appendix D.

Moreover, RFBs offer advantages like: flexible and modular design depending on the specific situation; good scalability; moderate maintenance costs; and cost-efficient storage media (Noack et al., 2015; Sánchez-Díez et al., 2021). RFBs especially diverge from other batteries by their long cycle life which is the result of the electrodes being spectators of the reaction, so the soluble redox species are not consumed (Reynard et al., 2018). These are major advantages over solid electrode batteries (e.g., LIBs) to meet the requirements for large-scale applications and grid integration such as cyclability, lifetime, high round-trip efficiency and depth of discharge (Hollas et al., 2018; Sánchez-Díez et al., 2021). Therefore, RFBs are establishing as an emerging and cost-effective technology for stationary electricity storage (Poza, n.d.). Since this battery technology is especially interesting for stationary applications and expected to become an economically viable alternative for large scale energy storage, it might serve multiple applications simultaneously as well in the future. Therefore, this technology is selected for the illustrative case study. An ex-ante LCA study of a developing organic redox flow battery technology as developed in the BALIHT research consortium is made which is used for the case study. This research consortium is part of the HORIZON2020 research and innovation programme call *LC-BAT-4-2019 Advanced Redox Flow Batteries for stationary energy storage*. Further technical details are included in section 6.1.

Critical review of current approaches in battery LCA studies and related methodological guidelines

This chapter describes the results of the literature review in section 4.1. Section 4.2 provides a critical analysis of the review results, suggests best practices, provides recommendations and drafts improved approaches.

4.1. Review results

This section discusses the results of the review. Details of the analysis of the studies is included in Table E1. The review results of the LCA studies are summarised and visualised in Figure 7.

4.1.1. Review of stationary battery LCA studies

4.1.1.1. Battery applications

Most of the LCA studies assessed an RET firming application, or the utilisation of a battery system for the increase of self-consumption application. Moreover, quite some studies analysed a wholesale arbitrage or end-consumer arbitrage application and several studies assessed a battery used for T&D investment deferral. Only some studies assessed a frequency regulation application. Four studies did not specify the application for which the battery was used. However, one of those studies (Jones et al., 2019) used a range of utilisation rates (i.e., cycle frequency) as a representation of different applications. From the fourteen applications distinguished in Figure 2, only six are assessed in current LCA studies.

4.1.1.2. Functional unit

Most functional units (FUs) are defined in terms of 1 kWh or MWh delivered electricity, regardless of the application. However, some defined it in terms of total kWh or MWh over the lifetime or total energy consumption over a specified period of time. Only Koj et al. (2015) define the FU in terms of MW, so power capacity and not energy delivered (MWh). In their study the battery is utilised for a frequency regulation application. Ahmadi et al. (2017) include a lifetime in the FU, but most studies include this in the LCI modelling. Finally, some studies specify a fixed period of time in the FU that the application should be served by the battery.

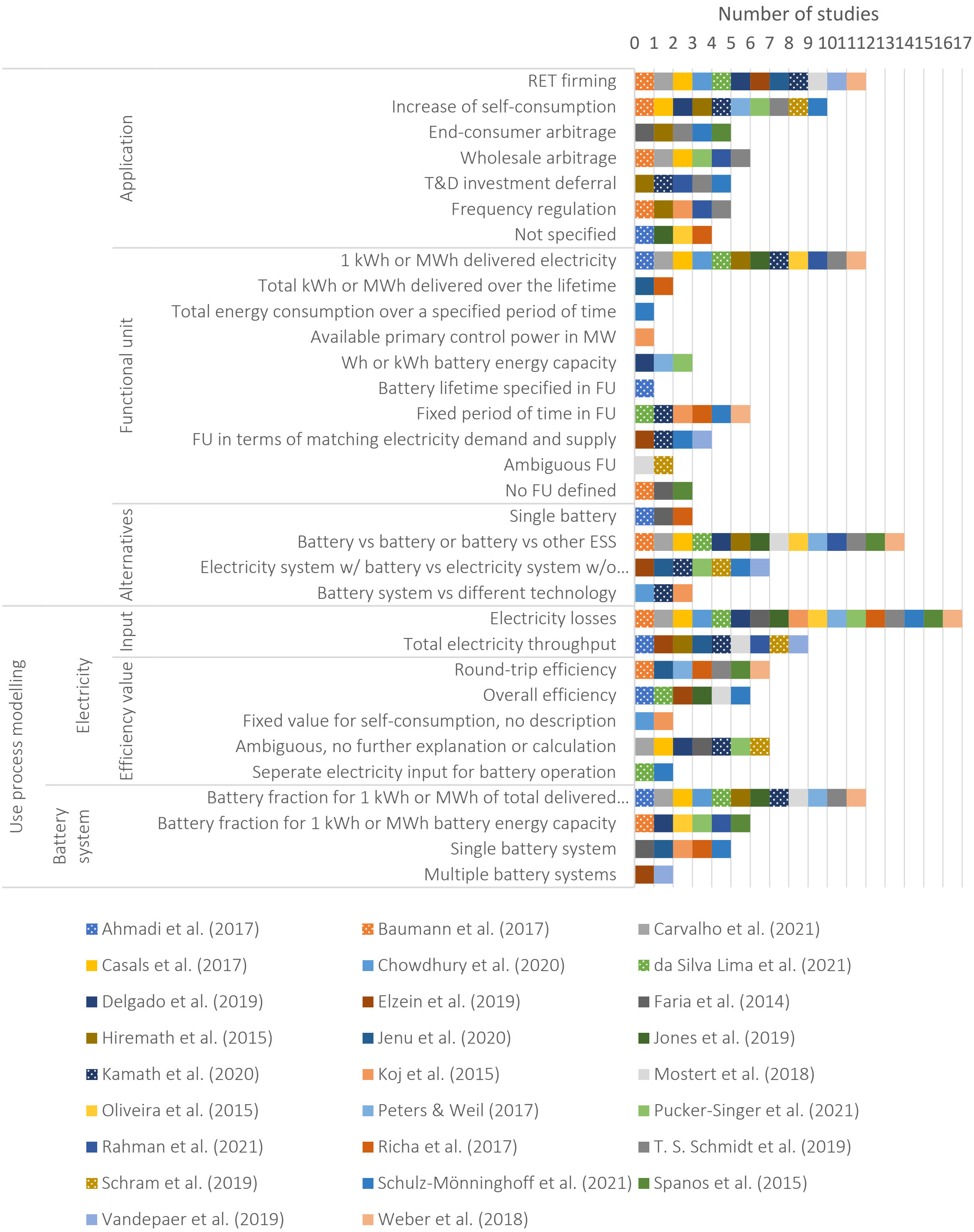
In studies that compare an electricity system without battery to a system with battery, the FU is mostly defined in terms of matching demand and supply over the battery's lifetime or a specified period of time. Even though Vandepaer et al. (2019) did not explicitly include meeting electricity demand in the FU, they state that the batteries are used to feed electricity into the Swiss grid system 'when required'. Three studies defined the FU in terms of Wh or kWh battery energy capacity. Schram et al. (2019) defined a FU of 1 kWh without giving any further explanation of what this entails. Mostert et al. (2018) did not define one FU, but state that the FU depends on the battery technology due to different battery efficiency values. They provide a formula to calculate the FU for each battery technology. Finally, three studies did not report a FU at all.

4.1.1.3. Alternatives

Most LCA studies either assess an individual battery technology or compare a battery technology to another battery technology or other ESS. The ones that diverge from this compare an electricity system with batteries to an electricity system without batteries (Elzein et al., 2019; Jenu et al., 2020; Kamath et al., 2020; Pucker-Singer et al., 2021; Schram et al., 2019; Schulz-Mönninghoff et al., 2021; Vandepaer et al., 2019). Or they compare a battery system to another kind of product system that is able to provide the same application, such as a coal power plant providing frequency regulation (Koj et al., 2015) or a combined cycle gas turbine to supply peak electricity demand (Chowdhury et al., 2020).

Figure 7

Overview of review results of the reviewed LCA studies



Note. ESS = energy storage system

4.1.1.4. Use process modelling

Electricity

There is a difference between LCA studies regarding the assumption about the electricity consumed by the battery, and related environmental impacts, which has to be imputed to the battery in quantifying the electricity input flow of the use process. Most LCAs model this by accounting only for the electricity losses due to efficiency losses of the battery system. However, what the efficiency entails exactly differs quite a bit between different studies. Richa et al. (2017) only include round-trip efficiency losses in their calculations. Other studies use the overall efficiency, which exists of the round-trip efficiency and the efficiency of for example inverters, cooling equipment and battery management systems. For example, da Silva Lima et al. (2021) use the round-trip efficiency complemented by AC to DC and DC to AC power converter efficiency. Elzein et al. (2019) use the battery overall efficiency existing of "the efficiency of the battery during charge (discharge) process" (p. 1628). Schulz-Mönninghoff et al. (2021) do the same, but refer to this as the total round-trip efficiency. Ahmadi et al. (2017) base the electricity losses on total efficiency losses which exist of round-trip and transmission efficiency losses. Mostert et al. (2018) simply state to use the overall efficiency. Jones et al. (2019) use the overall efficiency including inverters, transformers and cooling, however they refer to this as the round-trip efficiency. Several authors state to use the round-trip efficiency to calculate efficiency losses but do not further clarify what this round-trip efficiency comprises (Baumann et al., 2017; Jenu et al., 2020; Peters & Weil, 2017; T. S. Schmidt et al., 2019; Spanos et al., 2015; Weber et al., 2018). Two studies include a separate electricity input for the operation of the battery system. Schulz-Mönninghoff et al. (2021) model this as an average constant self-consumption of 4 kW during all hours over the whole lifetime, while da Silva Lima et al. (2021) include a fixed value of 0,5 kW of electricity for operation during the periods of charging and discharging. Finally, even though most studies account for efficiency losses or round-trip efficiency losses to calculate the electricity losses, how the electricity losses are calculated exactly varies between studies. See Table E1 for an overview of all calculation methods.

Some studies only provide a fixed value for the electricity losses without providing any description or calculations. Koj et al. (2015), for example, include self-consumption as 0,206 $MWh/MWh_{delivered}$ which includes the total efficiency losses and electricity consumption including battery management system, cooling and transformer losses. Chowdhury et al. (2020) assume a self-consumption of 0,379 $MWh/MWh_{delivered}$, but this is copied from the study of Immendoerfer et al. (2017), who calculated this value based on round-trip efficiency. Some studies are a bit ambiguous when it comes to the efficiency losses. For example, Pucker-Singer et al. (2021) state to include the total losses resulting from round-trip efficiency losses, but also auxiliary energy demand for cooling and heating of the battery container and the operation of the battery. However, no calculations or equations are included. Some studies only mention the efficiency that is included as a percentage, without any further explanation of how this leads to the electricity losses (Carvalho et al., 2021; Delgado et al., 2019; Faria et al., 2014; Kamath et al., 2020). Moreover, Schram et al. (2019) do not define anything about electricity losses or consumption during the use phase. And Casals et al. (2017) mention to include efficiency losses, but this is not further specified or calculated.

In some studies, the total electricity throughput, i.e., all electricity going through the battery including losses, is accounted for instead of only efficiency losses. This is mainly the case for studies in which electricity systems with and without battery are compared (Elzein et al., 2019; Pucker-Singer et al., 2021; Schulz-Mönninghoff et al., 2021). Or, for example, when a battery charged with PV electricity is compared to electricity from the grid (Jenu et al., 2020). Another example is when the battery system is compared to an electricity generation system such as a coal power plant (Koj et al., 2015) or a combined cycle gas turbine to supply peak electricity demand (Chowdhury et al., 2020). In most of these cases the FU also includes the total electricity output over the lifetime or a certain period of time, except from Chowdhury et al. (2020) and Pucker-Singer et al. (2021), who defined a FU of 1 kWh delivered and 1 kWh battery capacity respectively, but included total electricity throughput.

However, Hiremath et al. (2015) and Rahman et al. (2021) include total electricity throughput even though they compare battery technologies. Hiremath et al. (2015) suggest that only including electricity losses is insufficient and advocate for imputing all environmental impacts of the power source to the battery. They are in favour of this strategy because batteries, or ESSs in general, are being used for more than storage, so they cannot be treated just as storages. Batteries could be competing with other distributed conventional power supply systems like natural gas power plants because they might offer the same service(s) such as frequency regulation. Therefore, they state that accounting for just electricity losses will not help in comparing batteries with their competitors or even to get an idea about the overall environmental burdens to deliver 1 MWh of electricity through batteries. This choice is justified based on an example calculation of the environmental advantage of charging a lithium-ion battery with renewable electricity versus grid mix electricity. Once accounting for battery efficiency losses only and once accounting for all electricity stored in the battery. This example is represented below.

Assuming 100 kWh of electricity is delivered by battery A with 80% round-trip efficiency. Furthermore, assume CO_2 emissions of 87 g/kWh for PV electricity and 665 g/kWh for grid mix electricity (values taken from Hiremath et al. (2015)).

Providing 100 kWh electricity by PV electricity compared to grid mix electricity without the interference of a battery results in:
100 kWh · 87 g/kWh = 8,7 kg CO_2
100 kWh · 665 g/kWh = 66,5 kg CO_2
Difference in emissions: 66,5 – 8,7 = **57,8 kg CO_2**

Supplying the same electricity with battery A requires 100 / 80% = 125 kWh electricity input.

This results in the following difference in use phase emissions of CO_2 when accounting for *all stored electricity during use:*
125 kWh · 87 g/kWh = 10,9 kg CO_2
125 kWh · 665 g/kWh = 83,1 kg CO_2
Difference in emissions: 83,1 – 10,9 = **72,2 kg CO_2**

Only accounting for the emissions due to the *efficiency losses during use* of the battery results in:
(125 – 100) kWh · 87 g/kWh = 2,2 kg CO_2
(125 – 100) kWh · 665 g/kWh = 16,6 kg CO_2
Difference in emissions: 16,6 – 2,2 = **14,4 kg CO_2**

According to Hiremath et al. (2015), accounting for losses only underestimates the CO_2 emissions of charging a LIB with PV instead of grid mix electricity. Therefore, they claim that the emissions of all electricity charged into the battery should be accounted for.

Battery system

Most LCA studies model the battery input as the fraction of battery that is required to deliver one kWh or MWh of the total delivered electricity(Ahmadi et al., 2017; Carvalho et al., 2021; Casals et al., 2017; Chowdhury et al., 2020; da Silva Lima et al., 2021; Hiremath et al., 2015; Jones et al., 2019; Kamath et al., 2020; Mostert et al., 2018; Peters & Weil, 2017; T. S. Schmidt et al., 2019; Weber et al., 2018). This fraction is calculated by dividing the total battery system input by the calculated total electricity delivered over the battery's lifetime or the specified period of time. However, Carvalho et al. (2021) assume a value of 83,3 kWh delivered per kWh installed battery energy capacity. So the included battery fraction is (1/93,3) = 0,012. Some studies include the required battery fraction for 1 kWh or MWh *battery energy storage capacity* instead of *delivered electricity*, which is calculated based on the battery energy density (kg/Wh). Studies that defined a FU that includes total lifetime or a specified period of time based on the battery's lifetime include one total battery system (Faria et al., 2014; Jenu et al., 2020; Koj et al., 2015; Richa et al., 2017; Schulz-Mönninghoff et al., 2021). Finally, some studies include several batteries, which are studies that compare electricity grid systems with and without battery or electricity grid systems with different types of battery (Elzein et al., 2019; Vandepaer et al., 2019).

4.1.1.5. Value stacking

Eleven studies took into account multiple applications of batteries (Baumann et al., 2017; Carvalho et al., 2021; Casals et al., 2017; Delgado et al., 2019; Faria et al., 2014; Hiremath et al., 2015; Kamath et al., 2020; Pucker-Singer et al., 2021; Rahman et al., 2021; T. S. Schmidt et al., 2019; Schulz-Mönninghoff et al., 2021). Hiremath et al. (2015) included six stationary application scenarios: end-consumer arbitrage; increase of self-consumption; area and frequency regulation; support of voltage regulation; T&D investment deferral; and wholesale arbitrage. These applications differ in terms of the required power rating, battery energy storage capacity and cycle frequency. They assumed specific battery characteristic data and cycle frequency data for each application and, based on that, calculated the total electricity throughput for each application individually. This is reconsidered for each application, however, the applications are only assessed as individual applications; no multi-use is assessed. Baumann et al. (2017) assessed four applications: wholesale arbitrage; increase of self-consumption; frequency regulation; and RET firming. Again, these applications were only assessed individually. The same goes for all other studies that assessed multiple applications, except one. Only Schulz-Mönninghoff et al. (2021) model scenarios in which the battery is utilised to serve multiple applications simultaneously.

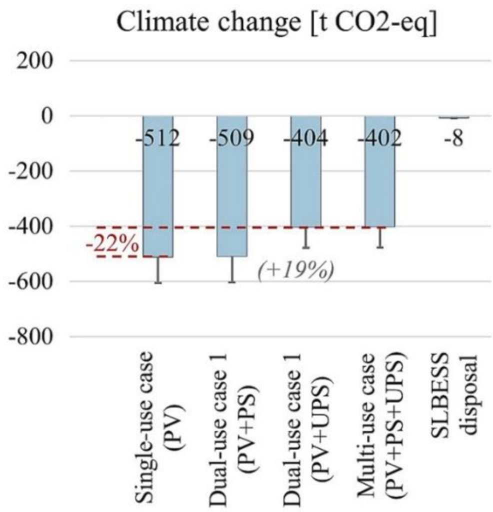
They assessed a battery that is used for increase of self-consumption of a production facility in Germany, which in this case means that the battery system is used to support increased use of their own PV electricity in the facility's grid (single-use case). This is compared to the business-as-usual (BaU) scenario, which is operation of the grid without battery system. They include three scenarios in which the battery serves additional applications. In dual-case 1, the battery provides integration from photovoltaic (i.e., increase of self-consumption in Table 1) and peak shaving which is reducing peak electricity demand from the grid (i.e., end-consumer arbitrage in Table 1). Dual-case 2 exists of integration from photovoltaic and uninterrupted power supply (i.e., end-consumer power reliability in Table 1). Finally, in the multi-use case, all three applications are served by the battery system. The authors use simulation software to investigate how providing several applications affects the energy flows in the facility's grid system.

Value stacking is included in the LCI modelling as follows. For dual-use case 1, the available battery energy storage capacity for storing PV electricity is similar to the single-use case. The difference compared to the single-use case is the cycle frequency which increases from 123 cycles per year to 125. When the battery is also utilised for end-consumer power reliability (dual-case 2), part of the energy storage capacity is reserved for this application, which means that the available energy storage capacity for storing PV electricity decreases. In this case, 1138 kW, the maximum peak power of the battery, has to be available for 15 minutes, which results in a total required energy capacity of 285 kWh (0,25 h · 1138 kW = 285 kWh). Therefore, 285 kWh of the energy storage capacity is permanently reserved to serve the power reliability application. This means that the available energy storage capacity to store PV electricity decreases from 1113 kWh tot 828 kWh. In these two use cases the cycle frequency increases to 139 and 140 cycles per year respectively.

In their study, the electricity discharged from the battery, which is stored PV electricity, is assumed to displace grid-mix electricity, resulting in environmental benefits. In dual-use case 1, total electricity losses from the battery are higher because this is a percentage of the total electricity throughput, which is higher because the battery is subjected to more cycles. However, the amount of displaced grid-mix electricity remains the same as in the single-use case. Since the amount of stored PV electricity is assumed to be the same, the environmental benefits are lower compared to those in the single use case due to the higher total amount of electricity losses. Despite the increased cycle frequency, the decreased available energy capacity to store PV electricity in dual-use case 2 and the multi-use case results in lower total amounts of stored PV electricity and thus displaced grid-mix electricity. This leads to lower environmental benefits compared to the single-use case, as shown in Figure 8.

Figure 8

Negative results in climate change impact category as result of different use cases of a lithium-ion battery in a DC grid of a production facility in Germany



Note. Results in climate change impact category for the DC grid over a period of 10 years for different use cases of photovoltaic optimization (PV), peak shaving (PS) and uninterrupted power supply (UPS), which correspond to increase of self-consumption, end-consumer arbitrage and end-consumer power reliability respectively in Table 1. Adjusted from "Integration of energy flow modelling in life cycle assessment of electric vehicle battery repurposing: Evaluation of multi-use cases and comparison of circular business models," by M. Schulz-Mönninghoff, N. Bey, P. U. Nørregaard, and M. Niero, 2021, *Resources, Conservation and Recycling, 174*, p. 8.

4.1.2. Review of Regulation (EU) No 2019/1020 Annex II and PEFCRs for High Specific Energy Rechargeable Batteries for Mobile Applications

Annex II of Regulation (EU) No 2019/1020 and the PEFCRs are only reviewed on how the FU and reference flow are defined and how the use process should be modelled in terms of electricity in- and output and battery system input. They other aspects, i.e., which application(s) is/are assessed, which alternatives are included and is value stacking included do not apply here.

4.1.2.1. Functional unit and reference flow

The FU in Annex II is defined as "one kWh (kilowatt-hour) of the total energy provided over the service life by the battery system, measured in kWh" (European Commission, 2020a, p. 4). One kWh of the total energy provided is 1/X fraction of the total energy provided by the battery over its lifetime. *Total energy provided over the service life (X)* should be obtained from the number of cycles multiplied by the amount of delivered energy per cycle. The corresponding reference flow is "the amount of product needed to fulfil the defined function and shall be measured in kg of battery per kWh of the total energy required by the application over its service life" (European Commission, 2020a, p. 4). Following the reference flow, all processes shall be matched to 1 kWh of the *total energy required by the application* of the total service life. Therefore, the total energy delivered by the battery that is required for the application, which differs per application, defines the quantity of inputs of all up- and downstream processes.

Annex II provides no further explanation on how the reference flow is defined. However, the FU and reference flow definitions in Annex II are identical to those included in the current PEFCRs for High Specific Energy Rechargeable Batteries for Mobile Applications (European Commission, 2018b). Hence, this explanation is assumed to apply to Annex II as well. The reference flow in Annex II and the PEFCRs is the amount of product that is needed, which is actually an input flow of the amount of battery system in the use process. Therefore, the explanation of how this should be included according to the PEFCRs is further discussed in section 4.1.2.2 about the battery system input.

4.1.2.2. Use process modelling

Electricity

Annex II explicitly states that the use phase, by which they mean the electricity input, should not be included in the system boundary of the LCA to calculate the carbon footprint since it is "not being under the direct influence of battery manufacturers" (European Commission, 2020a, p. 4). It may be included if it is demonstrated that choices made regarding the design of the battery can have a non-negligible contribution to the carbon footprint. This means that the environmental impacts resulting from the generation of the share of electricity that is lost due to efficiency losses of the battery and electricity consumed by the battery system are excluded from the assessment. The total impacts of the battery therefore result from the raw material acquisition and processing, main product production, distribution and EOL and recycling.

However, the PEFCRs for batteries for mobile applications (European Commission, 2018b) prescribes to include the use phase in the LCA. The use phase consists of the energy losses due to battery and charger efficiency over the battery lifetime. Energy losses are calculated by Equation 1.

$$Energy\ losses = (1 - energy\ efficiency) \cdot application\ service\ energy \qquad [kWh] \qquad (1)$$

where: application service energy = the total energy required per application

Battery system

Below, an example is provided to show how the reference flow as defined in Annex II is calculated, for which the steps are based on the current PEFCRs for mobile batteries. Table 2 provides the parameters used in the example calculation.

Step 1: Calculation of the quantity of FU per battery

$$QU_a = E_{dc} \cdot N_c \cdot A_{cc}$$

$$QU_a = 0{,}045 \cdot 400 \cdot 80\% = 14{,}4\ kWh$$

Step 2: Calculation of the quantity of FUs for application service

$$Nb_{batt} = \frac{AS}{QU_a}$$

$$Nb_{batt} = \frac{29{,}6}{14{,}4} = 2{,}06$$

Step 3: Calculation of the reference flow

$$Rf = \frac{Nb_{batt} \cdot mass}{AS}$$

For example, for a battery with a weight of 1000 kg:

$$Rf = \frac{2{,}06 \cdot 1000}{29{,}6} = 69{,}59\ kg\ battery/kWh$$

Table 2

Parameters used for example calculation of the reference flow in the PEFCRs for High Specific Energy Rechargeable Batteries for Mobile Applications

Symbol	Parameter	Battery	Unit
E_{dc}	Energy delivered per cycle	0,045	kWh/cycle
N_c	Number of cycles[a]	400	number
A_{cc}	Average capacity per cycle	80%	%
QU_a	Quantity of functional unit	-	kWh over service life / per battery
AS	Application service: total energy required per application	29,6	kWh
Nb_{batt}	Number of batteries to fulfil the total energy required by the application	-	number
Rf	Reference flow: amount of battery mass required to fulfill the service	-	kg battery/kWh

Note. [a] the number of cycles should be based on battery manufacturer data proving the life span of the battery in the application, which is either specific life cycle testing, or a measurement of the battery life in the application.

The literature review indicates that FUs, alternatives, reference flows and the way the use process inputs are modelled varies between studies. Moreover, the PEFCRs prescribe a completely different approach where the battery input is the reference flow instead of defining the delivered electricity as reference flow. This is the end of the review of current approaches in battery LCA studies and related methodological guidelines. The next section provides an analysis and discussion of the review results.

4.2. Review discussion

In this section the review results are analysed, recommendations are provided and improved approaches are drafted.

4.2.1. Goal and scope definition

Within the goal and scope definition phase the definition of the FU is ambiguous. However, there are several other elements that are ambiguous which all relate to harmonising system boundaries with the aim of the study and the inventory phase.

4.2.1.1. Functional unit

As discussed in section 4.1.1.2, some studies did not include a FU at all. This makes it inconvenient to understand what the authors assessed exactly. Therefore, it is recommended in general to include a discussion about the function and from that define the FU. One of the reviewed studies did not define a general FU, but defined one for each alternative battery technology by means of a formula to calculate the battery's electricity output, based on the battery's efficiency, from a unified electricity input from PV panels (Mostert et al., 2018). In their study, the electricity output for the same amount of electricity input is different for each battery technology since it depends on battery characteristics like efficiency and DoD. This means that the function on which the alternatives are compared, the battery's electricity output, is unequal.

Moreover, some studies use battery energy storage capacity (kWh) in the FU definition (Delgado et al., 2019; Peters & Weil, 2017; Pucker-Singer et al., 2021), which is remarkable because energy capacity is not the function of a battery. Storing electricity would only consider the battery energy storage capacity. The function of a battery is to store electricity, but eventually electricity always is the product that is obtained from the battery during the use phase which is used for a specific application. Energy storage capacity therefore is not an accurate FU for comparing battery technologies because it does not consider the use of a battery including cycle life and efficiency differences which influence the electricity output of a battery. In other words, it would result in an assessment of the production of the battery system only. Electricity delivery is what results from the battery use process and therefore this is argued to be the function of a battery. Therefore, electricity output (kWh) of a battery is a more meaningful metric for the FU. This is also emphasised by Porzio et al. (2021) and Spanos et al. (2015).

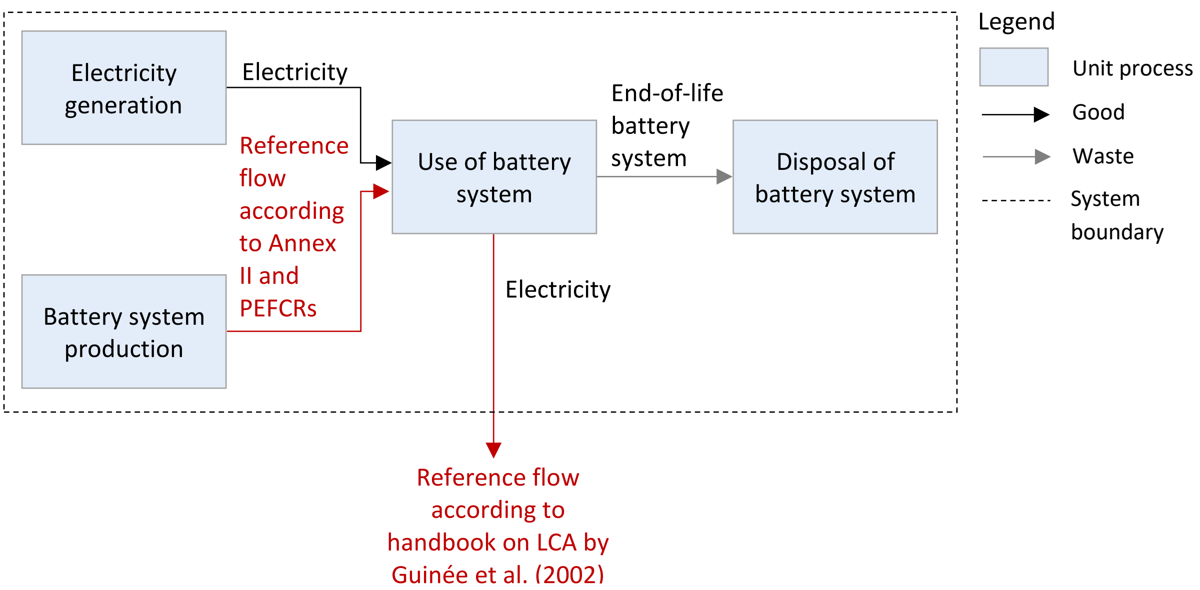
The ISO 14040 (International Organization for Standardization, 2006), on which Regulation (EU) No 2019/1020 Annex II and the PEFCRs for High Specific Rechargeable Batteries for Mobile Applications are based, does not provide a clear definition of a reference flow and how it relates to the FU (Guinée et al., 2002). The reference flow in Annex II, which is the same as in the PEFCRs (European Commission, 2018b), is defined as the "amount of product needed to fulfil the defined function" (European Commission, 2020a, p. 4). This reference flow is an input of the use process, as depicted in Figure 9, which differs from the adapted FU and reference flow definitions as specified by Guinée et al. (2002):

- *Functional unit:* quantified service provided by the product system(s) under study for use as a reference basis in a life cycle assessment study. For example, covering 25 m^2 of wall, with a coloured surface of 98% opacity, not requiring any other painting for 10 years.
- *Reference flow:* quantified flow generally associated with the use phase of a product system and representing one way of obtaining the FU. For example, covering 25 m^2 of wall with paint A.

Based on the above, the FU in Annex II *('One kWh (kilowatt-hour) of the total energy provided over the service life by the battery system, measured in kWh'*) is proposed to be adapted to '*Delivering one MWh electricity of the total electricity delivered over the battery's lifetime*'. The unit in the FU can be any SI prefix of Wh that is appropriate for the energy capacity of the battery under study; in the remainder of this study MWh is used for the sake of clarity. The reference flow as defined by Guinée et al. (2002) is a measure of the outputs from processes in the product system to fulfil the function as defined in the FU. The reference flow in Annex II (*'the amount of product needed to fulfil the defined function and shall be measured in kg of battery per kWh of the total energy required by the application over its service life')* refers to the assignment of the amount of battery which depends on how the process data, i.e., battery characteristics, are defined. However, according to the handbook on life cycle assessment by Guinée et al. (2002), this is part of the inventory analysis, which means it cannot take place before the goal and scope definition step. In the goal and scope phase only the function, FU and alternatives are determined. The combination of the FU and alternative results in the reference flow for each product system that is required to fulfil the FU. According to this definition, the reference flow is an output of the use process that is required to fulfil the FU, as depicted in Figure 9. The amount of battery and electricity that are required for the corresponding reference flow are determined during the inventory analysis. Therefore, the reference flow in Annex II and the PEFCRs is proposed to be adjusted to this format. Then, the reference flow is the combination of the FU and the alternative. For example, if a lithium-ion battery is assessed the reference flow becomes '*Delivering one MWh electricity of the total electricity delivered over the lithium-ion battery's lifetime*'. Calculating the amount of battery that is required to fulfil the defined reference flow is part of the LCI phase.

Figure 9

Constituents of the product system of a stationary battery system including the use phase depicting the difference between the reference flow according to Annex II and the PEFCRs and the handbook on LCA by Guinée et al. (2002)



In Annex II, the FU is assumed to be applicable to all batteries and for all applications. The FU always concerns energy provided (i.e., kWh) by the battery, no matter what application the battery under study is utilised for. The application is eventually incorporated in the guidance because the corresponding reference flow is based on the total energy '*required by the application'*. The FU as expressed in Annex II and the PEFCRs are only reflecting energy storage, i.e., kWh over the lifetime. Moreover, by far most LCA studies define the FU with kWh or MWh as unit, regardless of the application. However, not all applications are necessarily about providing energy storage. For example, in case of frequency regulation, the function of the battery is keeping the grid frequency stable, which is achieved by providing an extra power capacity instantaneously.

The grid frequency changes based on the increase or decrease in electricity output of generators and the increase or decrease in electricity demand as explained in section 2.1.1. Bids are placed into the regulation market based on power capacity rather than available energy. The term capacity is used here, which does not refer to a volume, but is the (maximum) output of an electricity generator or ESS and is measured in megawatts (U.S. Energy Information Administration, 2020). In this regard, a battery can be compared to a swimming pool which is available all the time. A battery utilised for frequency regulation does not aim at energy storage, instead the storage is used as an extra capacity that is available to provide power to the grid to balance the grid frequency. In this case it is the speed (J/s) at which the grid can be provided with electricity. To compare it to the example of the pool; it is not so much about the volume of the swimming pool, but about the speed at which the pool can be filled and drained. A more extensive explanation of the frequency balancing principle and how batteries are utilised for balancing the frequency is included in Appendix C. In case of voltage regulation, the aim is to maintain the local voltage within a specified range, which is also achieved by the injection or absorption of power to or from the battery (Eyer & Corey, 2010).

The lack of differentiation between applications in the FU is a shortcoming in Annex II and the PEFCRs, since, besides serving RET firming, currently most battery storage power capacity is used to serve arbitrage but also the frequency balancing market (IRENA, 2019; Malhotra et al., 2016). Battery systems are already a promising provider of fast spinning reserve services to regulate the grid frequency such as FCR and aFRR in recent years (Marchgraber & Gawlik, 2021). An explanation of these concepts is provided in Appendix C. In the United States, even 73% of battery storage power capacity provided frequency regulation in 2019 according to the U.S. Energy Information Administration (2021). Moreover, renewable energy technologies like solar and wind energy systems are intermittent and do not supply constant power. An increasing share of these technologies increases frequency deviations and therefore increases demand for frequency regulation to keep the energy grid stable (Bae et al., 2016; Marchgraber & Gawlik, 2021). Finally, an increasing share of renewables and decreasing share of conventional energy generators as a result of the energy transition, means that the provision of power quality applications, such as frequency regulation, by conventional generators has to be replaced, for which batteries are a potential solution (Akhil et al., 2015).

The function of a battery always is delivering electricity and therefore the FU can always be expressed in kWh or MWh as a unit of electric energy. However, this electricity is used for a specific economic application and therefore the application for which the electricity is used is closely connected to the FU. For this reason, every application in Table 1 is translated to a corresponding function for the FU which is included in Table 1. In the storage debate, generally storage technologies and applications are specified as power applications when the discharge duration is below 30 minutes and energy applications when the discharge duration is above 30 minutes (Manz et al., 2011). Based on this and the formulated functions as basis for the FUs, the applications in Table 1 can be divided in two subgroups:

- *Energy storage applications* for which the battery is utilised with the intention to store electric energy to be used at a later time for different purposes. These applications are aimed at storing electric energy for longer discharge duration from minutes to hours and therefore require larger energy storage capacity (Eyer & Corey, 2010). This group exists of all increased *utilization of existing assets, arbitrage* and *power reliability* applications in Table 1.
- *Power applications* for which the electricity stored in the battery is used to keep the power supply within the optimal frequency and voltage level. This comprises of the *power quality* applications in Table 1. These applications are aimed at providing power capacity to the grid,

which require power output (i.e., MW) generally for relatively short periods of time (seconds or a few minutes) (Eyer & Corey, 2010).

Resulting from this, the FU proposed before is split into a general FU for each subgroup. It is the application that defines which battery technologies are suitable, what power and energy capacity are required and how the battery is operated. Therefore, *specify application* is recommended to be included in the FU. The specification of the application and the related battery requirements, assumptions and application characteristics such as cycle frequency for the specific application(s) are recommended to be defined after the FU, for example in the form of a table such as Table 3. Defining these characteristics in the FU because this determines the total delivered electricity during the battery's lifetime is not necessary since this is a characteristic of the application and therefore can be included in a separate table. This way the FU is general and does not have to be defined for each application, which keeps things convenient. Moreover, adding the application characteristics in a table below the FU provides transparency and increases potential comparability between studies.

FU for energy storage applications:
Delivering one MWh electricity of the total electricity delivered over the battery's lifetime from a battery used for [specify application].

FU for power applications:
Delivering one MWh of electricity of the total electricity delivered over the battery's lifetime in order to provide X MW of power capacity from a battery used for [specify application].

In the second FU the required power of the battery system for the application is included in the FU since offering this power capacity is what it handles about in case of power applications. This way, alternatives that have more or less power are excluded from the assessment to prevent unfair comparisons.

The recommended FUs are defined in terms of one MWh of the total electricity delivered over the lifetime of the battery. Another option would be to specify a specific period of time that the application should be served in which the battery might have to be replaced, like some of the authors of the reviewed studies did, see section 4.1.1.2. Both ways lead to the same results when the FU is expressed per MWh delivered, as shown in Appendix F. However, in case of comparative assessment, it is important that this 1 MWh is the same 1 MWh, therefore *of the total electricity delivered over the battery's lifetime* is included in the FU definition.

When the environmental impact scores are expressed per MWh this might create the impression that results can be compared to each other between studies, while the application characteristics can be different between studies and therefore the results are not comparable. This, again, is reason to clearly define the application characteristics in the study. A more extensive explanation is included in Appendix G.

Table 3

Battery application input data

Application	Required power [MW]	Discharge duration [h]	Required energy capacity [MWh]	Cycle frequency [cycles/day]
Utility Energy Time-Shift	100	8	800	1
T&D Investment Deferral	10	5	50	0,68
Energy Management (community scale)	0,1	2,5	0,25	2
Increase of Self-Consumption	0,0025	4	0,01	0,6
Area and Frequency Regulation	2	0,25	0,5	34[a]
Support of Voltage Regulation	1	0,25	0,25	0,68

Note. [a]34 small cycles per day (at 5% DoD). Adapted from "A review and probabilistic model of lifecycle costs of stationary batteries in multiple applications," by B. Battke, T. S. Schmidt, D. Grosspietsch, and V. H. Hoffmann, 2013, *Renewable and Sustainable Energy Reviews, 25*, p. 246.

4.2.1.2. System boundaries

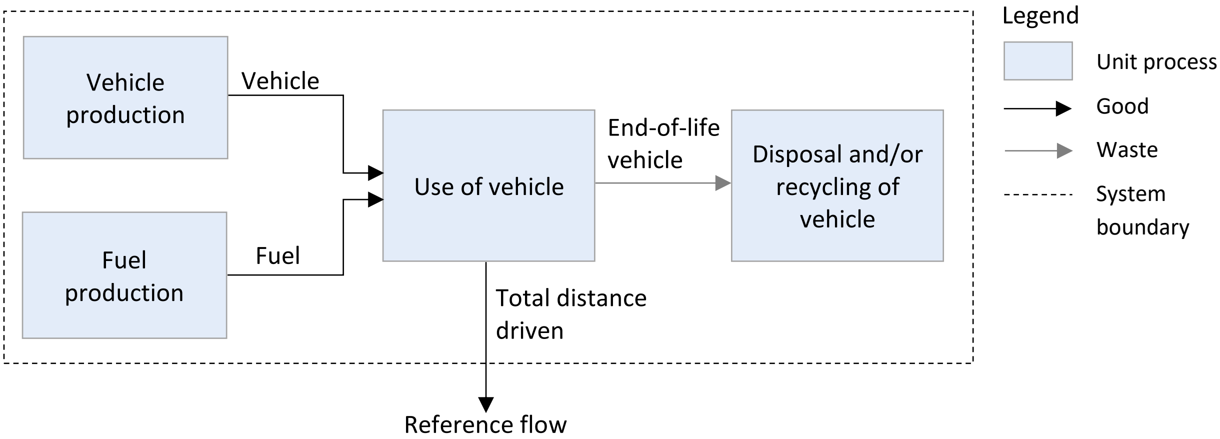
Include electricity input or not

In Annex II and the PEFCRs the amount of battery in kg of battery per kWh that is required to fulfil the defined function (reference flow) is determined based on the total amount of required energy by the application of the total service life. The required energy is the electricity delivered from the battery that is required to serve the application. The higher the total delivered energy, the lower the amount of battery in kg per delivered kWh since this is based on the total required energy. Next to that, electricity is needed for battery operation and part of the electricity is not retained from the battery due to efficiency losses. This means that in absolute terms a higher amount of delivered electricity also means more electricity is lost due to efficiency losses. However, according to Annex II this should not be included in the overall impacts because the use phase should be excluded.

The use phase of a battery could be compared to the case of an internal combustion engine vehicle, of which the simplified product system is depicted in Figure 10. The production and EOL processing and/or recycling of a vehicle determine the environmental impacts excluding the use of a vehicle. Now, if the environmental impacts are determined by the amount of vehicle in kilogram required to drive one kilometer (km), the total distance driven over the lifetime of the vehicle determines the amount of kilogram for one km. The higher the total driven distance over the lifetime, the lower the amount of vehicle in kg/km, the lower the total environmental impacts per km (Baumann et al., 2019). However, at the same time, the higher the total distance, the higher the total environmental impacts occurring from the use of the vehicle since more fuel is combusted. When the latter is not included in the overall impacts this provides a false impression of the actual overall impacts over the lifetime. Especially when two vehicles are being compared, this provides an incomplete comparison because a more efficient vehicle consumes less fuel and therefore has lower environmental impacts during the use phase than a less efficient vehicle.

Figure 10

Simplified product system of an internal combustion engine vehicle



Returning to the case of a battery, this implies that when the use phase impacts would be included in the assessment, the *relative contribution* of the battery production and EOL treatment to the overall impacts decreases when the total amount of electricity delivered by the battery increases. For example, if the total electricity input to deliver 144 MWh output is 180 MWh (80% round-trip efficiency), this means that during the use of the battery 36 MWh (180 MWh – 144 MWh) is lost. These losses result from efficiency losses of the battery and therefore the related environmental impacts can be attributed to the environmental impacts of the battery. Now, if this battery would be compared to another battery with a higher round-trip efficiency, the total lost electricity of that battery would be lower. Therefore, the environmental impacts related to the use phase are lower which affects the overall impacts, while both batteries deliver the same amount of electricity.

It should be noted, however, that Annex II and the PEFCRs are not equal to LCA, but provide guidelines on how to implement selected specific steps of LCA specifically for determining the carbon footprint or the PEF for a specific product category. In contrast, LCAs generally focus on comparing two product systems or identifying hotspots in the supply chain in order to propose possible improvements. However, eventually, both the PEFCRs and the carbon footprint calculated according to Annex II enables comparisons to a benchmark and therefore indirectly between products within the same category as well (Elsen et al., 2019). Battery system A could be better than the average performance in the category, whilst battery system B has an average performance. When comparing two battery systems, the environmental impacts related to the use phase of the battery could be important as explained above. The battery design defines the efficiency of the battery system. When the efficiency is higher, less electricity is lost during each cycle, resulting in lower environmental impacts. Both Hiremath et al. (2015) and Baumann et al. (2017) show, by means of sensitivity analyses, that life cycle environmental impacts are strongly dependent on the battery round-trip efficiency when the use phase is included. For these reasons, it is argued that including the electricity input is required, certainly in case of comparative LCA studies.

Include electricity throughput or electricity losses

Hiremath et al. (2015) mention that analyses of batteries that only consider battery efficiency losses will be of little help when a decision maker asks systemic questions. For example, how environmental impacts of serving a certain application by a natural gas generator compare to serving it by a battery system. Therefore, they argue in favour of including the total electricity throughput including losses, as described in section 4.1.1.4.

However, in their example, a battery charged with grid mix electricity is compared to a battery charged with PV electricity. This is actually a comparison of different applications of the battery. Charging it with PV electricity means that either RET firming, RET arbitrage or RET smoothing is served depending on the aim to store PV electricity. Charging a battery with grid mix electricity on the other hand implies that it is used for a different application such as arbitrage.

Of course, charging a battery with grid mix electricity results in higher environmental impacts than when it is solely charged with PV electricity. However, the transition from grid mix electricity to renewable electricity in their example, without a battery system, already reduces CO_2 emissions by 57,8 kg. The battery system actually increases emissions of both systems due to the losses of the battery. In case of renewable electricity this increase is 2,2 kg (10,9 – 8,7), while it is 16,6 kg (83,1 – 66,5) for a battery charged with grid mix electricity. So, the *difference in emissions* that actually occurs from the implementation of a battery is 14,4 kg CO_2. Expanding the calculation in section 4.1.1.4 by including a different battery technology B with a round-trip efficiency of 70% clarifies the explanation.

To deliver 100 kWh, this battery requires 100 / 70% = 143 kWh electricity input.

Accounting for *all stored electricity during use* results in:
143 kWh · 87 g/kWh = 12,4 kg CO_2
143 kWh · 665 g/kWh = 95,1 kg CO_2
Difference in emissions: 95,1 – 12,4 = **82,7 kg CO_2**

Only accounting for the emissions due to the *efficiency losses during use* of the battery results in:
(143 – 100) kWh · 87 g/kWh = 3,7 kg CO_2
(143 – 100) kWh · 665 g/kWh = 28,6 kg CO_2
Difference in emissions: 28,6 – 3,7 = **24,9 kg CO_2**

Comparing charging with PV electricity and grid mix electricity between battery A and B, the difference is 10,5 kg CO_2, no matter if only the efficiency losses or all electricity during use is accounted for (i.e., 82,7 – 72,2 = 10,5 kg CO_2 and 24,9 – 14,4 = 10,5 kg CO_2).

The difference in emissions between battery technologies is the same, no matter if only the electricity losses or all electricity during use is accounted for. The difference of 57,8 kg CO_2 results from charging the batteries with PV electricity instead of grid mix electricity. This reduction would have been gained anyway by the transition from grid mix electricity to renewable electricity, under both battery technologies. In fact, batteries are required to enable this transition. In other words, the *difference* in emissions *between* different battery technologies only emerges from the *difference in battery efficiency* (80% versus 70%). For that reason, it would not be fair to attribute all emissions of the total electricity throughput (i.e., electricity output and electricity losses) to the battery system when assessing a battery system or when comparing two battery technologies.

Of course, the choice of the electricity input source and including total electricity throughput or only the share resulting from the battery efficiency losses has implications for the inventory phase, but it is decided to discuss it in this section since it is related to the choice regarding the product system that is assessed. This relates to the aim of the study which is part of the goal and scope definition. While Hiremath et al. (2015) state that the goal was to assess the environmental impacts of four promising battery technologies, what they actually did in their explanation was comparing electricity systems with a battery for different applications. It is this distinction between aims of the study that is lacking in the argument of Hiremath et al. (2015).

For policymakers, it is helpful to compare the impacts of an *energy system* including a battery to a system without a battery, for a specific application. In this case, it would make sense to consider the impacts of all electricity stored in the battery. These are not necessarily the environmental impacts of the battery, but the impacts of delivering a certain application in an energy system with batteries. This is what matters for policymakers who are interested in knowing the total emissions of the energy system. This way they know how total emissions of the energy system will reduce or increase when implementing batteries compared to the status quo. Examples of such studies are Elzein et al. (2019), Jenu et al. (2020), Kamath et al. (2020), Pucker-singer et al. (2021) and Vandepaer et al. (2019).

In contrast, only the electricity input due to the efficiency losses of the battery have to be accounted for when the aim of the study is to compare *battery technologies* to each other. This is useful for battery developers who can only influence the battery technology under development. This comparison provides insight on how a battery performs compared to another battery for a specific application. Or it shows how the environmental impacts change as a result of altering (a component of) the battery. Only if a battery is compared to another battery, but the application for which the battery is used could also be served by a product system without a battery and the aim is to compare the battery to that product system as well, then all stored energy should be included to provide a fair comparison. An example of such an application is frequency regulation, which is also supplied by natural gas or coal power plants. This is assessed by Koj et al. (2015) and Ahmadi et al. (2017) for example.

Making this distinction and stating the goal clearly in the goal and scope section of the LCA is important since it determines what should be compared and what should be included in modelling the use process of a battery in the LCI. Therefore, an overview of different comparisons that should be made for different research aims is presented in Table 5.

Which battery efficiency

Part of the electricity that is charged into a battery is lost during each charge-discharge cycle. Round-trip efficiency is the percentage of electricity that is charged into a battery and is later retrieved (Mey, 2021). Therefore, the environmental impacts due to round-trip efficiency losses are the impacts resulting from the generation of electricity that is used to charge the battery but that is not recovered by the battery. The term round-trip efficiency is used inconsistently however, which is also described by Porzio and Scown (2021). Oftentimes it is used to refer to the DC-DC efficiency, while AC-AC efficiency is more useful since that is the efficiency from the point of interconnection to the electricity system. The latter includes efficiency of inverters as well. Some authors refer to the AC-AC efficiency as round-trip efficiency, while others refer to this as the overall efficiency or system efficiency, see section 4.1.1.4. Moreover, some authors also include the use of electricity to operate the battery system, for example for cooling equipment and battery management systems, in the overall efficiency as well (Jones et al., 2019). The efficiency of a battery system is a battery characteristic and is therefore part of LCI data. However, which efficiency value is used in the LCI depends on whether inverters are considered to be part of the battery system or not and therefore is determined by system boundaries set in the goal and scope phase. Additionally, consensus about how round-trip efficiency is defined would be beneficial.

Electricity mix

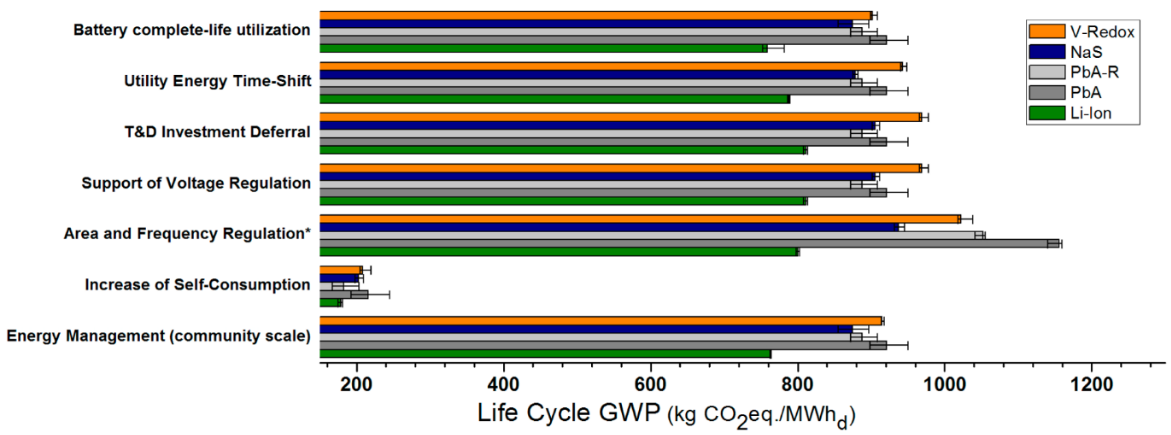
In practice, the electricity generation mix that will charge the battery for some applications varies over time, even per hour (Baumann et al., 2019). The electricity mix required to match demand is defined by unit commitment and dispatch cost optimisation as explained in the following section about including displaced electricity or not (Ryan et al., 2018). However, this electricity mix cannot be influenced by battery developers. Moreover, the application for which the battery is used determines the frequency and moments of charging, which means that the moments of charging cannot be shifted like in the case of charging an electrical vehicle. Since it is the application that defines the charging profile of the battery and the electricity mix to charge the battery is the same for both batteries in a comparative assessment, this means that considering an hourly defined electricity mix as input for the use process does not matter for comparative LCA studies of batteries. Therefore, including a temporal resolution in the modelling of the charging electricity is excluded from further analysis. A more extensive discussion on this topic is included in Appendix H.

Applications

What Hiremath et al. (2015) compared in their example calculation, see section 4.1.1.4, to justify including total electricity throughput instead of electricity losses only, are different applications for which the battery is used. A battery charged with grid mix electricity is generally utilised for a different application then when it is charged with renewable electricity. Batteries cannot be charged with renewable electricity for all applications. The rationale behind charging a battery with PV or wind energy is to store renewable electricity, either for RET firming, RET arbitrage, or RET smoothing. The application determines which electricity the battery is charged with. Therefore, the electricity input in the LCI phase should be in line with the application that is defined in the goal and scope phase. Hiremath et al. (2015) also show the life cycle global warming impact results of different applications served by the different batteries next to each other in one figure, as shown in Figure 11. On a side note, even though it is not necessarily incorrect to depict the results of different applications in one figure, it is prudent to explicitly note under the figure that applications cannot be cross compared. A more extensive discussion is included in Appendix I.

Figure 11

Life cycle impacts of battery systems for different stationary applications



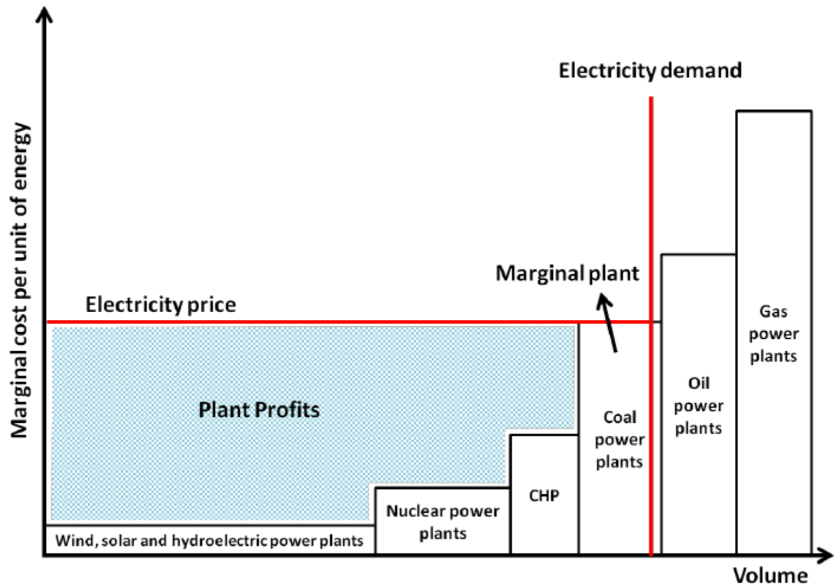
Note. From "Comparative Life Cycle Assessment of Battery Storage Systems for Stationary Applications," by M. Hiremath, K. Derendorf and T. Vogt, 2015, *Environmental Science and Technology, 49*(8), p. 4828.

Include displaced electricity or not

In practice, the environmental impacts occurring as a result of implementing a battery system in an electricity network is the difference between environmental impacts of an electricity network with battery system and a network without battery system. Some of the reviewed LCA studies consider the displacement of, an adjusted, electricity mix in the product system (Carvalho et al., 2021; Elzein et al., 2019; Jenu et al., 2020; Pucker-Singer et al., 2021; Schram et al., 2019; Schulz-Mönninghoff et al., 2021; Vandepaer et al., 2019). Because the electricity from a battery is generally assumed to substitute electricity supply from (an)other source(s), the implementation of batteries might alter the marginal electricity supply mix. That is, they might change the background system in the LCA product system. The marginal electricity mix is determined by the merit order, as shown in Figure 12, which is the sequence in which available sources of electricity generation contribute to the electricity market based on ascending order of price, commonly reflecting their marginal costs of production (Appunn, 2015). Figure 12 shows the marginal costs per kWh of electricity for each generation source on the y-axis and the volume that each generation source can supply on the x-axis. Unit commitment and economic dispatch optimisation determines which generating units will be turned on during which hours and at which level they have to run to match demand (Ryan et al., 2018). Of course, this does not apply to variable renewable energy sources such as wind and solar energy since these are not dispatchable, but supply is defined by the current sun irradiation and wind force.

Figure 12

Merit order dispatch in electricity markets



Note. From "Cross-Border Trade in Electricity and the Development of Renewables-Based Electric Power: Lessons from Europe," by H. Bahar and J. Sauvage, 2013, *OECD Trade and Environment Working Papers 2013/02,* p. 42.

A battery system that is used to store excess renewable electricity for example, enables the substitution of other electricity generators; the four columns on the right in Figure 12. Because the electricity from this battery will displace the most expensive generators, so those on the right side in Figure 12, this battery system might affect the dispatch of these generators at periods of high demand, i.e., the volume of electricity generation by these sources. This would change the *average annual marginal electricity mix* and thus the related environmental impacts compared to the current situation.

Taking into account the displacement of an (adjusted) electricity mix as a result of the (demand for a) battery is considered in a mode of LCA that is commonly called consequential LCA (CLCA). CLCA aims at capturing the environmental impacts of direct and indirect changes induced by a product (Vandepaer et al., 2019). Even though there is discussion about what CLCA entails exactly, an often used definition is "To provide information on the environmental burdens that occur, directly or indirectly, as a consequence of a decision (usually represented by changes in demand for a product)" (United Nations Environment Programme, 2011, p. 47). However, according to Cucurachi et al. (2018), CLCA is also about determining the environmental impacts as a consequence of the introduction of a new technology, or as a consequence of changes in policies. Accordingly, the environmental impacts of the implementation of batteries is an occurrence that could be assessed by means of a CLCA. The consequences in such product systems are traced forward in time by using data on marginal suppliers and substitution of displaced activities (Consequential-LCA, 2021).

Even though the current study refrains from a further discussion on consequential and attributional LCA (ALCA), it is argued why the consequential approach could be misleading for assessing a battery system. In a CLCA, to try to express the impacts of activity A, the impacts of any avoided activity B (avoidance credits) are subtracted from activity A and the outcome is called the impacts of A. This is not permitted in ALCA, but it is exactly what is done in CLCA modelling (Koffler, 2018). Subtracting avoided impacts from the product system under study could result in negative environmental impacts (negative with regard to the sign), for example like the results of the study by Schulz-Mönninghoff et al. (2021) as shown in Figure 8. This way, CLCAs could easily lead to confusing and misleading results. Putting this in terms of electricity systems, a comparison is made between product system A, an electricity system with battery, and product system B, an electricity system without battery, within the single assessment of a battery. This means that two things are subtracted on a single level; the impacts of product system A include the subtraction of the impacts of system B. This could result in negative impacts while these impacts are not actually negative; the impacts of system A are simply lower than those of system B. Environmental burdens are usually not actively reduced by consuming a product unless it is a product that fixes emissions.

Nevertheless, this is exactly what Vandepaer et al. (2019) did in their assessment. They state that batteries enable the use of renewable electricity that would otherwise be curtailed. Therefore, they assume that the electricity discharged from batteries and supplied to the grid displaces grid mix electricity in a 1:1 substitution ratio. The environmental impacts of the displaced electricity are subtracted from the impacts of the battery system, resulting in negative impacts. The actual effect of the battery system on the future marginal electricity mix is not considered though. For the displaced grid mix electricity, prospective marginal electricity mix scenarios for 2030 and 2040 are used. This mix exists of an increased share of renewable energy technologies which is based on the projections from the Swiss TIMES Energy Model were used to obtain average electricity mixes for 2030 and 2040 without variable renewable energy sources (solar and wind) and combined heat and power (CHP) plants. Solar and wind power units are not part of the displaced marginal mixes because it is assumed that the batteries are dedicated to capture their production. Therefore, they argue that a change in electricity demand will not result in a change in investments in renewable energy sources. CHP plants are not included because neither the electricity nor heat generates enough revenue to justify the installation of new CHP units in the future. The environmental impacts of the battery system do not include the environmental impacts of the electricity used to charge the battery which is generated by renewable energy sources, which they justify by stating that it would be curtailed in the absence of the battery. This assumption might hold for the RET firming application, however for another application it could be different. For example in the case of frequency regulation, the stored electricity does not necessarily *substitute* grid mix electricity but the batteries affect the *composition of* the electricity mix, as explained before, because the share of a specific electricity generator in the mix increases or decreases as results of the batteries that provide this service since frequency regulation is generally served by gas plants.

Jenu et al. (2020) also provide a comparison of electricity from a battery charged with PV to electricity from the grid. However, they subtracted the latter from the environmental impacts of the battery system. In the study by Elzein et al. (2019), the renewable electricity that is stored and discharged from the battery is assumed to replace electricity from coal and natural gas generators. The marginal electricity mix is adjusted towards a lower share of coal and gas corresponding to the amount of electricity output from batteries. This share results from an optimal operation of the batteries so that total grid operation costs are minimised. Their results show that the use of a battery results in negative emissions. In the study by Carvalho et al. (2021), in scenario B, the electricity discharged from the battery, which stores electricity from wind and solar plants, is assumed to avoid electricity from natural gas combined-cycle power plants. Their results show negative climate change impacts. Pucker-Singer et al. (2021) and Schram et al. (2019) assumed that PV electricity stored in the battery is supplied to the grid and replaces electricity from the grid. Therefore, the environmental impacts of replaced grid mix electricity are included as negative impacts. Finally, Schulz-Mönninghoff et al. (2021) assessed the implementation of a battery in an industrial facility's DC grid to store PV electricity. The business-as-usual (BaU) scenario is the situation of the facility's grid with PV electricity but without a battery. The increased amount of PV electricity that can be used by the facility due installing a battery system in the facility's grid is assumed to displace grid mix electricity. The environmental impacts resulting from this amount of grid mix electricity are subtracted from the environmental impacts of the electricity lost by the battery system only, which results in negative impacts. Even though subtracting two things on one level is arguable, if it is done anyway then it should be done adequately. Subtracting the impacts of the displaced grid mix electricity from the impacts of *only* the efficiency losses of the battery seems inadequate. Instead, the total impacts of the battery system should be compared to the total impacts of grid mix electricity. Therefore, the grid mix electricity environmental impacts should be subtracted from the environmental impacts of the total PV electricity input of the battery system including efficiency losses, not just from the efficiency losses.

More importantly though, the negative impacts in the studies mentioned above only reflect the difference in impacts between two alternatives. However, this is oftentimes misinterpreted by the readers of such studies (J. Guinée, personal communication, September 23, 2021). Instead of subtracting impacts, a proper way to quantify the effects of such systems is making a comparative LCA study. For assessing the environmental impacts of a battery in an electricity system, the total environmental impacts of the electricity system without battery should be compared to those of an electricity system with battery taking into account the possible changes in the marginal electricity mix (background). This entails defining how and to what extent the electricity mix is affected by batteries in the future. This handles about deriving future electricity mix scenarios with the integration of batteries. A single battery is a marginal product; in other words it will not affect the background system, which is the case when a short-term perspective is taken. However, when the goal is to assess the effects of batteries in a more distant future when a multitude of batteries is integrated in the electricity system, there might actually be an effect on the electricity mix, next to the already increased share of renewables in the future. Therefore, the total amount of integrated battery capacity for a specific application has to be known to define future electricity mix scenarios. Then the question arises at which total battery capacity the marginal electricity mix is affected. This again depends on the size of the electricity system under study in which the battery systems are integrated. For example, effects only occur for a change of 1 TWh in the electricity demand in Nordic countries (Mattson et al., 2008) and 14 GWh in the electricity system of France (Roux et al., 2017).

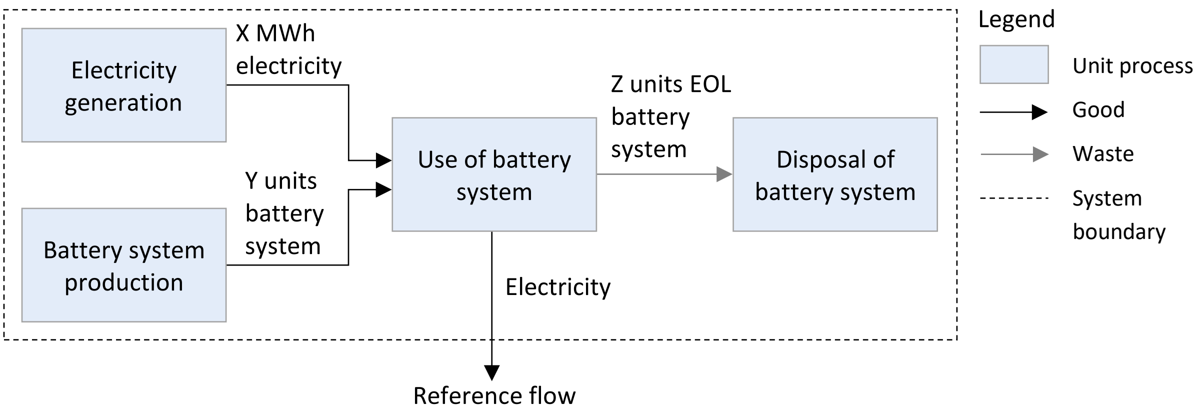
Albeit such comparative studies can be meaningful, they concern another question and aim than assessing the environmental impacts of a battery technology or comparing battery technologies. Such assessments fit to a question considering the effect on environmental impacts of a policy that specifies the integration of a total energy storage capacity in the electric power system in a particular time horizon. It requires a comparison of a regional, national or supra-national electric power system without batteries versus the same electric power system with the integration of batteries for a particular application. This is no longer about assessing the environmental impacts of a battery technology or comparing battery technologies, but about assessing the impacts of a (supra-) national policy. This contradicts to the statement by Pellow et al. (2020) that for integrating such changes in the electricity mix, a consequential LCA framework for grid-connected batteries, like the study of Ryan et al. (2018), is a best practice that should be adopted in future battery LCA studies. Ryan et al. (2018) did model the effect of a single battery in a small electricity system by coupling LCA results of a battery to unit commitment and economic dispatch optimisation modelling. However, it seems to be an adequate approach for such LCA studies assessing the effects of a policy in a systemwide analysis. Although their modelling comprises a small system and therefore it is questionable whether it provides useful insight into the interactions between stationary batteries and electricity generators as they would occur in a real-world, much larger system. The current study does not further go into this line of research and does not provide recommendations on how this could be modelled.

4.2.2. Use process modelling

The modelling of the use process varies between the reviewed LCA studies. In order to provide a recommendation on how to model the use process, the battery parameters and application characteristics and how they interact to fulfil the defined reference flow are identified based on the reviewed LCA studies. To this end, the FU and reference flow as defined in section 4.2.1.1 are assumed. Using this definition of the FU and corresponding reference flow, the amount of electricity and battery system are process inputs that are specified in the inventory analysis phase. Thus, the use process of a battery interacts with the electricity input and battery system input and output, as depicted in Figure 13. First, the electricity input is discussed, after which the battery system input is discussed. The battery output is not considered in this study. Moreover, the equation to define the battery system input fraction also applies to the battery output. The interaction of parameters is processed into equations, which are provided below and are defined to match with delivering one MWh over the battery's lifetime, corresponding to the FU of *delivering one MWh electricity of the total electricity delivered over the battery's lifetime from a battery used for [specify application]* in section 4.2.1.1. This is similar to modelling the unit process data as a single battery and the total electricity input over the battery's lifetime. In that case, LCA software that allows scaling automatically scales the electricity and battery system inputs to delivering one MWh when one MWh is derived from the use process. How the use process inputs can be modelled for the different comparisons is included for the distinguished goals in Table 5.

Figure 13

Constituents of the product system of a stationary battery system including the use phase



4.2.2.1. Electricity

In section 4.2.1.2 it is argued that only electricity lost due to efficiency losses of the battery during each cycle should be attributed to a battery system in case of assessing a battery system. This is also what most of the reviewed LCA studies did, however, oftentimes no clear information is provided on how the efficiency losses are determined, which impedes transparency. Moreover, it complicates replication of the LCA. Only some of the reviewed studies provide explanations of how the *electricity lost* is calculated or provide information that enables determining how it is calculated. Da Silva Lima (2021), for example, provide all parameters that are used to calculate the efficiency losses. Moreover, they provide the included values which enables tracing back the equations that are used to arrive at these values. Weber et al. (2018) provide the parameters they used to calculate the efficiency losses. Likewise, based on the statement that only efficiency losses are included and the provided battery parameters in the supplementary information of the study by Peters and Weil (2017), the example calculation provided in Table E1 is traced back. Even though Hiremath et al. (2015) assume that all electricity input should be included, they provide clear equations on how the total electricity input including efficiency losses is calculated. Moreover, Mostert et al. (2018), Rahman et al. (2021) and Schulz-Mönninghoff et al. (2021) all provide information on how the charged and discharged electricity and thus the efficiency losses are calculated. By analysing the studies mentioned above it is identified that the characteristics that define the charged and discharged electricity are: (1) the nominal battery energy capacity; (2) round-trip efficiency; (3) the share of the energy capacity that is used (i.e., depth of discharge ((DoD)); and (4) the total number of cycles. The amount of electricity that is charged into the battery is determined by: (1) the battery's nominal energy capacity; (2) the DoD; and (3) the total number of cycles. The *electricity lost* normalised to 1 MWh delivered over the battery's lifetime is the total lost electricity, i.e., the electricity charged into the battery minus the delivered electricity, divided by the total electricity delivered over the lifetime, see Equation 2. Based on the aforementioned studies, the example calculations below are established. The round-trip efficiency in the modelling recommendations provided below is assumed to refer to the AC-AC round-trip efficiency only including inverters. The AC-AC roundtrip-efficiency can be calculated from the DC-DC round-trip efficiency by multiplying it by the AC-DC and DC-AC inverter efficiencies respectively.

$$Electricity\ lost\ \ \frac{MWh_{charged} - MWh_{delivered}}{MWh_{delivered}} \qquad [MWh/MWh_{delivered}] \tag{2}$$

where:

$$MWh_{charged} = nominal\ battery\ energy\ capacity\ [MWh] \cdot DoD\ [\%] \cdot \#\ of\ cycles \tag{3}$$

$$MWh_{delivered} = nominal\ battery\ energy\ capacity\ [MWh] \cdot DoD\ [\%] \cdot \text{round-trip}\ efficiency\ [\%] \cdot \#\ of\ cycles \tag{4}$$

The *total electricity input* and thus the *total lost electricity* due to the round-trip efficiency of a battery system over the lifetime of the battery depends on the application for which a battery is used which defines the operational profile with regard to the cycle frequency. Therefore, example calculations are given for two different applications.

Example for a wholesale arbitrage application
- A battery with a power rating of 100 MW and a nominal energy capacity of 800 MWh
- 1 full cycle per day (Battke et al., 2013)

For a battery with a round-trip efficiency of 85%, operating at a DoD of 80% and a lifetime of 20 years, the electricity lost per MWh delivered is:

$$MWh_{charged} = 800\ MWh * 80\% \cdot (1 \cdot 365\ days \cdot 20\ years)\ cycles = 4{,}67 \cdot 10E^6\ MWh$$

$$MWh_{delivered} = 800\ MWh\ \cdot 80\% \cdot 85\% \cdot (1 \cdot 365\ days \cdot 20\ years)\ cycles = 3{,}97 \cdot 10E^6\ MWh$$

$$Electricity\ lost = \frac{4{,}67 \cdot 10E^6 - 3{,}97 \cdot 10E^6}{3{,}97 \cdot 10E^6} = 0{,}176\ MWh/MWh_{delivered}$$

Example for a frequency regulation application
- A battery with a power rating of 2 MW and a nominal energy capacity of 0,5 MWh
- 34 cycles per day (Battke et al., 2013):

For a battery with a round-trip efficiency of 85%, operating at a DoD of 5% and a lifetime of 20 years, the electricity lost per MWh delivered is:

$$MWh_{charged} = 0{,}5\ MWh \cdot 5\% \cdot (34 \cdot 365\ days \cdot 20\ years)\ cycles = 6205\ MWh$$

$$MWh_{delivered} = 0{,}5\ MWh\ \cdot 5\% \cdot 85\% \cdot (34 \cdot 365\ days \cdot 20\ years)\ cycles = 5274\ MWh$$

$$Electricity\ lost = \frac{6205 - 5274}{5274} = 0{,}176\ MWh/MWh_{delivered}$$

These example calculations show that the application does not have an effect on the lost electricity per MWh delivered. Therefore, only the round-trip efficiency has to be included as a parameter to model the electricity lost due to efficiency losses. This is also done by T. S. Schmidt et al. (2019), Spanos et al. (2015), Peters and Weil (2017) and Chowdhury et al. (2020). Resulting from the above it is recommended to model the electricity lost due to efficiency losses by Equation 5.

$$Electricity\ lost\ due\ to\ efficiency\ losses\ = \frac{100}{\eta} - 1 \qquad [MWh/MWh_{delivered}] \qquad (5)$$

where:

η = AC-AC round-trip efficiency of a battery system (%)

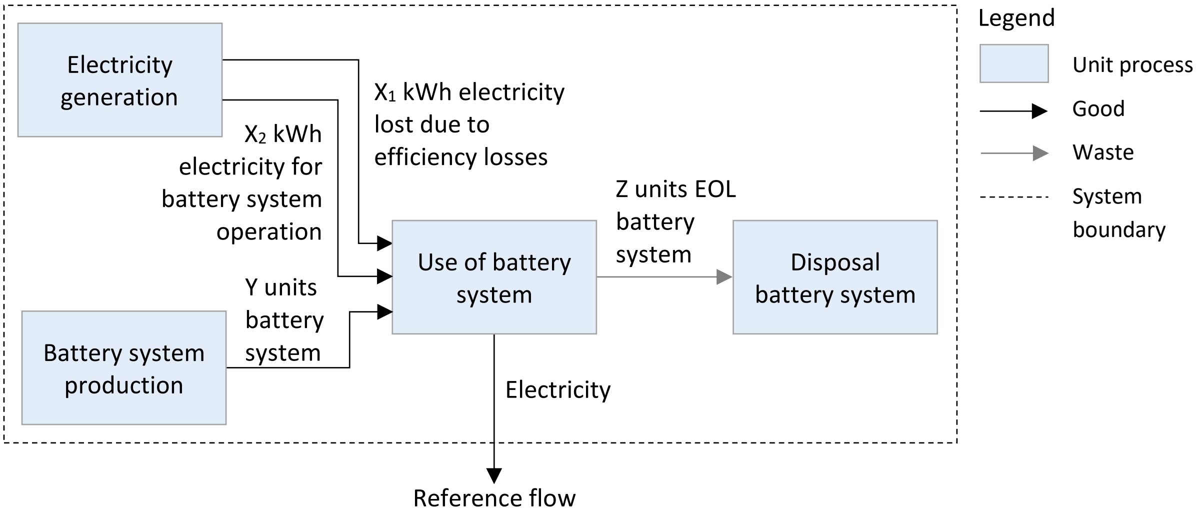
The round-trip efficiency depends on battery degradation. The performance of a battery decreases over time due to calendar degradation, which is degradation regardless of use (e.g., chemical degradation of the electrolyte over time), and cycle degradation, which is degradation as a result of each charge-discharge cycle. Degradation can occur in all battery components such as the membrane and the electrodes in case of a redox flow battery. Cycle degradation is driven by several factors among which operating temperature, charge/discharge rate (c-rate), average SoC and the DoD (Alipour et al., 2020; Porzio & Scown, 2021; Soskin, 2019). As the battery degrades over time it experiences energy efficiency fade, but also energy capacity and power fade. (Ahmadi et al., 2017). Energy efficiency fade decreases the round-trip efficiency and therefore the electricity losses during use increase over the lifetime of the battery. For most battery technologies, operation at high DoD, i.e., deep cycling, contributes to accelerated battery degradation and therefore reduces round-trip efficiency (Porzio & Scown, 2021). The ideal DoD and average SoC that result in least degradation and thus the highest average round-trip efficiency and cycle life varies per battery technology. Surprisingly though information is scarce because this concept and its measurement are relatively new and have not been a concern for manufacturers of electric vehicles for which much of the battery technology development that occurred in the past decades (Ahmadi et al., 2017).

In current LCA studies, the round-trip efficiency is generally modelled as an average of the round-trip efficiency at a 100% state of health, when the battery is new, and the round-trip efficiency at end-of-life. However, these efficiency values are presented as single fixed values, while according to Jones et al. (2019), the round-trip efficiency of a VRFB ranges between 42% and 77% and Rydh et al. (1999) show a round-trip efficiency range of 72% to 88%. Ahmadi et al. (2017) calculate the lost electricity per year and model round-trip efficiency fade by calculating the round-trip efficiency for each year assuming an exponential decrease during the first year and a progressive linear trend of 1,5% decrease per year after the first year. Richa et al. (2017) calculate the lost electricity for each cycle using a value for the round-trip efficiency that declines linearly, reaching 65% at the last cycle. Even though these are more refined approaches, it still results in the same lost electricity per MWh delivered as calculating it by taking an average round-trip efficiency over the battery's lifetime. The concept of round-trip efficiency fade and its measurement are relatively new and thus reliable data about cycling and the impact on lifetime and round-trip efficiency of different battery technologies is rare (Ahmadi et al., 2017; Porzio & Scown, 2021). This data would comprise of information about how the charge and discharge rate, operating temperature and SoC affect the fade of energy capacity, power, round-trip efficiency and battery lifetime (Porzio & Scown, 2021). Therefore, it is recommended to include the round-trip efficiency as a range in future LCA studies combined with uncertainty analysis, or at least sensitivity analyses to evaluate the effect of altering the round-trip efficiency on environmental impact scores of the battery system.

In addition to the electricity losses due to round-trip efficiency losses, electricity can be required for the operation of the battery even when it is standby (da Silva Lima et al., 2021; Jones et al., 2019). Depending on the type of battery, operational energy use consists of energy for the battery and energy management systems, cooling of the battery and pumping the fluid in case of a redox flow battery. Electricity required for the operation of the battery is recommended to be modelled as a separate electricity input, as depicted in Figure 14 by input X_2, because it enables LCA practitioners to separately assess the effects of a change in the round-trip efficiency and operational energy use on the overall environmental impact scores. This is useful for battery technology developers. Combining both electricity inputs into a single overall system efficiency makes such an analysis impossible. The operational electricity consumption per delivered MWh ($MWh_{operation}/MWh_{delivered}$) should be obtained from the battery producer.

Figure 14

Constituents of the product system of a stationary battery system with separate electricity inputs



4.2.2.2. Battery system

Some of the reviewed studies include the required battery fraction for 1 kWh or MWh battery energy storage capacity, see section 4.1.1.4 This is calculated based on the battery energy density (kg/Wh). This is fine if the FU is formulated in terms of battery energy storage capacity, which is actually not a function, but not if the FU is defined as kWh or MWh of electricity delivery like in the case of Rahman et al. (2021) and Oliveira et al. (2015). Using the energy capacity results in a battery fraction that is required per MWh nominal energy capacity, not per MWh of delivered electricity. The application defines the required power (W) and energy storage capacity (Wh) of the battery and therefore the battery material inputs depend on the requirements of the application. However, different applications also require different cycle frequencies, which results in different amounts of electricity delivered over the total battery lifetime. This is not taken into account when only the storage capacity is considered. This method also does not consider the battery round-trip efficiency which has an effect on the total delivered electricity over the lifetime. For a FU that considers the total delivered electricity, as the proposed FU in section 4.2.1.1, the included battery fraction should be based on the total electricity delivered over the battery's lifetime.

Based on the reviewed studies, Equation 6 is derived to define the battery fraction that is required to fulfil the FU as defined in section 4.2.1.1 by reversing the total electricity delivered expressed in MWh over the lifetime of the battery. The delivered amount of electricity is basically the quantity and type of electricity consumed to operate a battery for a specific application reduced by the electricity lost due to efficiency losses. To quantify the data in terms of the amount of electricity delivered it is necessary to know the battery characteristic data and the application specific input data. The total electricity delivered over the lifetime of a battery is derived by the following reasoning on the interaction of battery parameters and applications characteristics:

1. The nominal battery energy capacity (MWh) is based on the required energy capacity that has to be discharged from the battery per cycle for the specific application. This defines the maximum amount of electricity (MWh) that could be discharged from the battery per cycle.

Taking this as a basis also ensures comparability in case of comparative LCA studies. If batteries with similar nominal energy capacities would be compared, the usable energy capacity might be different due to different round-trip efficiencies of different battery technologies and different DoDs, which leads to an unfair comparison.

2. The usable share of the battery energy capacity which exists of the share of the nominal energy capacity that is used to serve the application, i.e., the DoD.
3. The annual number of cycles that the required energy capacity is discharged from the battery as defined by the application that the battery is utilised for. The number of times that the battery is charged-discharged per year, i.e. the annual cycle frequency, and thus how often the useable energy capacity is discharged is defined by the application for which the battery is used.
4. The share of the stored electricity that is maintained during each discharge as a results of the round-trip efficiency.
5. The battery's lifetime during which it serves the application. Battery lifetime reflects how long the battery can be utilised and therefore impacts how much electricity the battery can provide over its lifetime. By including the lifetime of the battery in Equation 6, the comparison of batteries normalised to 1 MWh delivered is fair. A longer lifetime results in more electricity delivered over the lifetime and therefore a lower required battery fraction to deliver 1 MWh. This way, the battery lifetime is reflected in the LCI instead of defining a certain period in the FU and calculating the corresponding required amount of batteries in that period, as explained in Appendix F.

$$Fraction\ of\ battery\ required\ for\ 1\ MWh_{delivered} = \frac{1}{C_{bat}\ [MWh] \cdot DoD\ [\%] \cdot annual\ cycle\ frequency\ [number] \cdot \eta^{0,5}\ [\%] \cdot \text{battery lifetime [y]}} \tag{6}$$

where:

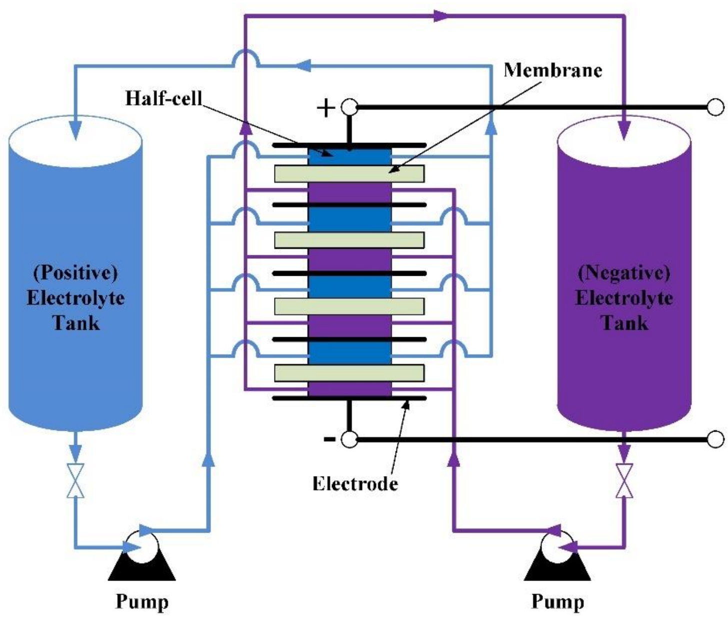
- C_{bat}

  Is the nominal installed battery energy capacity (MWh) that is required to ensure the rated power and discharge duration for a specific application, as defined by the application characteristics in the goal and scope section, are met over the battery's lifetime. This is based on the application characteristics: required power, discharge duration and the required energy capacity, as shown in Table 3. The required power and discharge duration result in the required *usable* battery energy capacity. For most battery technologies, cycle life is higher when the battery operates at a lower DoD, as depicted in Figure 18. Cycling at a high DoD, i.e. deep cycling, generally makes a strong contribution to cycle degradation and thus reduces cycle life. To maximise the health and therefore the performance and cycle life of the battery, ideally one would like to use its energy capacity to a limited degree. Therefore, batteries are oftentimes oversized to result in cycling at a lower DoD while providing the required energy capacity per cycle (Baumann et al., 2017; T. S. Schmidt et al., 2019). To define the nominal energy capacity, T. S. Schmidt et al. (2019) provide an equation that takes into account the EOL energy capacity criterion, see Equation 7. The nominal installed energy capacity is oversized based on the required energy capacity, taking into account the DoD at which the battery operates and the battery's discharge efficiency. Moreover, the formula by T. S. Schmidt et al. (2019) includes the EOL energy capacity criterion to guarantee a minimal percentage of the initial installed capacity at the EOL in order to account for the reduction in useable energy capacity. The energy retention reflects that batteries degrade over time, which means that the useable energy capacity of the battery in year one is higher than at the end of its lifetime. The EOL criterion for a stationary battery generally is 80% of the initial capacity (Jenu et al., 2020; Peters et al., 2016; T. S. Schmidt et al., 2019), however Porzio and Scown (2021) mention 60%.

Of course, the battery LCI data should correspond to this nominal energy capacity. A redox flow battery requires some attention. In contrast to most other types of batteries, the power rating and energy capacity of RFBs can be designed independently of each other according to the energy and power requirements of the application (Divya & Østergaard, 2009). The power rating is determined by the size of the active area of the cell stack (middle part in Figure 15), while the volume of electrolyte solutions (left and right part in Figure 15) determines the energy capacity (Rahman et al., 2021). The share of electrolyte to the total battery is lower at a lower energy/power ratio (Baumann et al., 2017). Since the energy/power ratio is nonlinear, the required power and discharge duration, and thus the resulting energy capacity, of the battery data used in the LCI should correspond to the power and energy capacity values used in the variable C_{app} in Equation 7.

Figure 15

System design of an organic redox flow battery depicting the separation of the cell stack (middle) and the electrolyte tanks (left and right)



Note. Adapted from "A Novel State of Charge Estimating Scheme Based on an Air-Gap Fiber Interferometer Sensor for the Vanadium Redox Flow Battery," by C. T. Ma, 2020, *Energies, 13*(2), p. 3.

$$C_{bat} = \frac{C_{app}}{DoD_{app} \cdot \eta^{0,5} \cdot CR_{EOL}} \qquad [MWh] \tag{7}$$

where:

- C_{bat} = nominal installed battery energy capacity of the battery system (MWh).
- C_{app} = required energy capacity for the application defined as the energy delivered per cycle (MWh). The energy delivered per cycle is defined by multiplying the required power (MW) per cycle by the discharge duration (h).
- DoD_{app} = depth of discharge at which the battery operates on average for the specific application as a percentage of the nominal capacity (%).
- $\eta^{0,5}$ = discharge efficiency based on the round-trip efficiency η (%). The charge and discharge efficiency are assumed to be equal and therefore the discharge efficiency is the square root of the round-trip efficiency.
- CR_{EOL} = energy capacity at EOL as a percentage of the nominal capacity (%).

Rahman et al. (2021) and Hiremath et al. (2015) assume the same formula, however without including an EOL energy capacity criterion. The energy capacity resulting from the formula by T. S. Schmidt et al. (2019) is based on the assumption that the battery should be able to deliver the required energy capacity at EOL. This means that during it's lifetime the battery will deliver more energy than required. The other way around, when this EOL criterion is not considered, the battery capacity is based on delivering the required energy capacity when it is new, so it will deliver less than the required capacity at EOL. This is further clarified by the examples below.

Nominal installed battery energy capacity calculated with CR_{EOL}

$$C_{bat} = \frac{60}{0,8 \cdot 0,75^{0,5} \cdot 0,8} = 108 \text{ MWh}$$

Delivered electricity per cycle when new: $108 \cdot 0,8 \cdot 0,75^{0,5} = 75\ MWh$
Delivered electricity per cycle at EOL: $108 \cdot 0,8 \cdot 0,75^{0,5} \cdot 0,8 = 60\ MWh$
A battery with this nominal energy capacity still delivers 60 MWh at EOL.

Nominal installed battery energy capacity calculated without CR_{EOL}

$$C_{bat} = \frac{60}{0,8 \cdot 0,75^{0,5}} = 87 \text{ MWh}$$

Delivered electricity per cycle when new: $87 \cdot 0,8 \cdot 0,75^{0,5} = 60\ MWh$
Delivered electricity per cycle at EOL: $87 \cdot 0,8 \cdot 0,75^{0,5} \cdot 0,8 = 48\ MWh$
A battery with this nominal energy capacity delivers 60 MWh per cycle when it is new, but only 48 MWh at EOL, which is less than the 60 MWh energy capacity that is required for the application.

Depending on the requirements regarding the EOL capacity, the nominal energy capacity should be defined. In the current study it assumed that in general it is expected that at EOL the required energy capacity for the application should still be reached (i.e., the first example).

Different battery technologies have different characteristics with regard to the maximum DoD before damage occurs and the performance and cycle life are reduced, as shown in Figure 18. For example, the degradation of a LIB is ten times more when it is operated near 100% DoD compared to when it is operated at 10% DoD (Soskin, 2019). In other words, it has a cycle life of about 15000 cycles when operated at 10% DoD, while this is only 3000 cycles when operated at 80% DoD (Thoubboron, 2021). This means that the battery can be cycled 15000 times before its EOL energy capacity criterion is reached when it is cycled at just 10% of its capacity. This is 3000 times when the battery is cycled at 80% of its capacity. On the other hand, an RFB can usually be used for its full capacity (100% DoD), however, insufficient data is available in literature to calculate cell degradation of (V)RFBs. One study for example states an operational SoC range between 5% and 95%, resulting in a DoD of 90% (Rydh, 1999). Lead-acid batteries are generally used at a DoD of about 50% DoD to prevent excessive cell damage (RELiON Battery, 2019). In some cases, the application determines whether the battery is subjected to shallow cycling, for example in the case of frequency regulation. The battery has to be available for a maximum of 15 minutes (Battke et al., 2013). In case of a battery that provides 2 MW of power capacity this results in a required energy capacity of 0,5 MWh. However, in practice the battery is discharged about 34 times a day with an average discharge duration of about 38 seconds (Battke et al., 2013). In practice only 0,021 MWh (2 MW · (38 / 3600)) of the 0,5 MWh required energy capacity is used, even though the battery *should be able to* deliver 0,5 MWh. Therefore, this application always results in shallow cycling.

In other cases it depends on the degree of oversizing whether the battery is subjected to shallow cycling or deep cycling. A battery is subjected to more shallow cycling when it is oversized. The lower the DoD at which the battery is intended to operate, the more a battery is oversized, which results in shallow cycling. Likewise, little oversizing results in deep cycling. A maximum allowable DoD can be set to optimise the battery size for a given application and battery technology with regard to life cycle costs (Baumann et al., 2017). This is a trade-off between battery oversizing (initial investment costs) and battery replacements (replacement costs). Higher installed energy capacity increases initial investment costs but increases battery cycle life, while lower installed energy capacity reduces investment costs, but increases replacement costs due to reduced cycle life and thus earlier required replacement. However, in case of some battery technologies the DoD does not have an effect on the cycle life. When serving an application that requires one cycle per day, the lifetime is defined by the calendar lifetime. The battery lifetime is not limited by the cycle life and therefore no further cost benefits can be gained through oversizing. In that case, the DoD is defined by the battery technology only, which is for example 10% and is determined by the minimal SoC of the battery to prevent damage. This is for example the case for a lithium-iron-phosphate (LTO) battery

From the above it appears that the DoD is determined either by the combination of the application and the battery technology, or by the battery technology only. However, in static battery size methods, such as Equation 7, the battery is assumed to operate at a certain DoD for each application and for each battery technology in order to match with the battery cycle life at that DoD because generally only cycle life data at 80% DoD operation is available.

- DoD
  Is the depth of discharge at which the battery operates as a percentage of the nominal installed energy capacity, which is generally based on the required minimum and maximum SoC of the battery technology. The value used here should correspond to the value used in the nominal installed battery capacity equation (Equation 7) and the value that is used to determine the cycle life at the battery lifetime parameter. Pellow et al. (2020) state that the DoD requirement depends on the application, while T. S. Schmidt et al. (2019) mention that it is a battery technology-specific parameter because different battery technologies have different characteristics with regard to the maximum DoD before damage occurs. However, both might actually be the case. Some applications are shallow cycling applications and thus result in a low DoD, for example in case of frequency regulation, as explained in the section about the nominal installed battery capacity parameter. It is also viable that a maximum operational DoD is set for a certain combination of application and battery technology in order to increase the cycle life for batteries (Baumann et al., 2017). A more extensive explanation is provided in the section about the nominal installed battery capacity parameter.

- Annual cycle frequency
  Is the number of annual charge-discharge cycles to provide the application for which the battery is utilised. Generally, it is presumed that during one cycle the amount of electricity corresponding to the required amount of electricity (MWh) for that application is withdrawn from the battery (Battke et al., 2013). Therefore, cycle frequency is generally expressed in equivalent full cycles (EFCs) of the required amount of electricity for the application. EFCs are charge-discharge cycles that do not use the full battery energy capacity converted to cycles of the full energy capacity. For example, 34 cycles at 5% DoD corresponds to $34 \cdot 5\% = 1{,}7$ cycles at 100% DoD, so 1,7 EFCs. However, EFCs do not quantify the DoD and are therefore unable to distinguish one cycle at 100% DoD from two cycles at 50% DoD or ten cycles at 10% DoD (Soskin, 2019) as depicted in Figure 16.

  Information about operational characteristics is scarce though and several studies (Baumann et al., 2017; Hiremath et al., 2015; Rahman et al., 2021; T. S. Schmidt et al., 2019) partly use the application-specific input characteristics from Battke et al. (2013) which are shown in Table 3. Different authors use different cycle frequency requirements for a specific application as shown in Table 4. This does not pose any issues for comparisons between batteries within an assessment because all battery technologies are modelled with the same cycle frequency. However, the assumption on the number of cycles might potentially have an effect on the environmental impact results of a battery technology; assuming a different cycle frequency might therefore increase or decrease *the difference* in environmental impacts *between* battery technologies.

Figure 16

Representation of two different load profiles with different DoD: 1 cycle at 100% DoD and 2 cycles at 50% DoD, while both profiles are reflecting 1 EFC

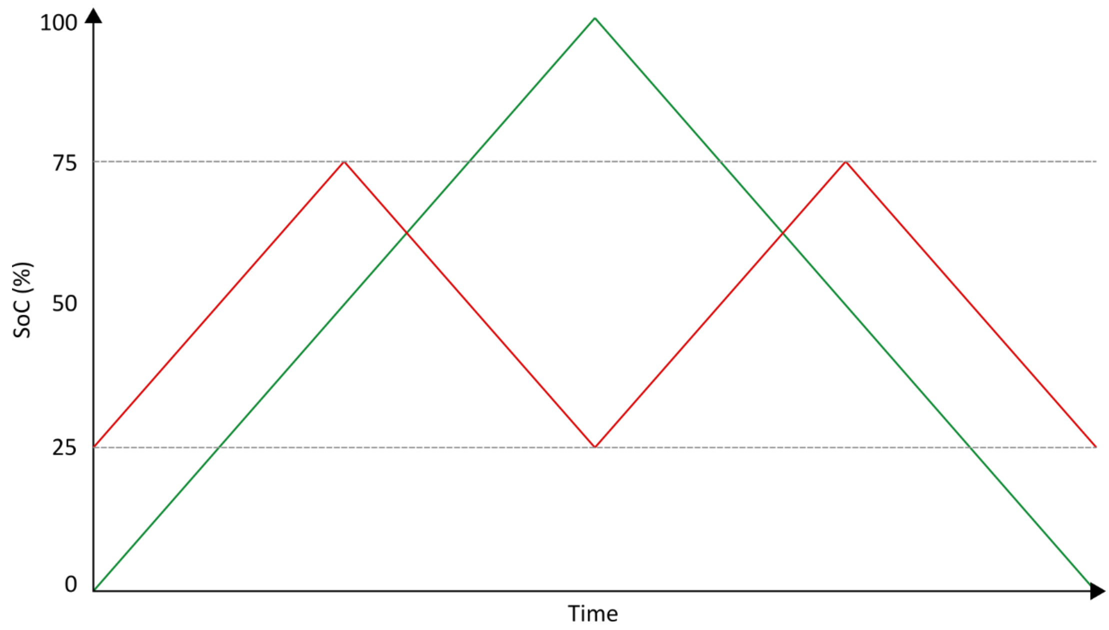


Table 4

The variation in cycle frequency values for the same application between different LCA studies

	Annual number of cycles for application						
Author	**Wholesale arbitrage**	**Area and frequency regulation**	**T&D investment deferral**	**End-consumer arbitrage**	**Increase of self-consumption**	**Voltage regulation**	**RET firming**
T. S. Schmidt et al. (2019)	365	176	250	104	250	-	-
Hiremath et al. (2015)	365	620 (12410)[a]	248	730	219	248	-
Rahman et al. (2021)	365	620 (12410)[a]	248	-	-	248	-
Baumann et al. (2017)	730	620 (12410)[a]	-	-	365	-	409

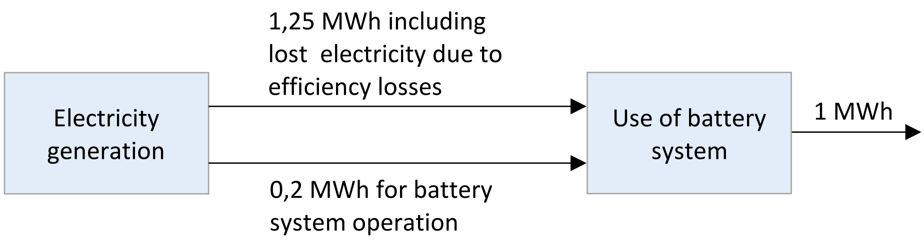
Note. [a] 12410 cycles using 5% of the battery's energy capacity corresponds to 620 cycles at full capacity.

- $\eta^{0,5}$
  Is the discharge efficiency which is considered to be half of the round-trip efficiency because the efficiency is assumed to be the same in the charge and discharge direction (Bordin et al., 2017). Therefore it is estimated as the square root of the round-trip efficiency η, which refers to the AC-AC round-trip efficiency including efficiency losses of inverters.

  Only round-trip efficiency is included in Equation 6 to account for efficiency losses to derive the total delivered electricity over the battery's lifetime. The overall battery system efficiency could also be included by taking into account electricity for battery operation. However, operational energy is not considered to be part of efficiency losses because the electricity input is required to run the battery and is not meant to be stored and discharged again. Like in the case of a PV installation, the efficiency losses due to cables and the inverter reduce the amount of energy that can be derived from 1 m^2 of PV panel. In other words, it affects the electricity throughput and therefore the electricity output. This is different from operational energy in the case of a battery, which does not affect electricity throughput and thus output, but could be thought of as energy consumed by a TV. This is also depicted in Figure 17. If, for example, the pumps in an RFB become more efficient and therefore the operational electricity input decreases from 0,2 to 0,1 $MWh/MWh_{delivered}$, the overall battery system efficiency increases from 69% to 74%, but the required fraction of battery system to deliver 1 MWh is still the same, as shown in the example calculation below. Only the required amount of electricity input decreases. This indicates that operational electricity has no effect on the total electricity delivered over the lifetime by a certain battery system and hence not on the fraction of battery system that is required to deliver the required total amount of electricity. Therefore, only the round-trip efficiency has to be included as parameter in Equation 6.

Figure 17

Illustrative use of a battery system with separate electricity inputs to indicate the difference between round-trip efficiency and overall efficiency of a battery system



Round-trip efficiency: $\frac{1\,MWh}{1{,}25\,MWh} \cdot 100\% = 80\%$

Overall battery system efficiency: $\frac{1\,MWh}{(1{,}25\,MWh + 0{,}2\,MWh)} \cdot 100\% = 69\%$

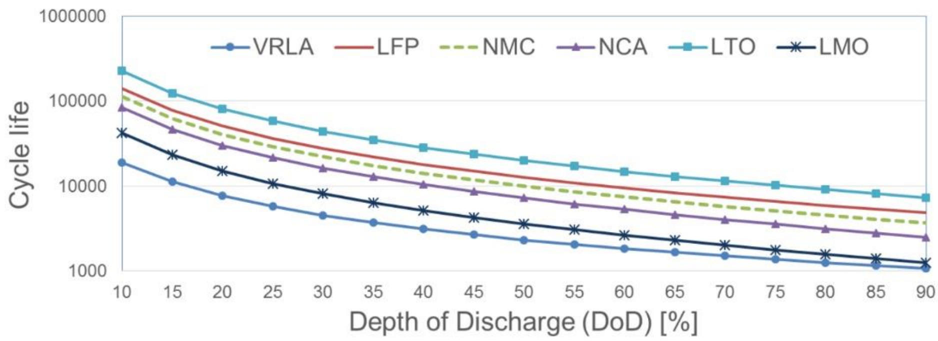
When the operational energy input decreases (e.g., due to more efficient pumps):

Overall battery system efficiency: $\frac{1\,MWh}{(1{,}25\,MWh + 0{,}1\,MWh)} \cdot 100\% = 74\%$

- Battery lifetime
  Battery lifetime reflects how long the battery can be utilised and is a function of battery degradation, which depends on how the battery is cycled and utilised during the use phase but also how it degrades over time (Ryan et al., 2018). The calendar lifetime is determined by what is called calendar degradation, which refers to ageing processes causing degradation of a battery cell independent of cycling (Keil et al., 2016). The calendar lifetime is the number of years before the EOL energy capacity criterion is reached and is generally provided by the battery manufacturer. The EOL energy capacity criterion is commonly set at 80% of the installed energy capacity when the battery was new (Jenu et al., 2020; Peters et al., 2016; T. S. Schmidt et al., 2019). The cycle life of a battery, on the other hand, is the number of cycles the battery can perform before the EOL energy capacity criterion is reached (T. S. Schmidt et al., 2019). The more cycles a battery completes, the more it degrades, however, the fading of the cycle life also heavily depends on the DoD at which the battery is cycled (Baumann et al., 2017; Porzio & Scown, 2021). Hence, with shallow cycles, the cycle life will be higher. The relation between DoD and cycle life is different for each battery technology, as shown in Figure 18.

Figure 18

Dependency of cycle life on the depth of discharge of different battery technologies



Note. VRLA = valve regulated lead acid, LFP = lithium-iron-phosphate with graphite anode, LTO = lithium-iron-phosphate with lithium-titanate anode, LMO = lithium manganese oxide, NCA = lithium nickel cobalt aluminium oxide, NMC = lithium nickel cobalt manganese oxide. Adapted from "CO_2 Footprint and Life-Cycle Costs of Electrochemical Energy Storage for Stationary Grid Applications," by M. Baumann, J. F. Peters, M. Weil and A. Grunwald, 2017, *Energy Technology, 5*(7), p. S3.

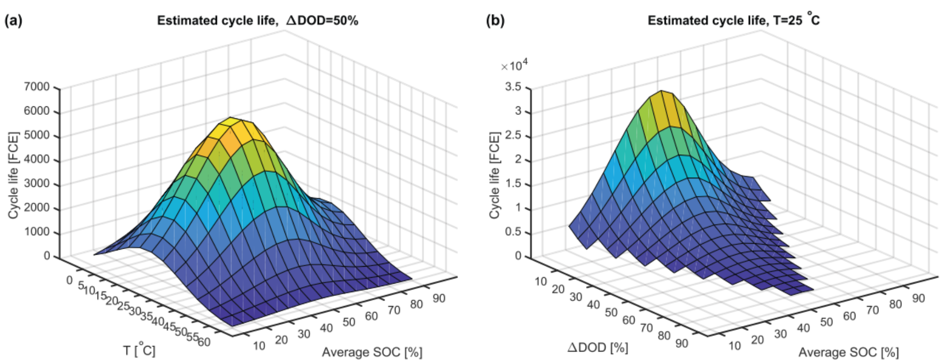
Even if a battery is cycled infrequently or is shallow cycling, it is still degrading due to calendar degradation and thus the calendar lifetime is posing a limit on the use of a battery. However, different applications have different requirements with regard to cycle frequency as shown in Table 3. Therefore, the application potentially has an effect on the lifetime of the battery as a result of the required number of cycles for that application. This means that the battery lifetime based on calendar degradation might have to be adjusted based on the cycle life if the latter results in a shorter lifetime than the calendar lifetime. Therefore, the lifetime to be included in Equation 6 is the minimum of the battery's calendar lifetime and its cycle lifetime. Cycle lifetime is defined in this study as the equivalent number of years that the battery can operate according to the operating conditions of the application (Terlouw et al., 2019). It is calculated by dividing the battery's cycle life by the annual cycle frequency required for a specific application, see Equation 8.

$$Cycle\ lifetime = \frac{cycle\ life}{annual\ cycle\ frequency_{app}} \qquad [years] \tag{8}$$

The main stress factors that influence the cycle life are the DoD, the charge/discharge rate (c-rate), the average SoC and the operating temperature (Alipour et al., 2020; Jenu et al., 2020; Porzio & Scown, 2021; Soskin, 2019). Figure 19 provides the results of a cycle life model developed by Jenu et al. (2020) for nickel manganese cobalt oxide (NMC) Li-ion battery cells in which the cycle life is estimated at different combinations of DoD, average SoC and operating temperature by using stress factor models for these three stress factors. In this case, the highest cycle life is obtained at an average SoC of 50% and a DoD of 5%. However, in the end, it results in the same amount of delivered electricity, since cycling at a lower DoD results in a higher cycle life, but the battery delivers less electricity per cycle. A further break down of how variations in these factors impact the cycle life would benefit the analysis of how battery characteristics influence environmental impact scores. However, there is no uniqueness in literature about how to assess these factors quantitatively and how their interaction effects the cycle life of different battery technologies. Therefore, it is not yet feasible to include it in modelling the use process in an LCA. For this reason, generally simply the cycle life expressed in EFCs for battery operation at a specific DoD, commonly 80%, is used (T. S. Schmidt et al., 2019). This value results from what is called an event-oriented ageing model, which only considers the DoD and uses cycle life versus DoD curves, such as Figure 18, and is generally provided by battery manufacturers (Silvera Diaz et al., 2021).

Figure 19

Estimated cycle lives based on a cycle life model for nickel manganese cobalt oxide Li-ion cells



Note. (a) Estimated cycle life with different temperatures and average SOCs when the cycle DoD is 50%. (b) Estimated cycle life with different cycle DoDs and average SOCs when the temperature is 25 °C. Reprinted from "Reducing the climate change impacts of lithium-ion batteries by their cautious management through integration of stress factors and life cycle assessment," by S. Jenu, I. Deviatkin, A. Hentunen, M.Myllysilta, S. Viik and M. Pihlatie, 2020, *Journal of Energy Storage, 27*, p. 9.

Different studies assume different calendar lifetimes for the same battery technology. Moreover, in case of some battery technologies, the lifetime of a battery is more complex since distinct components might have different lifetimes. For example, Weber et al. (2018) refer to the calendar lifetime as the lifetime of the cell stack of a VRFB or the battery cells of a LFP-LTO battery. The electrolyte and all other battery components are assumed not to be replaced over a period of 20 years. Therefore, it is not clear what the lifetime of the other components is. Moreover, it is unclear what the cycle life of a battery entails exactly. It could mean that the whole battery system is EOL after this number of cycles is reached or that a component has to be replaced after which it can perform another number of cycles. This is similar to the case of a vehicle. The lifetime of the tires, as a component of the vehicle, does not define the lifetime of the entire vehicle. In case of an RFB, cycle life might perhaps only refer to the electrolyte since "the chemical and electrochemical stability of redox species both play a crucial role in the cycling lifetime" (Zhong et al., 2020, p. 4).

If this is the case then it would not be fair to define the required battery system fraction based on either calendar or cycle lifetime. For example, Baumann et al. (2017) and Hiremath et al. (2015) assume that two VRFBs are used in 20 years based on a calendar lifetime of 15 and 10 years respectively. However, when only particular components have to be replaced during these 20 years, their method might overestimate the C2G environmental impacts of the battery technology. Therefore, for certain battery technologies, considering the calendar lifetime or the cycle lifetime to be the lifetime of the whole battery system might not be right, but replacement activities could be reflected in the modelling. If components of a battery cannot be replaced then the calendar or cycle lifetime might indeed define the lifetime of the total battery system.

A way to reflect this in the modelling is defining the total battery system's economic lifetime depending on the battery technology and considering which and how often components might have to be replaced during this lifetime. Additional materials required for replacements are included in the LCI of the battery system production processes. This approach requires a lifetime of the total battery system and components. This might be complex since determining when a component or battery system is EOL is ambiguous. When a component has to be replaced, it might well be that other components are replaced at the same time even though these have not reached their technical end-of-life. This might be more economical because replacement activities have to be carried out anyway. Moreover, it could be decided to replace the whole battery system by a more efficient system even though it has not reached its technical EOL. Besides technical aspects, economic considerations and innovation might be involved here. This is similar to defining the lifetime of solar panels. The technical lifetime of solar panels is stated to exceed 20 years and they are even expected to last 25 to 30 years. However, economically it may be optimal to replace existing solar panels in just seven years when considering the current and anticipated costs of electricity, the rapidly decreasing costs of PV panels and the increasing conversion efficiency of novel solar technologies (Sodhi et al., 2022).

Table 5

Overview of different comparisons that should be made for different research aims

Research aim	Assess the environmental performance of a battery technology and/or identify options for improvement by analysing the effects of changes in processes in terms of technology, inputs and product composition on the total environmental impact.	Assess the environmental performance of serving an application with a battery system compared to the current situation in which the application is provided by an electricity generator or another technology.
Comparison	• Battery technology A versus battery technology A with improved product system (process, inputs, or composition) based on identified hotspots • Battery technology A versus battery technology B	Battery technology versus conventional product system providing the same application. E.g., frequency regulation by a battery versus frequency regulation by a natural gas power plant.
FU	For energy storage applications: *Delivering one MWh electricity of the total electricity delivered over the battery's lifetime from a battery used for [specify application].* For power applications: *Delivering one MWh of electricity of the total electricity delivered over the battery's lifetime in order to provide X MW of power capacity from a battery used for [specify application].*	
How to model the use process in the LCI	**Electricity** • Electricity losses: $Electricity\ lost\ due\ to\ efficiency\ losses\ = \frac{100}{\eta} - 1\ \ [MWh/MWh_{delivered}]$ where η is the AC-AC round-trip efficiency of a battery system [%] • Operational electricity use [$MWh_{operation}/MWh_{delivered}$] **Battery system** Fraction required for delivering 1 MWh of the total electricity delivered over the lifetime of the battery: $Fraction\ of\ battery\ required\ for\ 1\ MWh_{delivered} = \frac{1}{C_{bat}\ [MWh]\ \cdot\ DoD\ [\%]\ \cdot\ annual\ cycle\ frequency\ [number]\ \cdot\ \eta^{0,5}\ [\%]\ \cdot\ \text{battery lifetime [y]}}$	**Electricity** • Electricity throughput: $Electricity\ throughput\ = \frac{100}{\eta}\ \ [MWh/MWh_{delivered}]$ where η is the AC-AC round-trip efficiency of a battery system [%] • Operational electricity use [$MWh_{operation}/MWh_{delivered}$] **Battery system** Fraction required for delivering 1 MWh of the total electricity delivered over the lifetime of the battery: $Fraction\ of\ battery\ required\ for\ 1\ MWh_{delivered} = \frac{1}{C_{bat}\ [MWh]\ \cdot\ DoD\ [\%]\ \cdot\ annual\ cycle\ frequency\ [number]\ \cdot\ \eta^{0,5}\ [\%]\ \cdot\ \text{battery lifetime [y]}}$

4.2.3. Value stacking

Schulz-Mönninghoff et al. (2021) assess the environmental performance of a battery serving multiple applications at a time. In their assessment it is assumed that the electricity discharged from the battery displaces grid mix electricity which results in environmental benefits. They conclude that in the dual-use and multi-use cases, the environmental benefits are lower compared to the single-use case. In the first dual-use case this is because the electricity losses are higher, while the amount of displaced grid mix electricity is similar to the single-use case. In the second dual-use case and multi-use case the environmental benefits are even lower since less battery capacity is available to store PV electricity and therefore the amount of displaced grid mix electricity is lower. In their assessment, environmental benefits are only resulting from replacing grid mix electricity by PV electricity discharged from the battery, which is remarkable. The peak shaving (i.e., end-consumer arbitrage in Table 1) and uninterrupted power supply (i.e., end-consumer power reliability in Table 1) applications are assumed to only improve economic profitability but do not lead to environmental benefits. The authors state that the environmental benefits of serving these applications occur outside the scope of the system under investigation and therefore they are not included in the model. Reducing the peak power demand might for example displace the electricity supply by natural gas power plants to match peak electricity demand (Ahmadi et al., 2017; Sathre et al., 2015). This is not included in their model which makes the results from this study ambiguous. Including the effect on environmental impact scores resulting from serving the other two applications might have an effect on the overall environmental impact results. This might even change the order of the extent to which the four use cases result in environmental benefits as shown in Figure 8.

The study by Schulz-Mönninghoff et al. (2021) is the only LCA study in which the effect of value stacking is assessed. However, it does provide questionable results since they subtract the impacts of grid mix electricity from the impacts of the battery system that is charged with solar energy, which is a consequential LCA. Their results imply worse environmental performance of a battery serving multiple applications compared to serving a single application. However, this might be misleading since they do not subtract the displaced environmental impacts of the two other applications. Moreover, their study only provides insight about how serving multiple applications effects the environmental impacts of a battery in a local grid system by displacing electricity from another source. It does not provide information about the effect of value stacking on environmental impact scores in case of a (comparative) battery LCA study.

This is the end of the literature review discussion. In the chapter 6, some of the issues identified in the literature review discussion are further analysed by assessing the effect of some of the parameters in Equation 6 on the environmental impact scores of a battery system in an illustrative case study. Since actually none of the LCA studies, except Schulz-Mönninghoff et al. (2021), assesses value stacking, the next chapter elaborates on the implications of modelling the use phase when incorporating value stacking in battery LCA studies.

Incorporating value stacking in battery LCA studies

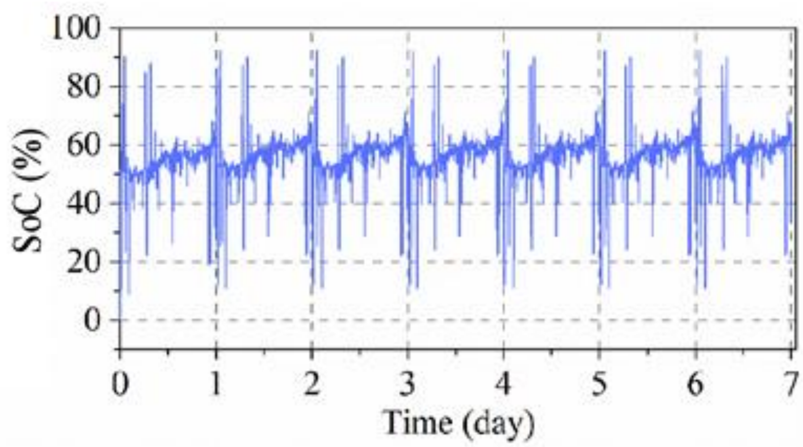
In this chapter the effect of value stacking on the operation of a battery system is discussed. Subsequently, the difficulties and challenges for the goal and scope and LCI phases when incorporating simultaneous multi-use in modelling the use phase in a battery LCA study are identified and solutions are proposed in a qualitative way.

5.1. Effect of value stacking on operation of a battery system

Displaying the SoC of a battery with a certain time interval over a period of time provides a SoC profile. This gives an overview of the charging-discharging behaviour, i.e., the operational profile of the battery. Figure 20 shows a SoC profile of a battery that is utilised for frequency regulation only. The battery has to be ready to charge or discharge for frequency regulation at certain periods of time and therefore requires the availability of a minimum amount of electric charge all the time. Therefore, the battery is only partially charged or discharged and the SoC mostly fluctuates between 40% and 60%, and on average it is about 50%.

Figure 20

SoC profile of a battery serving frequency regulation

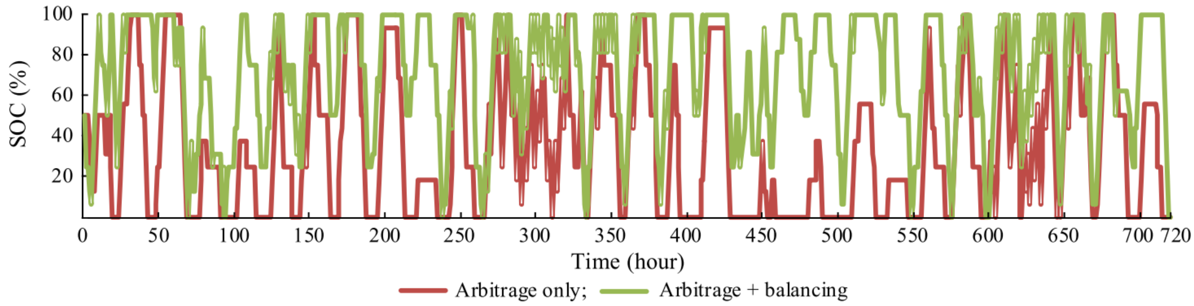


Note. From "A Review of Lithium-Ion Battery Capacity Estimation Methods for Onboard Battery Management Systems: Recent Progress and Perspectives," by J. Peng, J. Meng, D. Chen, H. Liu, S. Hao, X. Sui, and X. Du, 2022, *Batteries*, *8*(11), p. 7.

Combining applications from a technical point of view means that operational profiles, which refers to the charge-discharge behaviour, that are required for each application have to be matched (Stephan et al., 2016). The power (W) and energy (Wh) capacities of the battery have to be distributed between the applications in such a way that they match the application's dispatch requirements. Figure 21 depicts the SoC profile for 15 days of a battery from a study by Teng and Strbac (2016), in which the business case for batteries serving multiple applications is assessed. When serving both arbitrage and balancing (i.e., reserve capacity in Table 1) applications, the battery tends to maintain the SoC above a certain level to be able to capture rare but high revenue streams for balancing (green line in Figure 21). For example, in the European Network of Transmission System Operators for Electricity (ENTSO-E) network, a battery must be able to provide the assigned frequency regulation power at any time for an extra 15 minutes (Englberger et al., 2020). This means that a certain SoC is required for the that frequency regulation is provided. Thus, a certain application requires a specific dispatch of electricity and depending on the current SoC at a specific moment in time, the battery's energy management system determines whether the application is served or not, which influences the SoC and therefore the ability to serve other applications at a later point in time. Therefore, it is more or less a continuous interplay; the application(s) determine(s) the required SoC, but in case of multiple applications, the SoC also determines which application(s) could be served at each point in time considering market demand and revenue. This results in a different operational profile compared to serving a single application, which is the red line in Figure 21.

Figure 21

State of charge of a battery providing arbitrage only or arbitrage and balancing



Note. From "Business cases for energy storage with multiple service provision," by F. Teng and G. Strbac, 2016*, Journal of Modern Power Systems and Clean Energy, 4*(4), p. 620.

An important challenge when it comes to the stacking of applications is the question which applications are compatible when they are served concurrently. This depends on the *technical compatibility* of the battery system and *operational compatibility* of applications (Eyer & Corey, 2010). For example, some battery technologies do not tolerate many cycles at a high DoD since it heavily reduces their cycle life. On the other hand, operational compatibility depends on operational conflicts which involves competition for a battery's power capacity and/or energy capacity by different applications. Operational conflicts are associated with *location-related*, *time-related* and *priority-related* constraints of applications (Marchgraber & Gawlik, 2021). For example, the application *increase of self-consumption* requires a location behind-the-meter, at the end-consumer, which means it cannot be combined with an application that requires a different location in the electricity supply chain. The *time-related* constraints refer to the feasibility of providing applications at the same time. Some applications require concurrent operation, while others do not. For combining applications this has to be considered and compiled into power and energy reservations or constraints. This ensures that the battery can provide concurrent applications, but also that providing an application now does not preclude providing a constraint application in the future. A constraint application has hard requirements and mostly relates to power reliability applications (Electric Power Research Institute, 2018). For example, a specific application may require to keep the power level in a distribution network below a threshold and therefore the battery has to discharge at a certain power at certain time intervals. Moreover, a battery can only provide a limited duration of (an) application(s) before it runs out of charge, which means that the SoC must be carefully monitored (Bowen et al., 2019). In other words, the SoC has to be maintained in an acceptable range for future applications. Finally, another consideration for battery multi-use are *priority-related* constraints which refers to the prioritisation of certain applications over others in case a conflict of interest arises (Electric Power Research Institute, 2018). For example, the battery operator may want to ensure that the battery is available for discharging during peak load periods no matter the energy market prices in those periods (Marchgraber & Gawlik, 2021). Another option is that the main aim of the battery operator is to store excess renewable energy, regardless of possible higher financial revenues when other applications are served in those periods (Marchgraber & Gawlik, 2021). Or T&D investment deferral might be so valuable for system stability, that it may have priority over applications that gain revenue on the energy market, such as wholesale arbitrage.

Eyer and Corey (2010) provide a general indication of the compatibility of couples of applications in a synergies matrix, which is shown in Table 6. The compatibility is indicated as excellent, good, fair, poor and incompatible based on operational conflicts. Note that the applications in Table 6 diverge from the applications in Table 1 since a different application classification scheme is used.

Table 6

Application synergies matrix

● Excellent ◉ Good ⊙ Fair ○ Poor ⊗ Incompatible

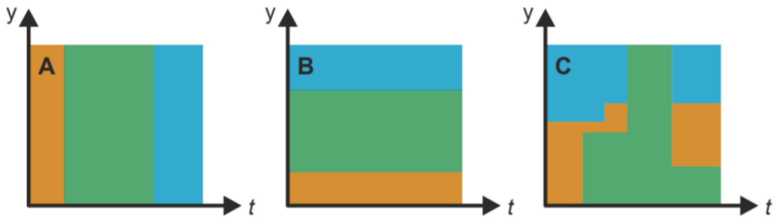
Application	Electric Energy Time-shift	Electric Supply Capacity	Load Following	Area Regulation	Electric Supply Reserve Capacity	Voltage Support[1]	Transmission Congestion Relief[1]	T&D Upgrade Deferral[1]	Time-of-Use Energy Cost Management[1]	Demand Charge Management[1]	Electric Service Reliability[1]	Electric Service Power Quality[1]	Renewables Energy Time-shift	Renewables Capacity Firming	Wind Generation Grid Integration
Electric Energy Time-shift		●	◉	⊙*	◉	●	●†	●†	⊗	⊗	⊗	⊗	◉	◉	⊙
Electric Supply Capacity	●		◉*	⊙*	◉*	●	◉†	●†	⊗	⊗	⊗	⊗	⊙X*	⊙X*	⊗
Load Following	◉	◉*		⊙*	◉*	◉	⊙X	◉X*	⊙*‡	⊙*‡	⊗	⊗	◉	⊗	⊗
Area Regulation	⊙*	⊙*	⊙*		◉*	⊗	⊙X*	⊗	⊗	⊗	⊗	⊗	○	○	⊗
Electric Supply Reserve Capacity	◉	◉*	◉*	⊙*		●	⊙*	◉*	◉*‡	◉*‡	⊗	⊗	◉*	⊙*	○*
Voltage Support[1]	●	●	◉	⊗	●		◉	●	◉‡	◉‡	◉‡	◉‡	◉#‡	◉#‡	⊗
Transmission Congestion Relief[1]	●†	◉†	⊙X	⊙X*	⊙*	◉		◉X†	◉†	◉†	○	⊗	◉#	◉†	⊗
T&D Upgrade Deferral[1]	●†	●†	◉X*	⊗	◉*	●	◉X†		◉†	◉†	○	⊗	◉#	◉†	⊗
Time-of-Use Energy Cost Management[1]	⊗	⊗	⊙*‡	⊗	◉*‡	◉‡	◉†	◉†		●†	●	●	◉#	◉†#	⊗
Demand Charge Management[1]	⊗	⊗	⊙*‡	⊗	◉*‡	◉‡	◉†	◉†	●†		●	●	◉#	●†#	⊗
Electric Service Reliability[1]	⊗	⊗	⊗	⊗	⊗	◉‡	○	○	●	●		●	◉#	◉#	⊗
Electric Service Power Quality[1]	⊗	⊗	⊗	⊗	⊗	◉‡	⊗	⊗	●	●	●		⊗	⊗	⊗
Renewables Energy Time-shift	◉	⊙X*	◉	○	◉*	◉#‡	◉#	◉#	◉#	◉#	◉#	⊗		●	⊙X
Renewables Capacity Firming	◉	⊙X*	⊗	○	◉*	◉#‡	◉†	◉†	◉†#	●†#	◉#	⊗	●		⊙X
Wind Generation Grid Integration	⊙	⊗	⊗	⊗	○*	⊗	⊗	⊗	⊗	⊗	⊗	⊗	⊙X	⊙X	

Note. Applications are technically compatible if the same storage system can be used for both applications. They are operationally compatible if there are no operational conflicts among the applications. From *Energy Storage for the Electricity Grid: Benefits and Market Potential Assessment Guide* (p. 121), by J. Eyer, and G. Corey, 2010, Sandia National Laboratories.

This matrix is just a general indication of the possible (in)compatibility of couples of applications. The actual implementation of multi-use by batteries is the most relevant challenge, since combining applications is not as simple as stacking different application characteristics as shown in Table 3. Central to serving multiple applications is the question of how the limited energy and power capacities of the battery system are allocated to the different applications. Batteries can serve multiple applications in three ways: sequential, parallel and dynamic, which differ in the way the applications are stacked, as shown in Figure 22. The y-axis shows the degree of allocation, which can be a portion of the battery's power or energy capacity. The x-axis depicts the time. Sequential multi-use (A) entails the exclusive service of one application at a time (Englberger et al., 2019). Parallel multi-use (B) is battery operation in which the power or energy capacity is divided in a predefined proportion between different applications that are served simultaneously. The shares can be viewed as virtual batteries which each serve an application. Dynamic multi-use (C) is a hybrid of sequential and parallel multi-use. Where the degree of allocation per application is fixed over time in parallel multi-use, dynamic multi-use adjusts the allocation of the battery's power or energy capacity dynamically over time. Oftentimes one application is defined as primary application and thus the battery's dispatch requirements for this primary application and the resulting battery idle times determine its compatibility with the secondary application's dispatch requirements (Litjens et al., 2018a; Stephan et al., 2016).

Figure 22

Three methodologies of stacking applications in multi-use: sequential, parallel and dynamic



Note. From "Unlocking the Potential of Battery Storage with the Dynamic Stacking of Multiple Applications," by S. Englberger, A. Jossen and H. Hesse, 2020, *Cell Reports Physical Science, 1*(11), p. SI4.

The combination of applications is generally optimised for profit, since, as the name already indicates, the main aim of value stacking is increasing the financial viability or profitability of the battery system. For the economic optimisation of multiple applications provided by a battery system, different modelling tools are developed. Examples include StorageVET (Electric Power Research Institute, n.d.), REopt (National Renewable Energy Laboratory, n.d.), the model by Arteaga and Zareipour (2019), the control framework by Namor et al. (2019) and mu_opt (Englberger et al., 2021). These tools assume so-called virtual battery systems, which are virtual shares of the total battery system, to allocate the power or energy capacity to different applications for each time interval, for example every 5 minutes or hour (Marchgraber & Gawlik, 2021). The aforementioned tools focus on the optimisation of allocating the battery power or energy capacity to different applications based on the prediction of certain variables like market prices, peak demand and renewable energy production (Marchgraber & Gawlik, 2021). Such optimisation models result in an operational planning of how the battery could best be operated to maximise revenues.

Table 7 provides an overview of the results of such an optimisation model for multi-use of a lithium-ion battery system serving several applications to maximise revenues from a study by Englberger et al. (2020). These results show that the number of EFCs increases when the battery system serves multiple applications. This is a trade-off between more intensive use of the battery and decreased battery lifetime due to increased battery degradation. Even though the economic optimisation by Englberger et al. (2020) is a proper theoretical optimisation, it could be questioned if such a battery operation, as a result of optimising four applications, will be 'accepted' in practice because it will influence the battery lifetime. However, the economic performance is optimised taking into account early replacement of the battery. Put simply, the increased revenues of more intensive use outweigh early replacement costs. In that sense it might well be that battery operators are willing to trade-off lifetime for increased revenues. However, this is all reasoned from an *economic point of view*. It is not clear how value stacking relates to the *environmental performance* of the battery system. The battery lifetime potentially decreases and therefore it requires early replacement. On the other hand, a single battery now serves multiple applications that would otherwise have to be served by distinct batteries with longer lifetimes or other product systems such as a conventional electricity generation plant for an application like frequency regulation. In the next section, the challenges and solutions for taking into account value stacking in an LCA of a battery system are identified.

Table 7

Overview of techno-economic performance of a lithium-ion battery system under single-use and multi-use operation

	Annual Operating Profit/EUR kWh^{-1}					EFC	SOH/%	EOL/a
Scenario	PS	SCI	FCR	SMT	Total			
PS	43.3	−0.8	0	0	42.6	46.1	96.5	14.9
FCR	0	0	47.5	−1	46.5	128.6	96.5	14.7
SMT	0	0	0	58.8	58.8	214.7	95.1	9.5
PS + FCR	43.2	−0.7	45.4	−1.1	86.8	159.7	96	13.1
PS + SMT	42.9	−0.7	0	57.3	99.5	261	94.5	8.3
FCR + SMT	0	0	41.3	51.2	92.5	266.2	94.9	9.3
PS + FCR + SMT	42.9	−0.7	38.9	50.6	131.7	300.7	94.5	8.6

Note. PS = peak shaving, SCI = self-consumption increase, FCR = frequency containment reserve, SMT = spot-market trading, EFC = equivalent full cycle, SOH = state of health, EOL = end-of-life. From "Unlocking the Potential of Battery Storage with the Dynamic Stacking of Multiple Applications," by S. Englberger, A. Jossen and H. Hesse, 2020, *Cell Reports Physical Science, 1*(11)*,* p. 3.

5.2. Challenges and solutions for modelling value stacking in an LCA of a battery system

5.2.1. Goal and scope definition

5.2.1.1. Multifunctional product system

A difficulty that occurs from the modelling of a battery serving multiple applications is related to the FU. The FU indicates how much of the function is to be considered in the LCA study (Guinée et al., 2002). In case the product offers more than one function the product system becomes multifunctional. Even though battery applications are not equal to functions, they are closely connected since the application defines the operation of the battery, as explained in section 4.2.1.1, but also the battery energy capacity and therefore which alternatives can be used. Therefore, if a battery serves multiple applications, the electricity delivered by the battery is used for different applications and it can be argued that the product system becomes multifunctional. Udo de Haes et al. (1996 as cited in Guinée et al., 2002) distinguished two types of multifunctional product systems. A product system can be

defined by the primary function and all other functions are facultative. But a product system can also be intrinsically multifunctional, meaning that it cannot be reduced to one function. There are two ways to deal with the multifunctionality problem. A monofunctional approach can be applied, which means that only the primary function of the system is considered and the other functions it fulfils are neglected. On the other hand, the multifunctional approach considers both the primary as well as other functions in the analysis. Taken together, Guinée et al. (2002) conclude there are three ways to solve the product system multifunctionality problem:
1. Take into account the primary function only and neglect all other functions
2. Take into account the primary function and all, or a selected number of, additional functions
3. Allocate between the primary function and the additional functions not included in the analysis.

To avoid allocation, another option is to compare only alternative product systems that fulfil all selected functions. The alternative product system could for example be expanded with another technology so that it fulfils all functions. This is approach is called system expansion (Guinée et al., 2002).

The appropriate choice depends on the goal of the study; there is no rationale to prefer one option over another. In case value stacking is a given and the goal of the study is to compare a battery serving multiple applications to an alternative product system in which all these applications are served as well, then system expansion is an appropriate solution. The product system in which the battery serves multiple applications can be compared to a product system that is expanded with multiple batteries which each serve a distinct application. Another option is expanding the alternative product system with alternative technologies that serve a specific application, for example a natural gas power plant that provides frequency regulation. To this end, serving applications has to be quantified which requires a suitable unit to express this. When the goal is to assess the effect of value stacking on the environmental performance of a battery and thus to compare a battery providing multiple applications to a battery serving only one application then allocating between different applications is an appropriate choice. This way, one application of the multifunctional product system can be compared to an alternative product system that serves just this single application. This may be compared to the joint production situation as defined by Frischknecht (2000), for which physical causalities may be identified to determine the applications' allocation factor. However, a challenge might be to determine an adequate indicator as a basis for allocation between applications. Neglecting the additional applications in the analysis is no adequate solution, since this ignores the philosophy of value stacking.

The FU has to correspond to the selected option. For example, in case of comparing two battery technologies and it is chosen to expand the alternative product system with two or more batteries, than the FU as defined in section 4.2.1.1 can be used and simply be adjusted to multiple batteries and multiple applications. Formulated in general terms this becomes: *Delivering one MWh electricity of the total electricity delivered over the battery's lifetime from a battery used for [specify applications].*

5.2.1.2. Selection of equivalent alternative product systems in case of system expansion

The selection of alternative product systems requires attention and should be in line with the goal of the study. In case the goal of the study is to compare a battery serving multiple applications to an alternative product system in which all these applications are served as well, different options to expand the alternative product system are possible. For example, a battery utilised for RET firming and frequency regulation can be compared to a product system in which one battery serves RET firming and another battery serves frequency regulation. However, another possibility would be to compare it to a product system including a battery serving RET firming while frequency regulation is served by a natural gas power plant.

5.2.1.3. Interaction between multi-use optimisation and the FU

Generally, the FU is defined in advance which is translated in a reference flow for each alternative to match the FU (Guinée et al., 2002). The optimisation of allocating the battery power or energy capacity to different applications determines the quantity that each application is served. Since battery parameters are different for distinct battery technologies, the optimisation and therefore the optimal way how and how much each application is served resulting from an optimisation algorithm is likely to vary between battery technologies. Therefore, in case of battery versus battery comparisons, it is difficult to define the FU in the goal and scope section since it results from an optimisation model and might be different for both battery technologies, even though they serve the same set of applications. In a way, the FU depends on the optimisation of the stacking of applications, which determines how much of each application is actually served by the battery. Therefore, the FU could perhaps best be defined by including something along the line 'the operational profile based on economic optimisation of serving [define applications] over the lifetime of the battery'. However, a problem that occurs from this is that the assessed battery technologies might not necessarily be comparable. Even though they serve the same set of applications, they serve each of these applications to a different extent. Therefore, another option to solve this is defining the FU including a fixed extent to which each of the applications is served. Taking on a system expansion approach, the alternative product systems are extended with a single-function battery to complement the missing degree of serving an application.

5.2.2. Use process modelling

Below the potential implications of the adjusted operation due to value stacking on the modelling of the use process inputs as defined in section 4.2.2 are identified.

5.2.2.1. Electricity

In section 4.2.2, the electricity input due to lost electricity (Equation 5) and operational electricity are defined as the electricity inputs that are required to fulfil the FU. The total amount of delivered electricity increases due to value stacking as a result of increased cycle frequency. Therefore, both total electricity lost due to efficiency losses and total operational electricity increase in absolute terms, but per MWh delivered these remain constant. Therefore these input flows remain the same when value stacking is modelled.

5.2.2.2. Battery system

In section 4.2.2, Equation 6 is derived to define the battery fraction that is required to fulfil the FU. In this section, the possible effect of value stacking on each of the parameters is discussed.

C_{bat}

When a battery is intended to be utilised for multiple applications, different ways to define the required nominal battery energy capacity are possible. One way is to optimise the size for the primary application like in the study of Stephan et al. (2016). They define a primary application which has to be fulfilled and which therefore determines the battery energy capacity. The idle capacities determine the battery capacities (at each time interval) that can be used to serve the secondary application(s). Another option would be that the battery that serves multiple applications has a higher energy capacity to be able to fulfil all applications. The question here is what determines the battery energy capacity in case of serving multiple applications; the application that requires the largest energy capacity or the sum of the capacities for the distinct applications. This is a choice that should be made in consultation with the battery operator and battery technology developers and should be in line with the goal and scope of the study.

DoD

When Equation 7 is filled in for a battery that serves a single application, the DoD at which the battery operates on average for this application is used. However, in case of serving multiple applications the average DoD might change. Some applications are shallow cycling applications and thus result in a low DoD, for example frequency regulation, as explained in the section 4.2.2.2. But another application might require cycling at a high DoD. However, it is also viable that a maximum operational DoD is set for the specific battery technology. As explained in section 4.2.2.2., the DoD is determined by the combination of the application and the battery technology, or by the battery technology only. At an increased cycle frequency due to serving multiple applications, the cycle lifetime could be reduced. Therefore, it might for example be that utilising the battery at a lower DoD in case of serving multiple applications, and thus installing a larger battery energy capacity, results in a longer lifetime and lower lifecycle costs, as explained in section 4.2.2.2. Moreover, it could be that the battery requires a certain SoC at a certain time to serve one of the applications at a later point in time. Therefore, how exactly the SoC profile resulting from optimisation of applications looks like is unclear and therefore determining the DoD at which the battery cycles for multiple applications is difficult.

Annual cycle frequency

Table 7 provides an overview of the results of optimised dynamic multi-use of a lithium-ion battery system serving several applications to maximise revenues (Englberger et al., 2020). The table shows the EFCs and battery lifetime of single-use and different multi-use scenarios. As can be seen in his table, the number of EFCs increases when the battery is used for multiple applications. However, the total number of EFCs in case of multi-use is lower than the sum of the number of EFCs when single batteries serve individual applications. When three distinct batteries serve PS, FCR and SMT they perform in total 46,1 + 128,6 + 214,7 = 389,4 EFCs. While a single battery that serves PS, FCR and SMT performs 300,7 EFCs. In case of multi-use, the battery performs more cycles, but it performs less cycles for each application compared to when the same battery serves a single application. In case of comparing single-use and multi-use batteries this is something that should be corrected for in such a way that both product systems deliver the same number of cycles and thus the same total electricity output.

$\eta^{0,5}$

As discussed in section 5.2.2.1, the round-trip efficiency and therefore the discharge efficiency does not change as a result of value stacking.

Battery lifetime

What emerges from the results in Table 7 as well is that the battery lifetime decreases when a battery is used for multiple applications which is the result of accelerated battery cycle degradation. The lifetime is potentially decreased due to more intensive utilisation, but whether or not this is the case depends on the battery technology. In case the calendar lifetime is still decisive even though the number of cycles has increased, then increased utilisation will not affect the battery lifetime.

In the next chapter, some of the findings from the literature review discussion are further analysed by assessing the effect of some of the parameters in Equation 6 and value stacking on the environmental impact scores of a battery system in an illustrative case study.

6

Illustrative case study of an organic redox flow battery

This chapter provides an illustrative case study in which some of the issues identified in the literature review discussion are put in an illustrative context to assess the relative effect of these issues on a battery's environmental impact scores. First, a description of the case is given including a justification for the issues identified in the literature review that are included in this case study and a description of the selected battery technology. Next, the results of the case study are discussed.

6.1. Case study description

6.1.1. Justification for the issues included in the illustrative case study

In this section a justification is provided for the issues that are identified in the literature review discussion which are decided to be included in the case study.

- Annual cycle frequency for application
  The cycle frequency value required for specific applications varies across the studies as shown in Table 4. However, the assumption about the value for the cycle frequency might potentially have an effect on the environmental impact scores of a battery technology. Rahman et al. (2021) assessed the effect of the cycle frequency on the overall environmental impacts by means of a sensitivity analysis in which they take a minimum and maximum value for the cycle frequency. According to them, the cycle frequency does not have a large effect on the overall life cycle impact scores. However, the included ranges are quite narrow. For example, they took a minimum cycle frequency value of 248 and a maximum of 250 for T&D investment deferral. Hiremath et al. (2015) also analysed the effect of cycle frequency on the overall impacts of the battery by assessing different applications which each demand a different number of cycles. They did, however, not vary the cycle frequency for each specific application and only assessed the effect on the C2G impact scores.

  However, both Hiremath et al. (2015) and Rahman et al. (2021) include the total electricity throughput in the use process modelling; the electricity losses and the electricity output. Therefore, the use phase impacts, i.e., the environmental impacts resulting from the electricity generation, are a significant contributor to the overall impacts. In case only electricity losses and operational electricity are included, as argued in section 4.2.2.1, the relative effect on the total life cycle environmental impact scores is expected to be lower. Therefore, the effect of varying the cycle frequency on the overall environmental impact scores is estimated in this case study.

- Battery lifetime
  The battery lifetime included in Equation 6 is the shortest of the calendar and cycle lifetime, which are both technical lifetimes. Different studies assume different calendar lifetimes for battery technologies, for example for an RFB it varies between 5 and 20 years (Arbabzadeh et al., 2017; da Silva Lima et al., 2021). Moreover, the battery's cycle life depends on the temperature, charge/discharge rate, DoD and average SoC during operation, as discussed in section 4.2.2.2. The cycle life at different combinations of these factors is unknown for most battery technologies. Therefore, it is infeasible to include it in modelling the use process. However, to provide insight on the effect of the cycle life on overall impact scores, minimum and maximum cycle life values can be analysed. Cycle lives vary between studies as well; for RFBs it ranges from 10000 to 15000 (da Silva Lima et al., 2021; Hiremath et al., 2015; Weber

et al., 2018). Hiremath et al. (2015) assume a mean cycle life value of 13000 cycles for a VRFB and asses the effect on the overall impacts by changing the cycle life up to 40%. They conclude that the cycle life plays a considerable role when only C2G impacts are considered, but the total life cycle impacts only weakly depend on the cycle life. Their explanation for this is the fact that the lower the total electricity delivered over the lifetime of the battery, the higher the contribution of C2G impacts when results are normalised to 1 MWh delivered electricity.

However, they attribute the environmental impacts of the total electricity throughput to the battery and not just of the efficiency losses. Therefore, a change in cycle life and thus in total electricity delivered will only have a small effect on the overall impact scores. Therefore, in this case study the effect of battery lifetime on the environmental impact scores is assessed when only efficiency losses and operational electricity are included. Moreover, as discussed in section 4.2.2.2., in case certain components of the battery system can be replaced, the lifetime might actually be based on an economic lifetime during which only components are replaced. The effect on the environmental impact scores of taking this perspective is considered in this case study as well.

- Round-trip efficiency
  Baumann et al. (2017), Hiremath et al. (2015) and Rahman et al. (2021) state that the life cycle environmental impacts strongly depend on the round-trip efficiency. Hiremath et al. (2015) even state that round-trip efficiency is the major battery characteristic parameter that influences life cycle impacts. They reveal a decrease of 1,3% in the total life cycle greenhouse gas emissions as a result of a percent increase of the round-trip efficiency of a VRFB. However, both the studies by Rahman et al. (2021) and Hiremath et al. (2015) include the total electricity throughput in the modelling of the battery use process, but the round-trip efficiency only changes the share of electricity that is lost during use. A percent increase of the round-trip efficiency only influences the share that is lost; the share of electricity that is charged and also discharged remains unchanged. Based on this reasoning it is expected that the effect on the environmental impact scores of a change in the round-trip efficiency will be larger when only round-trip efficiency losses and operational electricity are attributed to the battery system, as advocated for in section 4.2.2.1. Therefore, in this case study the sensitivity of the life cycle impact scores towards the round-trip efficiency is assessed when only operational energy and efficiency losses are considered.

- Value stacking
  As discussed in section 5.1, higher utilisation of a battery as a result of serving multiple applications simultaneously might decrease the battery's lifetime but results in economic optimisation. None of the LCA studies assessed value stacking except from the study by Schulz-Mönninghoff et al. (2021). They subtracted the impacts of grid mix electricity from the impacts of the battery system that is charged with solar energy. However, they do not subtract the environmental impacts that are displaced as a result of serving two other applications by the battery system, which leads to ambiguous results. According to them, climate change benefits are lower in case of value stacking than in case of using a battery for a single application. Moreover, their assessment is not aimed at evaluating the effect of value stacking on the environmental performance of a battery system, but they assess the effect of implementing a

battery used for different combinations of applications on the environmental impact scores of a local energy system.

Therefore, the main goal here is to illustrate the effect of value stacking on LCIA scores of a battery system and the sign of this change in impacts. The solutions for modelling value stacking as described in section 5.2 are applied in this illustrative case study to get a first impression of the effect of value stacking on the LCIA scores of a battery system.

The parameters that are chosen to be included in the case study are not necessarily the most important parameters or those that have most effect on the environmental impact scores of a battery system. Which parameters are paramount to the environmental impacts is only known when the effect of all parameters and the combinations of parameters, since they also interact with each other is assessed, which is beyond the scope of this study. Moreover, it should be noted that this case study is illustrative which means that it is not aimed at providing absolute results or drawing conclusions about the battery technology itself. It is mainly aimed at providing an impression of the relative effect of the (assumptions about) the parameters and value stacking on the environmental impact scores of a battery system.

6.1.2. Description if the selected battery technology and technical information of the LCA

The redox flow battery technology is chosen for this illustrative case study, which is justified in section 3.1.2. More information about the working principle of an RFB is included in Appendix D. The vanadium redox flow battery (VRFB) and zinc-bromine redox flow battery can be defined as the state-of-the-art, where the VRFB is most successful and the only one that reached commercial maturity (Alotto et al., 2013; Sánchez-Díez et al., 2021). However, VRFBs still present some challenges. Vanadium is a scarce metal that is being mined only in a few countries across the globe. It is subject to high supply risk and has a high economic importance, which leads to increasing and highly volatile raw material prices of vanadium pentoxide (V_2O_5), which is the basic substance for producing the electrolyte (Minke et al., 2017). Next to the criticality aspect, oxides of vanadium, which are used in VRFBs, are associated with toxicity and are detrimental to human health (Ghosh et al., 2015). Moreover, limited energy density values result in a bulkier system than lithium-ion battery systems (Moore et al., 2016) Finally, most RFBs are designed to work at room temperature (<40 ºC) to prevent electrolyte degradation and battery malfunction. Sulphuric acid-based VRFBs only work between 10 °C and 40 °C. This generally requires a cooling system, especially in warm weather regions, since the battery heats up due to charging and discharging cycles. This has promoted research for alternatives (Sánchez-Díez et al., 2021; Winsberg et al., 2017).

Given that most of the forementioned issues emanate from the chemistry of the electrolyte, replacing the electrolyte seems to be a straightforward solution. Using redox active organic molecules has emerged as a substitute for inorganic compounds (Sánchez-Díez et al., 2021; Singh et al., 2019; Wang & Sprenkle, 2016). Therefore, the development of organic redox flow batteries (ORFBs) is of high interest (Gentil et al., 2020; Kwabi et al., 2020; Narayan et al., 2019; Singh et al., 2019). Organic refers here to using organic redox species, which are species based on earth abundant elements as carbon (C), hydrogen (H), oxygen (O), nitrogen (N) and sulphur (S). Future research on RFBs, among which ORFBs, will pave the road to the 2030 targets as stated in the Strategic Energy Technology Plan (SET

Plan). The European Commission is supporting this research through the HORIZON2020 calls LC-BAT-3 and LC-BAT-4, which are fully devoted to RFBs (National Agency for Research and Development, 2019). BALIHT (www.baliht.eu) is one of the research consortia which are part of the research and innovation programme call *LC-BAT-4-2019 Advanced Redox Flow Batteries for stationary energy storage*. The aim of the BALIHT research project is to develop an organic redox flow battery using electrolytes synthesised from lignin. Lignin is a structural material present in most plants to provide its rigidity. The aim is to use lignin from the paper and pulping industry, in which it currently is a waste stream. Moreover, their battery is aimed to work at higher temperatures, which makes cooling obsolete and therefore decreases operational electricity use. A more extensive elaboration regarding redox flow batteries, the shift towards ORFBs and the BALIHT project is provided in Appendix J.

Since the case study is illustrative it concerns a simplified LCA and reporting on the four phases of an LCA has been omitted. The FU as defined in section 4.2.1.1 is used in this case study: *Delivering one MWh electricity of the total electricity delivered over the battery's lifetime from an organic redox flow battery used for wholesale arbitrage*. Application characteristics data are used from Battke et al. (2013) as shown in Table 3, in which utility energy time-shift is similar to wholesale arbitrage. Default values for the battery parameters are included in Table 8. The battery system modelled in this case study is a 1 MW/8,3 MWh ORFB. Process data is to a large extent based on the LCI data of the LCA study by Weber et al. (2018) who asssessed a VRFB and is one of the few studies that provides a complete LCI. Since the adopted datasets by Weber et al. (2018) are for a VRFB battery with a power of 1MW and an energy capacity of 8,3 MWh, the data for a 200 kW/200 kWh ORFB that is available from the BALIHT research project is scaled to 1 MW/8,3 MWh. Some components have been adjusted compared to the VRFB modelled by Weber et al. (2018) of which the main adjustment is the electrolytes which are organic electrolytes developed in the BALIHT project instead of vanadium based electrolytes. Moreover, the bipolar plate and cell frame material, both part of the cell stack, are adjusted to the materials used in the BALIHT project. Even though other materials are developed and tested in the project, the membrane used in the cell stack is assumed to be a Nafion membrane, for which data from Weber et al. (2018) is used but is adjusted to the dimensions of the membranes used in the BALIHT project. More information about these adjusted components, the LCI data and calculations regarding is confidential and is therefore not included in this research. For reference the processes and chemicals used for this battery are documented in the project documentation (www.baliht.eu). The ecoinvent 3.7.1. database is used for background processes (Wernet et al., 2016). The open source LCA software Activity Browser is used. The assessment focused on five impact categories: climate change, freshwater ecotoxity, human health carcinogenic effects, ozone depletion and acidification, based on the PEF ILCD EF 3.0 impact assessment method.

Table 8

Default values for the battery parameters in the illustrative case study

Parameter	Value	Unit
C_{bat}	8,3	MWh
DoD	80	%
Annual cycle frequency	1233	EFCs
η	75	%
Battery lifetime	13	years

6.2. Case study results

6.2.1. Annual cycle frequency for application

Two battery applications are selected for which the cycle frequency is varied ranging from 20% less to 20% more than the default value, as shown in Table 9. Wholesale arbitrage is selected since this application has a cycle frequency of 365 cycles per year, which is oftentimes used in LCA studies of batteries that don't define an application. Frequency regulation has the highest required cycle frequency and therefore this is selected as a second application. The default value is based on the most common value in Table 4.

Table 9

Cycle frequency values that are modelled to analyse the effect of cycle frequency on the overall impact scores of a battery system

Scenario / Application	Annual cycle frequency [# of cycles]				
	-20%	**-10%**	**Default**	**+10%**	**+20%**
Wholesale arbitrage	292	329	365	402	438
Frequency regulation	496	558	620	682	744

Figure 23 and Figure 24 show the comparative environmental impact scores of the ORFB in case of serving wholesale arbitrage and frequency regulation with different cycle frequencies. When the cycle frequency is increased by 10-20% for an application with a cycle frequency of 365 cycles per year, the overall impacts decrease by about 16-19%, 14-17% and 24-29% for the freshwater ecotoxicity, human toxicity and ozone layer depletion impact categories respectively. The effect on climate change and acidification impacts is much smaller, 3-4% and 3-3,5% respectively. For the frequency regulation application with 620 cycles per year, the overall impacts decrease by about 12-15%, 10-13% and 22-27% for the freshwater ecotoxicity, human toxicity and ozone layer depletion impact categories respectively. Climate change and acidification impacts decrease by 2-2,5% and 1,5-2% respectively.

In both cases, the difference in climate change and acidification impact scores are small. The impacts reduce considerably when the cycle frequency increases for the freshwater ecotoxicity, human toxicity and ozone layer depletion impact categories. This is due to the fact that efficiency losses and operational energy remain the same per delivered kWh of electricity. The required battery fraction per delivered kWh of electricity reduces as a result of delivering more electricity in total over the lifetime. This mainly affects the impact categories in which the C2G end EOL phases have a relatively large contribution which are freshwater ecotoxicity, human toxicity and ozone layer depletion, as shown in Figure 30.

Figure 23

Comparison of impact scores of different required cycle frequency values of a single-use ORFB in case of serving wholesale arbitrage

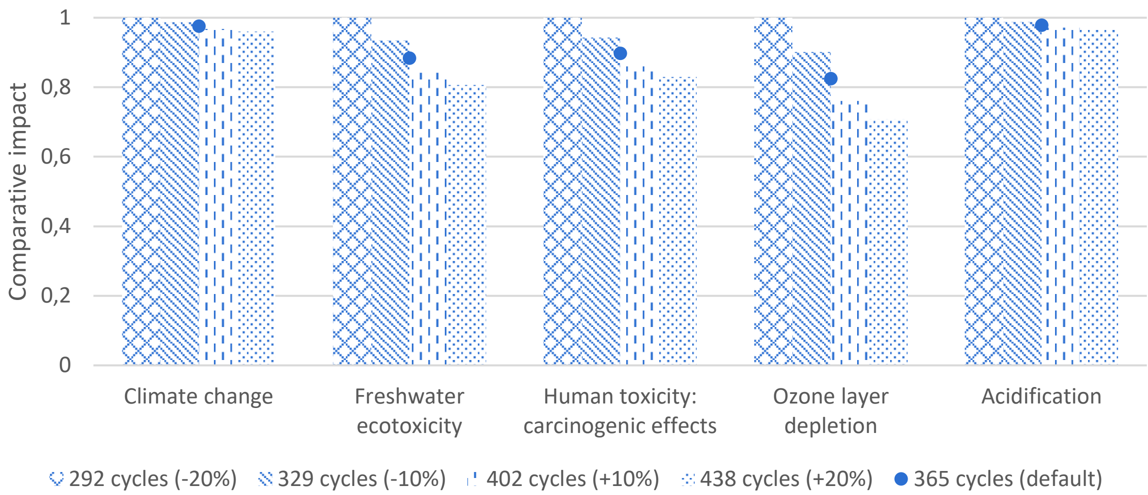
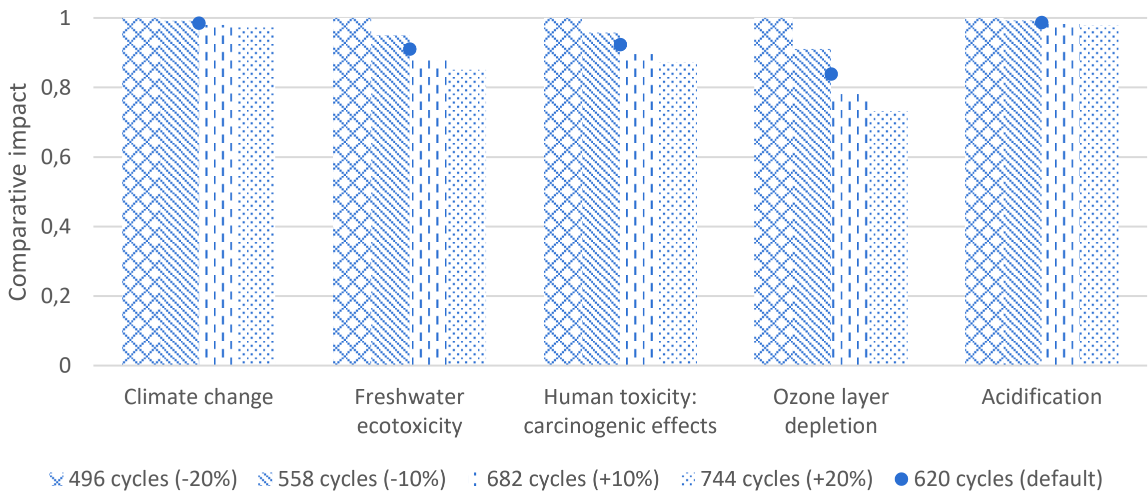


Figure 24

Comparison of impact scores of different required cycle frequency values of a single-use ORFB in case of serving frequency regulation



6.2.2. Battery lifetime

Both Weber et al. (2018) and da Silva Lima et al. (2021) state that certain components of an RFB can be replaced, while Hiremath et al. (2015) and Baumann et al. (2017) assume that the whole battery system is replaced after EOL. Requiring one battery system and replacing certain components instead of requiring two entire battery systems affects the C2G and EOL impacts. Since the battery technology used as an example in this case study is an ORFB of which components can be replaced, the effect of different battery lifetime scenarios on the battery's total LCIA scores is estimated. Several scenarios in which the battery's lifetime is varied are defined as shown in Table 10.

Table 10

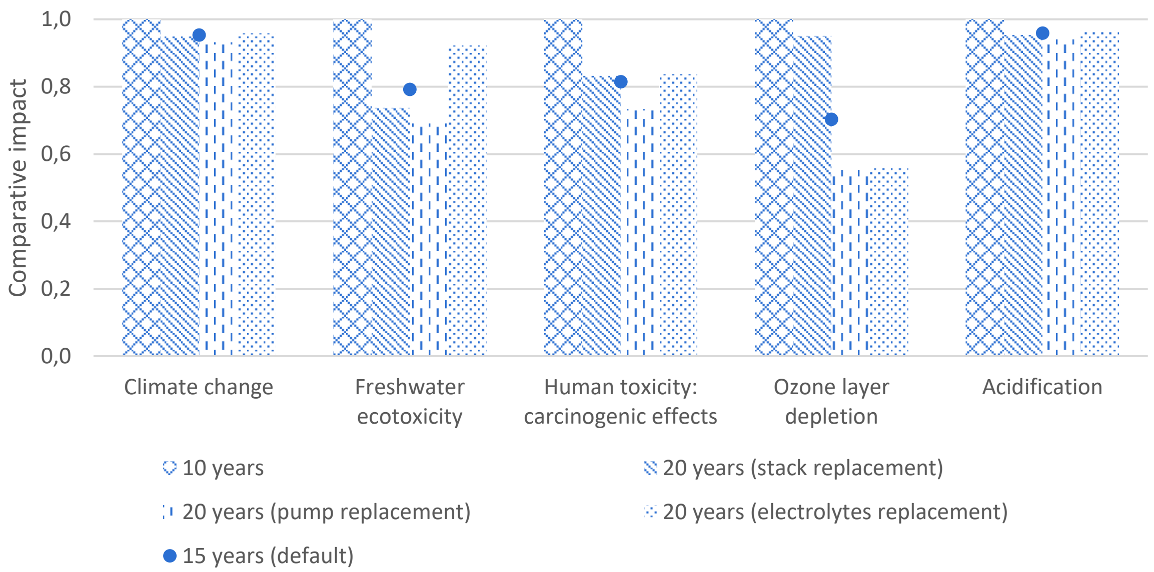
Lifetime scenarios for an organic redox flow battery

Scenario	Description
15 years calendar lifetime (default)	15 years battery lifetime based on the calendar lifetime of a VRFB as mentioned by Baumann et al. (2017). It is assumed that the entire battery system is EOL after 15 years.
10 years calendar lifetime	10 years battery lifetime based on a calendar lifetime of 10 years that is decisive for the EOL as mentioned by Hiremath et al. (2015) and Arbabzadeh et al. (2017). It is assumed that the entire battery system is EOL after 10 years.
20 years battery lifetime with two replacements of the pumps	20 years economic battery lifetime. This is based on the study by da Silva Lima et al. (2021) who state that only the pumps and fans have to be replaced twice during 20 years of operation of the VRFB. The ORFB included in this case study does not have a cooling system and therefore it is assumed that only the pumps have to be replaced twice during an economic battery lifetime of 20 years. The LCI is adjusted so that it includes three times the amount of pump for the assembly of the balance of plant and three times the amount of pump waste disposal.
20 years battery lifetime with one-time replacement of the cell stack	Weber et al. (2018) state that the calendar lifetime of 10 years refers to the cell stack only. The total battery system has a lifetime of, at least, 20 years. Therefore, this scenario assumes an economic battery lifetime of 20 years during which the cell stack will be replaced once. This is reflected in the LCI by adjusting the battery assembly process inputs into 10 stack units instead 5 and the same goes for the battery disassembly process.
20 years battery lifetime with one-time replacement of the electrolytes	According to the BALIHT research consortium, the lifetime of the electrolytes is uncertain. A scenario in which the battery has an economic lifetime of 20 years is modelled during which the electrolytes are replaced once.

Figure 25 shows the environmental impact scores of the lifetime scenarios. A reduction of the lifetime from 15 to 10 years result in higher impacts, especially for freshwater ecotoxicity, human toxicity and ozone layer depletion. Ozone layer depletion impact scores are even 40% lower when the economic lifetime of the battery is 20 years and pumps or electrolytes are replaced during these 20 years instead of replacing the whole battery system in 10 years time. Overall, any change in lifetime does not have a great effect on the climate change and acidification impacts due to the fact that the C2G and EOL impacts contribute less to these categories than to the other categories. A change in the lifetime does not have an effect on the required electricity inputs per MWh delivered (i.e., the use phase), but only on the required battery fraction. The scenario in which the pumps of the battery system are replaced during an economic lifetime of 20 years results in lower impacts in all categories. It is noticeable that the impacts on freshwater ecotoxicity, human toxicity and acidification increase when the electrolytes are replaced during a period of 20 years compared to replacing the whole battery after 15 years.

Figure 25

Comparison of impact scores resulting from different battery lifetime scenarios for a single-use ORFB in case of serving an application requiring 365 cycles per year



Note. 10 years = 10 years calendar lifetime, 20 years (pump replacement) = 20 years battery lifetime with two replacements of the pumps, 20 years (stack replacement) = 20 years battery lifetime with one-time replacement of the cell stack and 20 years (electrolytes replacement) = 20 years battery lifetime with one-time replacement of the electrolytes. See Table 10 for a description of the different scenarios.

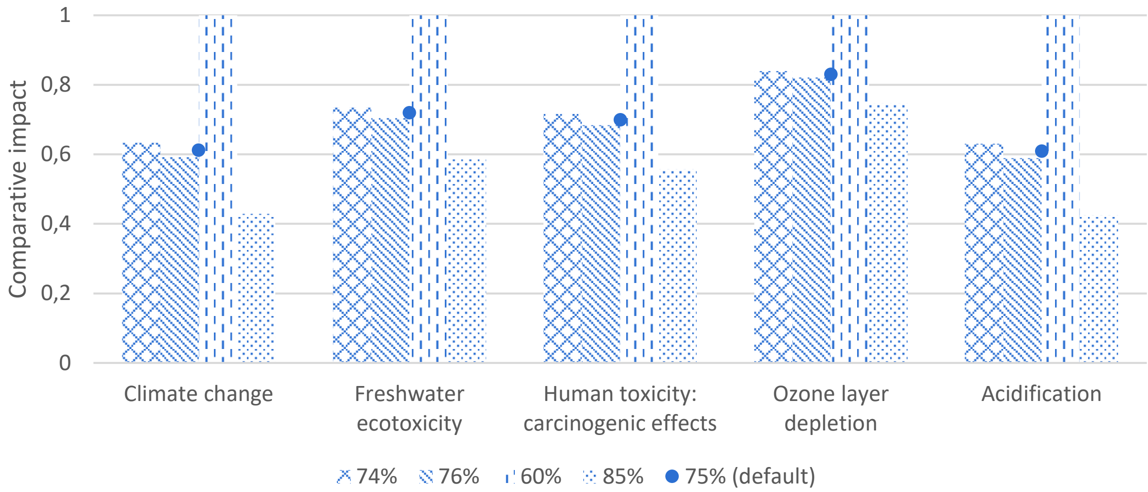
6.2.3. Round-trip efficiency

It is estimated what the effect of a change in round-trip efficiency of 1% is on the overall environmental impact scores when only round-trip efficiency losses and operational electricity are included in the modelling as recommended in section 4.2.2.1. Moreover, several studies include lower and upper values for the round-trip efficiency of an RFB, which vary considerably between studies. Therefore, a lower and upper value for the round-trip efficiency are included as well. In total, five scenarios are included; the default value of 75% (Baumann et al., 2017; Hiremath et al., 2015; Rahman et al., 2021; Weber et al., 2018); 74% and 76% which are a decrease and increase of 1% compared to the default value; a lower value of 60% (Hiremath et al., 2015) and an upper value of 85% (Baumann et al., 2017).

Figure 26 shows the effect on the overall impact scores from changing the round-trip efficiency values from the default value. An increase of one percent of round-trip efficiency leads to a corresponding decrease of 3%, 2%, 2%, 1% and 3% for the different impact categories respectively. In contrast to the 1,3% decrease in the climate change impact category due to an increase in round-trip efficiency of 1% as stated by Hiremath et al. (2015), this analysis shows a reduction of 3,3%. Acidification impacts also reduce by 3,3%. Particularly the climate change and acidification impact categories are affected by a change in round-trip efficiency since the use phase is a large contributor to these impact categories. For the other impact categories the reduction is about 1-2%, since the contribution of the use phase towards the total impacts is lower. The lower and upper round-trip efficiency values considerably affect the impacts scores of all impact categories, and especially the climate change and acidification categories. It should be noted that this is the case in a scenario in which the battery is charged with electricity from the European electricity mix.

Figure 26

Comparison of impact scores resulting from varying the round-trip efficiency of a single-use ORFB in case of an application requiring 365 cycles per year



6.2.4. Value stacking

The main goal here is to illustrate the effect of value stacking on the environmental impact scores of a battery system and the sign of this change in impacts. Therefore, a battery serving multiple applications is compared to the same battery serving a single application, i.e., the left column in Table 5. Comparing a multi-use battery to an alternative product system containing a conventional technology such as a natural gas power plant is refrained from in this case study. It is the aim to illustrate the effect on the environmental impact scores of a battery and not to compare the impact scores of an application served by the multi-use battery to the current situation in which that application is served by another energy technology.

A precise approximation of the actual optimisation of different applications is not within the scope of this study. It has been chosen that the battery in this case study serves the applications peak shaving (PS), frequency containment reserve (FCR) and spot market trading (SMT) that are stacked in the study by Englberger et al. (2020) so that the results from their study, as shown in Table 7, can be used. These applications correspond to T&D investment deferral, area and frequency regulation and utility energy time shift (i.e., wholesale arbitrage in Table 1) respectively in the application characteristics Table 3. Moreover, Jongsma et al. (2021) concluded that this combination of applications results in the highest revenues and is a combination of applications that is already profitable. Their combination of applications is referred to as day-ahead, FCR and aFRR, and the congestion market which corresponds to wholesale arbitrage, area and frequency regulation, and T&D investment deferral in Table 1. This supports the assumption that this combination of applications seems to be a proper scenario to assess in this case study. In the remainder of this study these applications are referred to as T&D, FR and WA.

In the next section, a discussion is provided regarding the assumptions made for each of the parameters in Equation 6 and which values are used for these parameters in case of value stacking. The value for each parameter is shown in Table 11.

C_{bat}

The issue of determining the energy capacity of a battery used for multiple applications, as described in section 5.2.2.2, only applies to comparative LCA studies in which two different battery technologies serving multiple applications are compared. The goal of the current case study is to illustrate whether value stacking affects the environmental performance of the same battery. Therefore, defining the battery energy capacity is not that important and a battery with a certain energy capacity can be chosen as a basis. This specific battery that is used for a single application is now used for multiple applications for reasons of economic profitability. Moreover, this is an illustrative case study which is not aimed at modelling value stacking as accurate as possible. For these reasons, the batteries in the single application product system are assumed to have the same power (W) and energy capacity (Wh) as the one in the multi application product system. The same 1 MW/8,3 MWh ORFB is assumed as in the previous analyses.

DoD

Since it is assumed that part of the battery is reserved for an application, the simple assumption is made that the battery operates at the same DoD for an application like in the case of serving a single application, even though this might not be the case in reality. Moreover, in case of an RFB, due to its high cycle life, the cycle lifetime in years is not extended when the battery operates at a lower DoD. Therefore it is the RFB technology itself that defines the DoD and not the application. For reasons of simplicity it is assumed that the total cycle frequency for all applications is performed at the same average DoD as in the case of serving a single application. The ORFB is assumed to operate at a DoD of 80%.

Annual cycle frequency

The case study is illustrative and not intended to model value stacking as accurate as possible. Therefore, existing results of the optimisation of multiple applications served by a lithium-ion battery from a multi-use optimisation framework are adopted (Englberger et al., 2020) as shown in Table 7. Even though these results are for a different battery technology than the battery that is modelled in this case study, the results are assumed to be representative to illustrate the philosophy of value stacking. When the battery is utilised for FCR and SMT, and for PS, FCR and SMT, the total number of EFCs increases, but is about 20% less than the sum of the number of EFCs for each battery serving a single application.

However, the annual EFCs in their results deviate quite a lot from the cycle frequency values from Battke et al. (2013) in Table 3, which are used by several authors in LCA studies assessing single-use batteries (Baumann et al., 2017; Hiremath et al., 2015; Rahman et al., 2021; T. S. Schmidt et al., 2019). According to Battke et al. (2013), these applications require 248, 620[1] and 365 EFCs per year respectively. Since these values are regularly used in other LCA studies, it is decided to use the values of Battke et al. (2013) and assume the reduction in the total number of EFCs which is based on the

[1] 1,7·365 = 620 because 34 cycles at 5% DoD correspond to 1,7 EFCs per day

results of Englberger et al. (2020). Even though this reduction of 20% is just based on one analysis from just one study, it is assumed to be a good starting point to get a first impression of the effect of value stacking on the LCIA scores of a battery.

$\eta^{0,5}$

As discussed in section 5.2.2.1, the round-trip efficiency of the battery system is assumed to remain similar compared to the scenario of serving a single application. The same round-trip efficiency value of 75% as in the previous analyses is assumed.

Battery lifetime

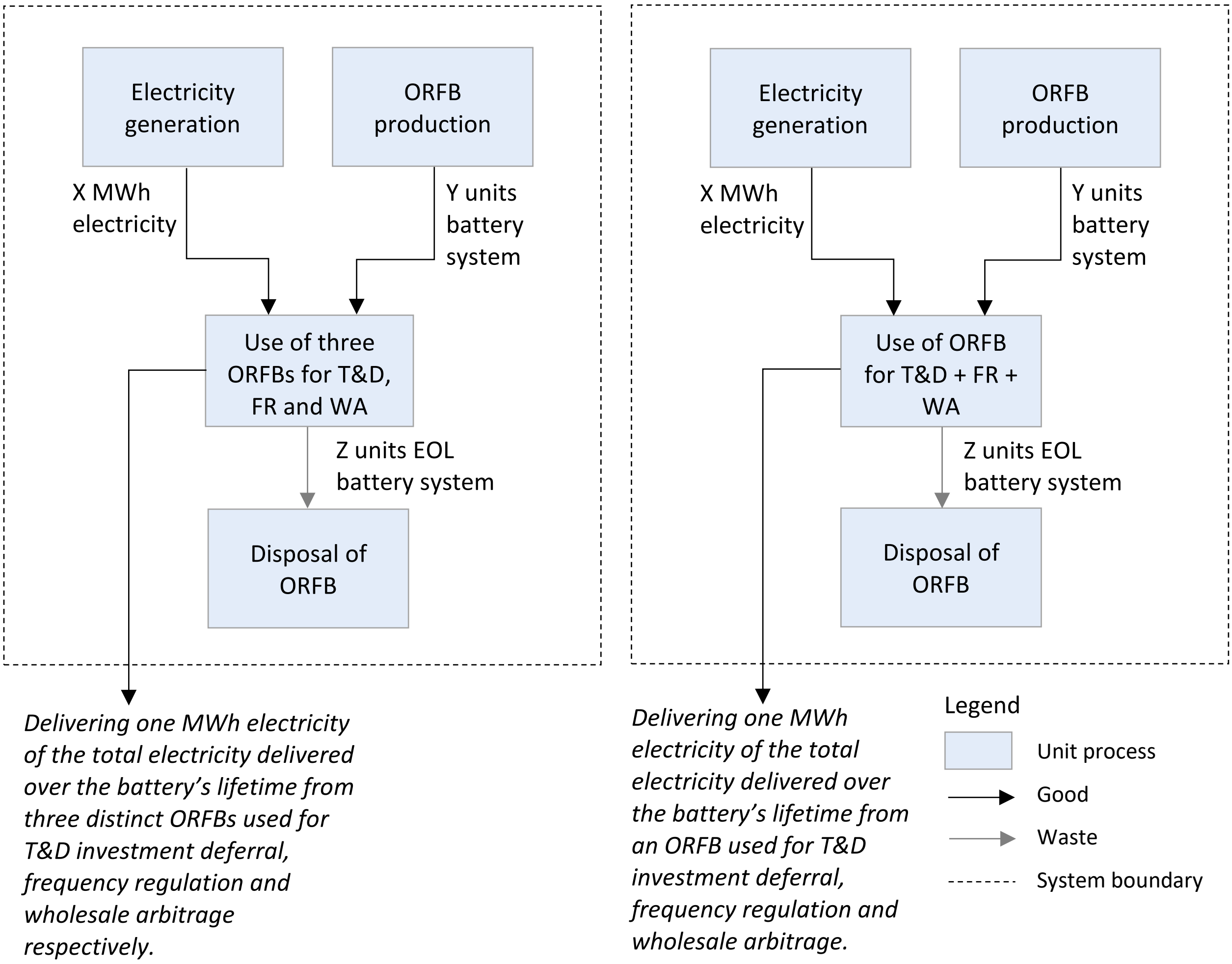
Whether the lifetime might decrease as a result of the increased number of cycles depends on the battery technology. An RFB has a cycle life somewhere between 10000-15000 cycles and a calendar lifetime between 10 and 20 years (Arbabzadeh et al., 2017; Baumann et al., 2017; da Silva Lima et al., 2021; Hiremath et al., 2015; T. S. Schmidt et al., 2019; Weber et al., 2018). Therefore, the battery lifetime of this type of battery is not likely to be affected by an increased cycle frequency. A calendar lifetime of 15 years (Baumann et al., 2017) and cycle life of 13000 cycles is assumed.

The reference case in this case study is a product system with one battery that serves a single application. However, it is not clear how the cycle frequency of a battery serving multiple applications is divided among the different applications and therefore how to allocate part of the impacts to one of the applications in order to compare this to the single battery serving a single application. Moreover, it should be noted that it is unclear at which DoD the share of the battery that serves an application at each time slot operates. The cycle frequency seems to be a representation of the amount of electricity delivered for each application. The number of EFCs for each application is assumed to be performed at the same DoD as the total number of EFCs (the average DoD). But the actual DoD of the cycle frequency for each individual application is unclear and therefore the total delivered electricity for each application might not be linear to the number of cycles. Moreover, is not possible to trace back how the cycle frequency is reduced for each of the combined application in the results of Englberger et al. (2020); only the reduction of the cycle frequency for the combination of applications is known. Therefore, allocating based on the cycle frequency is not possible. To avoid allocation, it was decided to expand the alternative product system with two batteries which each serve one of the other applications that the multi-use battery is serving. This way both systems serve the same set of applications. This is the system expansion approach as described in section 5.2.1.1. The system with three distinct batteries is referred to as 'single-use' and the single battery system serving multiple applications is referred to as 'multi-use' in the following sections. The product systems of the single-use and multi-use alternative are shown in Figure 27.

However, the single-use battery serving the same set of applications does serve each of these applications to a lesser extent as a result of operational constraints when combining the applications, as described in section 5.1. Based on the number of EFCs in Table 7 , the multi-use battery provides about 20% EFCs in total than the distinct batteries as a result of optimising the stacking of applications. Moreover, the battery serving multiple applications has a reduced lifetime as a result of the increased total number of EFCs; 13 years (13000 / (248 + 365 + 620) · 80%) = 13 years) instead of the calendar lifetime of 15 years. The number of EFCs corresponds to the total delivered electricity since this is the number of times that the battery is charged and discharged. Therefore, this implies that this battery delivers less electricity over its lifetime compared to the distinct batteries. Even though this is what actually happens in reality; the comparison between both systems is not fair since both systems do not deliver the same amount of electricity. This is compensated for by expanding the multi-use product system with an artificial amount of battery so that it delivers the same amount of EFCs, and thus electricity, as the three distinct batteries, as depicted in Figure 28 and explained in the next section.

Figure 27

Product systems of single-use ORFBs (left) and multi-use ORFB (right) in case of serving T&D investment deferral, frequency regulation and wholesale arbitrage



The distinct batteries are subjected to 248 + 365 + 620 = 1233 EFCs per year, which is based on the results of Englberger et al. (2020). All three batteries have a lifetime of 15 years which is based on a calendar lifetime of 15 years (Baumann et al., 2017). In total, these batteries are subjected to 1233 EFCs · 15 years = 18495 EFCs. The multi-use battery is assumed to be subjected to 1233 · 80% = 986 EFCs per year. Therefore, additional battery is required to provide 247 EFCs per year in order to perform the required 1233 EFCs per year. Moreover, subjecting the battery to 986 EFCs per year results in a battery lifetime of 13000 / 986 = 13 years based on a cycle life of 13000 EFCs. In these 13 years the expanded battery system can provide 1233 · 13 years = 16029 EFCs. In order to provide 18495 EFCs in total, the battery system has to be further expanded with an artificial amount of battery to perform the remaining 18495 - 16029 = 2466 EFCs. In total, it results in 18495 / 13000 = 1,42 battery system to match the multi-use product system with the single-use product system in terms of total delivered electricity. Based on this, Equation 6 is adjusted for value stacking by replacing the enumerator by "number of batteries" as shown in Equation 9.

$$Fraction\ of\ battery\ required\ for\ 1\ MWh_{delivered} = \frac{Number\ of\ batteries}{C_{bat}\ [MWh] \cdot DOD\ [\%] \cdot annual\ cycle\ frequency\ [number] \cdot \eta^{0,5}\ [\%] \cdot \text{battery lifetime [y]}} \tag{9}$$

Table 11

Parameter values used in Equation 6 to define the battery fraction for both the single-use and multi-use product systems

Parameters	Multi-use	Single use T&D	Single use FR	Single use WA	Unit
Cbat	8,3	8,3	8,3	8,3	MWh
DoD	80	80	80	80	%
Annual cycle frequency	1233	248	620	365	EFCs
η	75	75	75	75	%
Battery lifetime	13	15	15	15	years

Note. T&D = T&D investment deferral, FR = frequency regulation and WA = wholesale arbitrage (which correspond to PS, FR and SMT respectively in Englberger et al. (2020)).

Figure 28

Depiction of system expansion of the multi-use battery in order to match with the total delivered electricity of the single-use batteries

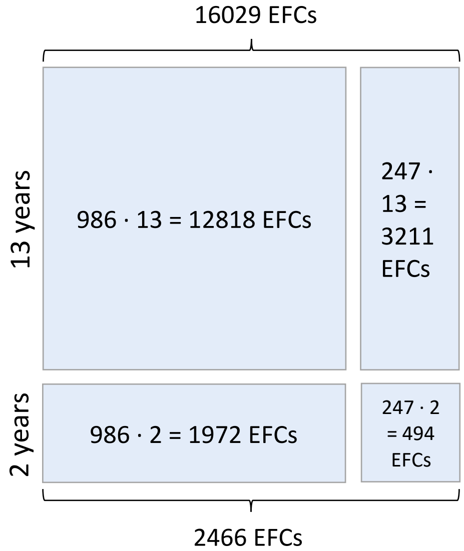


Figure 29 shows the impact scores of the single-use ORFBs compared to a multi-use ORFB. The multi-use battery has a considerably smaller impact on all impact categories, but the difference is smallest for the climate change and acidification categories.

Figure 29

Comparison of impact scores of single-use ORFBs and multi-use ORFB in case of serving T&D investment deferral, frequency regulation and wholesale arbitrage

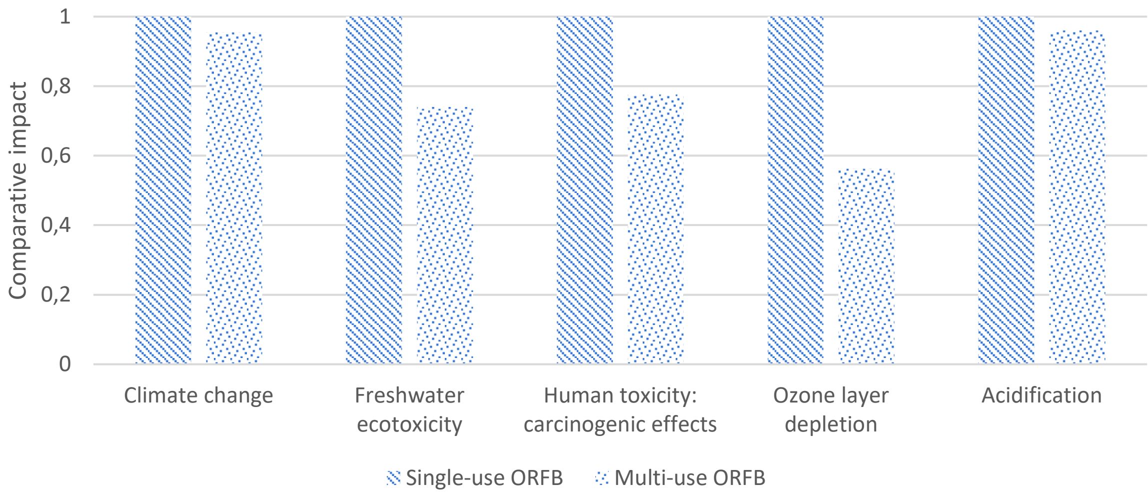


Figure 30 and Figure 31 show the contributions of the use phase and the C2G and EOL phase for the single-use and multi-use case respectively. In both cases, the environmental impacts related to the use, i.e., electricity lost due to round-trip efficiency losses and operational electricity, are the largest contributor in most impact categories except ozone layer depletion and freshwater ecotoxicity in the single-use case.

Figure 30

Relative contribution to each impact category of the use phase (i.e., electricity input) and the C2G and EOL phase for the single-use case

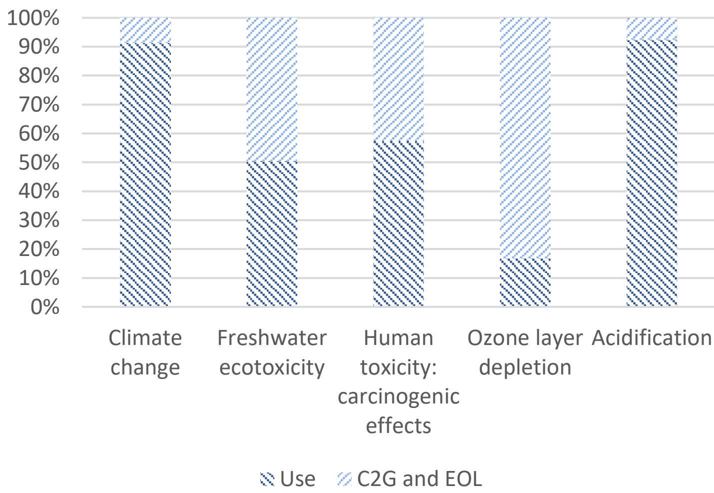
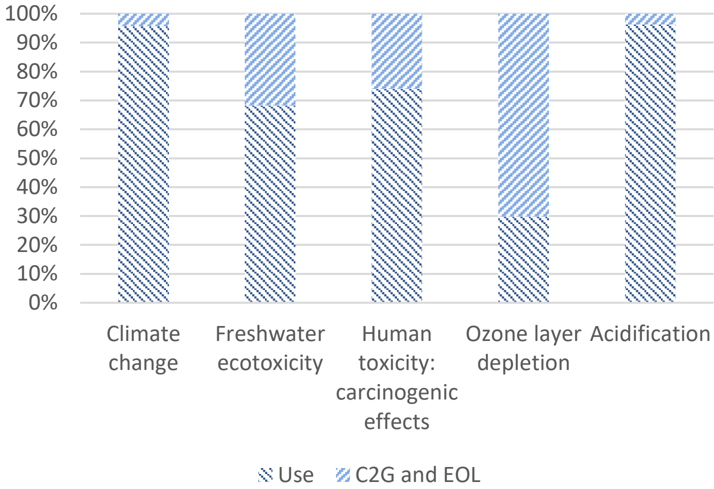


Figure 31

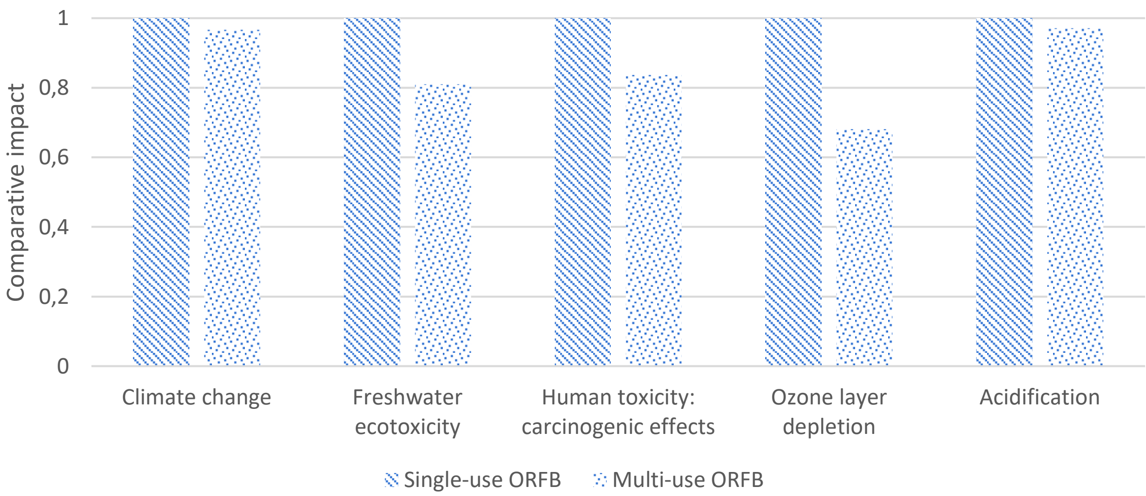
Relative contribution to each impact category of the use phase (i.e., electricity input) and the C2G and EOL phase for the multi-use case



The results above are based on an ORFB with a cycle life of 13000 cycles which results in a reduction of the battery's lifetime of 2 years compared to using the battery for a single application. Cycle lives of RFBs vary between studies ranging from 10000 to 15000 (da Silva Lima et al., 2021; Weber et al., 2018). When the cycle life is lower, this decreases the battery lifetime even further and potentially reduces the benefits of value stacking regarding environmental impact scores. Figure 32 shows the impact scores of the single-use ORFBs compared to a multi-use ORFB in case the battery cycle life is assumed to be 10000 cycles instead of 13000. Even though multi-use is somewhat less beneficial with regard to environmental impacts compared to the when the battery cycle life is 13000 cycles, value stacking is still beneficial compared to utilising batteries for single applications.

Figure 32

Comparison of impact scores of single-use ORFBs and multi-use ORFB in case of serving T&D investment deferral, frequency regulation and wholesale arbitrage, with a reduced battery cycle life

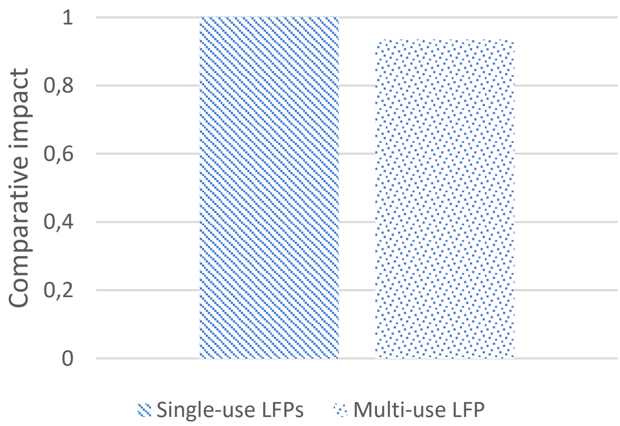


The lifetime of an RFB is not restricted considerably due to the increased number of cycles as a result of its high cycle life. However, other types of batteries have lower cycle lives and therefore the lifetime of such battery technologies is influenced much more by increased utilisation. For this reason, a simplistic LCA model is made for the use of a lithium iron phosphate (LFP) LIB and a valve regulated lead acid (VRLA) battery to evaluate the effect of value stacking in the case of batteries with lower cycle lives. The VRLA battery technology is selected because VRLA batteries are one of the most mature electrochemical storage technologies and hold the third biggest share in stationary storage on a global level (Baumann et al., 2017). This battery technology has a very low cycle life of just 1400 cycles and a calendar lifetime of about 18 years (Baumann et al., 2017). The LIB technology is selected because it is the most used battery technology. It has a cycle life of 5000 cycles and a calendar lifetime of about 15 years (Baumann et al., 2017). This way the effect of value stacking on battery technologies with half of the cycle life of an RFB (LFP LIB) and a technology with a very low cycle life (VRLA) is evaluated.

The models are similar to the ORFB model, so the batteries are serving T&D, FR and WA, except that the disposal of the batteries is disregarded due to a lack of data (Baumann et al., 2017). The system expansion approach is performed in the same way as in case of the ORFB. 3,7 batteries are required in case of multi-use (18495 EFCs / 5000 cycles = 3,7) and 4 batteries are required in case of single-use ((248 EFCs · 15 years / 5000 cycles) + (365 EFCs · 15 years / 5000 cycles) + (620 EFCs · 15 years / 5000 cycles) = 4). C2G environmental interventions are adopted from Baumann et al. (2017) which are limited to CO_2 emissions. Therefore, this evaluation only includes the climate change impact category. Figure 33 shows the climate change impact scores of the single-use LFPs compared to a multi-use LFP. The reduction in impact is nearly the same as in the case of the ORFB. Due to its very low cycle life of a VRLA, the same number of batteries is required to fulfil the total number of EFCs for the combined applications in case of single-use and multi-use. Due to the low cycle life the battery is already maximally utilised in case of single-use and therefore there is no difference in environmental impact scores between single-use and multi-use.

Figure 33

Comparison of climate change impact scores of single-use LFPs and multi-use LFP in case of serving T&D investment deferral, frequency regulation and wholesale arbitrage



As shown in Figure 30 and Figure 31, the use phase contributes most to the overall impact scores, except from ozone layer depletion. However, in the analyses above the batteries are charged with electricity from the average European electricity mix. It is interesting to analyse how value stacking affects the environmental impacts in case the battery is used to store renewable electricity and serves a second application simultaneously. The Energy Information Administration (2021) expects that future battery storage will increasingly be used for renewable energy storage, since most planned projects in the upcoming three years are co-located with renewable energy generation. Therefore, next to the scenario in which the ORFB is used for T&D investment deferral, frequency regulation and wholesale arbitrage, a scenario in which RET firming and frequency regulation are combined is assessed. All parameter values are equal to the T&D, FR and WA scenario, except from the cycle frequency. This is assumed to be 365 for RET firming and 620 for frequency regulation based on the cycle frequency values of Battke et al. (2013). The same reduction of 20% regarding the total number of EFCs in case of combining applications is assumed due to a lack of more detailed information.

In this case, the electricity to charge the battery is assumed to be different from the T&D, FR and WA scenario. Here, the battery used for RET firming is assumed to be charged with wind energy, while the battery utilised for frequency regulation is charged with electricity from the European electricity mix. Both product systems are visualised in Figure 34. To reflect this in the LCA model, the electricity inputs are separately modelled for electricity from wind energy and electricity from the European electricity mix. The ratio (X_1 and X_2 in Figure 34) is based on the required cycle frequency for each application since the cycle frequency correlates with the electricity charged into the battery. Therefore, 365 / (365 + 620) $\cdot$ 100% = 37% of the electricity input is provided by wind energy and 63% is provided by the European electricity mix.

In the multi-use case, the battery is assumed to be charged solely with wind energy. It is assumed that the battery provides positive frequency regulation with RET electricity that is stored in the battery. Negative frequency regulation is provided by charging the battery with wind energy in case of over-frequency as a result of a spike caused by an overproduction of wind energy. See Appendix C for an explanation about frequency balancing. This also demonstrates the overlap between applications; the electricity stored with the aim of frequency regulation at the same time reflects RET firming since the stored electricity can be used later on. Whether or not this assumption reflects reality is not entirely sure, however, it may possibly be the case in reality.

Figure 35 shows the impact category scores of the single-use ORFBs compared to a multi-use ORFB in case of serving RET firming and FR. Compared to the previous case it is noticeable that the impact scores in the climate change, freshwater ecotoxicity and acidification categories are much lower in the multi-use scenario compared to the single-use scenario. The human toxicity and ozone layer depletion impact scores are less reduced. This is due to the fact that the use phase is the largest contributor in the former impact categories and these impacts result from the environmental interventions related to the electricity lost due to efficiency losses and operational electricity. When the electricity input is replaced by electricity from renewables with lower environmental interventions, value stacking has a much greater effect on those impact categories, since the relative impacts of the C2G and EOL phases on the overall impacts are smaller.

Figure 34

Product systems of single-use ORFBs (left) and multi-use ORFB (right) in case of serving RET firming and frequency regulation

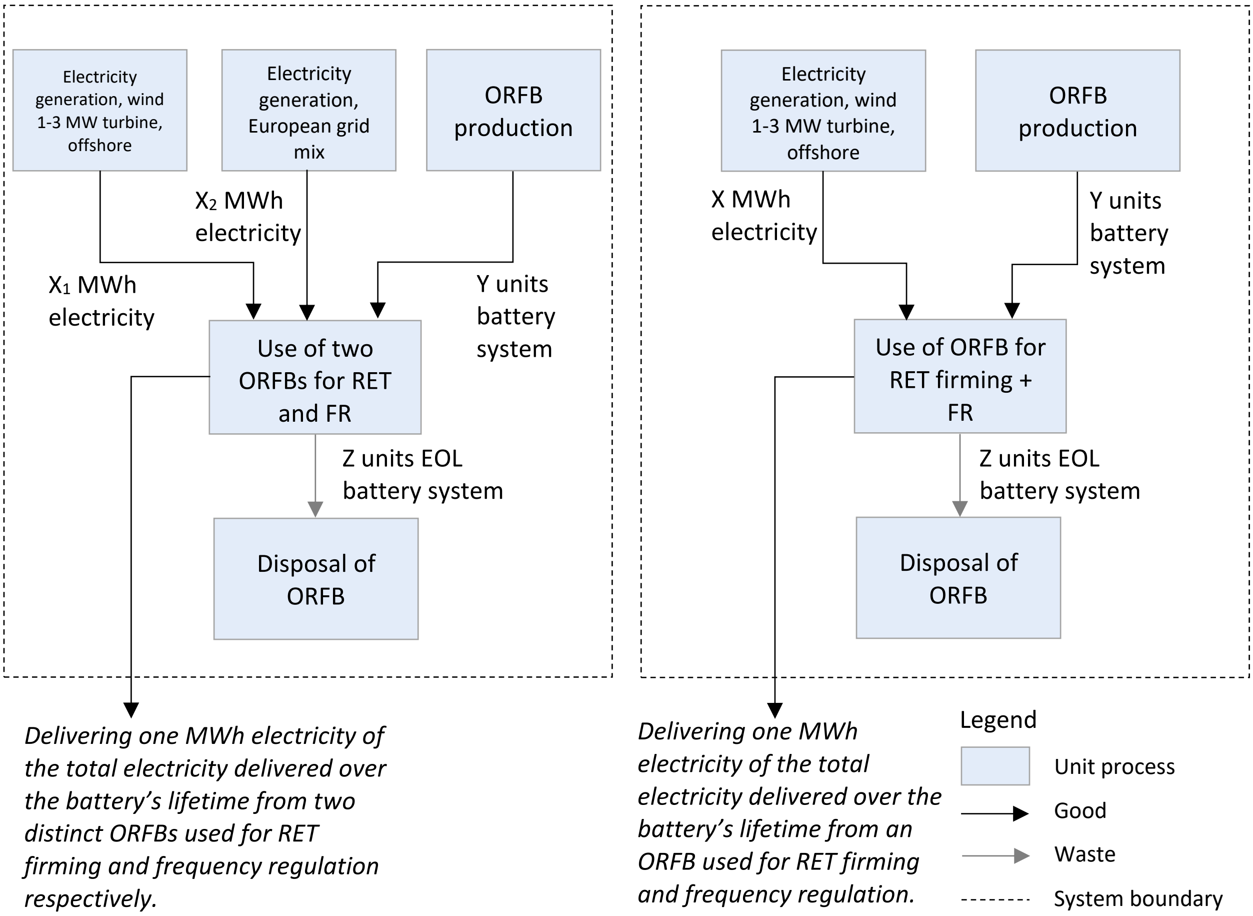
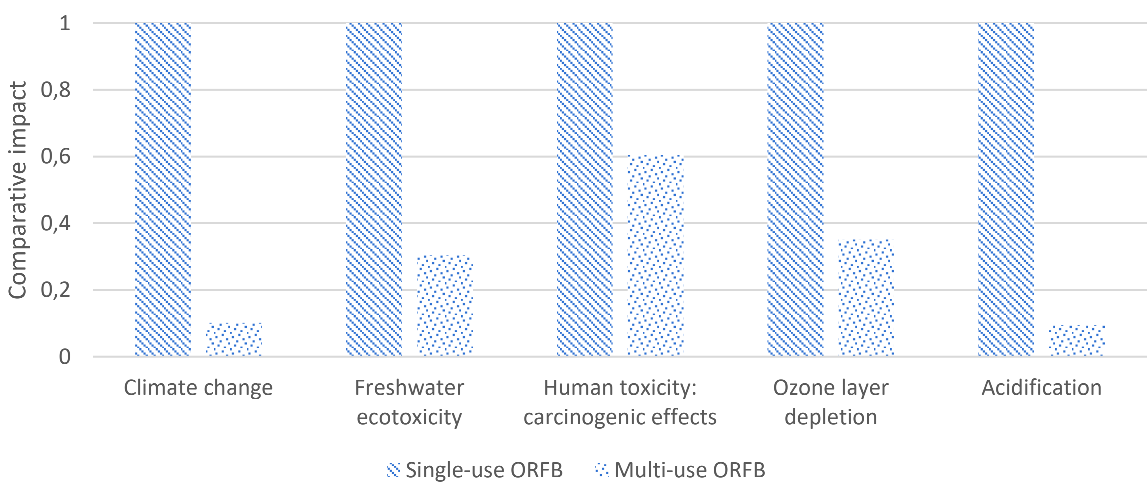


Figure 35

Comparison of impact scores of single-use ORFBs and multi-use ORFB in case of serving RET firming and frequency regulation (FR)



7

Discussion

This chapter discusses the limitations of this study, provides an interpretation of the findings and suggestions for further research and ends with a closing debate about the current tendency of applying batteries for other applications than renewable energy storage. Finally, the scientific, societal and Industrial Ecology relevance of this research are discussed.

The focus of this research is the use phase in LCA and footprinting studies of a stationary battery system and related methodological guidelines, which relates to the electricity input and battery system input. However, it is also relates to the EOL battery system output. The same formula to calculate the battery fraction for the input flow can be applied to the output flow. This study refrained from looking into the effect of recycling or other EOL treatment on the environmental impact scores of a battery system. Which options are available? How could recycling be modelled. What is the effect on the battery system's LCIA score? How does this affect the comparative impacts of different battery technologies? However, this is a research in itself. A more general starting point for such a research is a critical review of the Circular Footprint Formula, which is integrated into the guidance for the development of PEF Category Rules (PEFCRs) (European Commission, 2017).

The operational electricity for the battery is recommended to be included as a fixed value expressed in $MWh/MWh_{delivered}$ that is requested from the battery technology developer. This is also what is applied in the case study. Another option would be to request the power of the operational equipment of the battery system and multiply this by the number of hours that the battery is operational and divide it by the energy capacity of the battery, as shown in Equation 10. However, it is difficult to find any data or make assumptions about the number of hours that the battery is operational per cycle.

$$Operational\ electricity = \frac{Operational\ power\ per\ cycle\ [MW] \cdot hours\ per\ cycle[h]}{nominal\ battery\ energy\ capacity\ [MWh]} \quad [MWh/MWh_{delivered}] \tag{10}$$

In Equation 6 to define the required battery fraction, C_{bat} is the nominal battery energy capacity when the battery is new. Taking this value for this parameter assumes that all cycles over the battery's lifetime are provided at the battery capacity when it was new. This is not the case in reality since the battery energy capacity generally reduces over the battery's lifetime. Therefore, C_{bat} might perhaps be changed in $\frac{C_{bat} + (C_{bat} \cdot CR_{EOL})}{2}$ where $C_{bat} \cdot CR_{EOL}$ reflects the reduced battery capacity at EOL. Then it corrects for the reduction in capacity by taking the average energy capacity over the battery's lifetime, but still meets the required energy capacity for the application.

Moreover, Equation 7 is a static battery size method in which it is assumed that the battery operates at a certain DoD regardless of the application in order to match with the battery cycle life at that DoD. This is the case since generally only cycle life data at 80% DoD is available. Moreover, such methods use the maximum required energy capacity as a basis, even though this capacity might only be used occasionally in practice, so the battery could be sized smaller. Instead, Baumann et al. (2017) use dynamic load profiles for the optimisation of the DoD. The size is optimised by minimising the overall lifecycle costs by identifying an optimal equilibrium between initial investment costs for an oversize battery versus a smaller battery with reduced battery lifetime and thus higher replacement costs for the given application (Baumann et al., 2017). Unfortunately they do not provide the source of the dynamic load profiles. Moreover, their optimisation is based on cost minimisation, but it is not clear how this reflects on the environmental impacts. Assessing the effect on LCIA results of such dynamic profiles compared to the static size method is suggested for future research. Moreover, future battery LCA studies could study how battery size reflects on the environmental impacts. What does result in lower impacts; to oversize a battery which has a longer lifetime or instal a smaller battery with a shorter lifetime and replace it over time?

Another point of discussion is the use of EFCs in Equation 6. When using EFCs, every cycle is assumed to be performed at the same DoD and the nominal installed battery capacity and the battery's degradation are also based on this DoD. EFCs do not quantify the DoD of cycles and are therefore unable to distinguish between one cycle at 100% DoD, two cycles at 50% DoD or ten cycles at 10% DoD. Even though the number of cycles expressed in EFCs might be equal, the actual number of cycles and cycle depth might be different. The operational profile of a battery can be irregular, which means that each cycle has a different DoD and thus that each cycle has a different effect on degradation and thus battery cycle life. Moreover, EFCs do not provide any information about the exact moments of charging. Using EFCs is quite a simplification since DoD is a large contributor to battery degradation. Even though using EFCs is fine for estimating the total electricity delivered from the battery it might be too simplistic to determine the battery lifetime. Instead of using EFCs and an average DoD, the Rainflow cycle counting tool can be used (Soskin, 2019). This is an algorithm that takes an irregular load profile and quantifies the DoD, the mean SoC and the time period of each cycle. This information provides a more adequate estimation to derive the battery's degradation and therefore it's cycle life, which has an effect on the battery lifetime parameter. However, publicly available typical load profiles for different applications are required to improve the modelling instead of using average load assumptions such as average number of cycles per day. Future research could focus on how the Rainflow cycle counting tool can be integrated in the modelling of the battery fraction input, but at the same time this requires the development of cycle life models of different battery technologies, taking into account DoD, operating temperature, average SoC and C-rate, to be able to use the outcomes of the Rainflow tool.

In the current research it is assumed that using an average electricity mix background dataset is adequate for (comparative) battery LCA studies, as discussed in Appendix H. However, it might be that the charging patterns are different for different battery technologies even if they serve the same application because the batteries have different operational parameters like the ramp rate. A lower ramp rate implies a longer charging duration and therefore charging with a different electricity mix. Consequently, the charging pattern for different battery technologies might be different even though the batteries serve the same application. To assess whether more real-world electricity demand and generation modelling has an effect on the comparative results, the inherent variations of electricity generation have to be modelled with temporal differentiation, i.e., dynamically. A dynamical approach is generally described by the function dx/dt, but this is not applicable to LCA. A potential semi-dynamical approach requires hourly actual electricity generation data per electricity source of the specific region or country where the battery is installed. Second, real-world operational profile scenarios based on a simulation model or empirical data for different battery technologies serving specific applications are required instead of average cycle frequency assumptions. This way, electricity consumption and production can be resolved at an hourly time step throughout a year, which results in the actual electricity input from each electricity generating technology. However, robust information about operational profiles is still lacking (Pellow et al., 2020).

Some of the reviewed studies are consequential LCAs. Instead of subtracting impacts, as done in some of these studies, a proper way to quantify the effects of such systems is making a comparative LCA study. In case of electricity systems this means comparing the total environmental impacts of the electricity system without battery to those of an electricity system with battery taking into account possible changes in the marginal electricity mix. Such a study could be useful for policy makers, though this might be complex. A difficulty that has to be overcome is defining the change in the background system (i.e., electricity mix) as a result of the implementation of batteries. How do/does (a) battery system(s) influence the electricity system for different battery applications? Does the total battery energy storage capacity have a marginal or significant effect on the electricity system? This also depends on the size of the electric power system in which the batteries are integrated. Another question is how to scope the electric power system; which size? Defining a general FU for such studies like the general FU proposed in the current study for battery system LCA studies would benefit the field. The FU as defined by VandePaer et al. (2019) might be a good starting point: “The integration of surplus electricity from VRES via batteries resulting in the supply of 1 megawatt-hour (MWh) of electricity for the 2030 Swiss electricity system.” Future research could focus on these questions.

Since the results from the illustrative case study show that round-trip efficiency has a significant effect on the battery system’s LCIA scores, it is recommended to battery developers to focus on improving this battery parameter. However, the results from the illustrative case study apply to a battery charged with electricity from the European electricity mix. The effect is presumably smaller when the battery is charged with renewable energy, which is recommended to be assessed in future research. Moreover, the implications of just three parameters has been assessed in the case study. These are not necessarily the most important parameters or those that have most effect on the environmental impact scores of a battery system. To know which parameters are paramount to the environmental impact scores, more parameters and combinations of parameters should be assessed among which the battery energy capacity and depth of discharge. This was beyond the scope of this study but is recommended for further research. And finally, the case study is illustrative and only is applied for an RFB, therefore the results may not necessarily apply to other battery technologies.

To overcome the difficulty of defining an allocation factor when modelling value stacking in the case study, it was decided to apply system expansion to make sure that both product systems deliver the same number of EFCs. The aim of this case study was to gain a first impression of the effect of value stacking on the environmental impact scores of a battery system for which it was argued that the system expansion method was appropriate. In future research the allocation approach may be applied in order to compare single applications to each other or to compare the single applications of a multi-use battery to the same application served by another energy technology. The latter is a scenario that should be assessed in future research in order to investigate whether a battery applied for multiple applications leads to environmental benefits compared to the current situation in which the application is served by another technology.

A remark should be made about defining the battery energy capacity of the single-use batteries when assessing the implications of value stacking in the case study. It is assumed that all single-use batteries have the same energy capacity as the multi-use use battery. However, in reality every application would probably require a different battery energy capacity, which has an effect on the C2G and EOL impacts. However, this does not matter a lot since this is accounted for by taking the fraction of battery that is required to deliver 1 MWh as defined by Equation 6. Moreover, the system expansion approach that is applied in the case study to equalise the total delivered amount of electricity (i.e., EFCs) by both product systems is redundant since this is already accounted for by Equation 6 as the battery's lifetime is taken into account to define the required battery fraction. In other words, a battery with a larger energy capacity delivers more electricity over its lifetime and therefore less battery fraction is required to deliver 1 MWh. A short example clarifies this point; 1 battery / (986 cycles · 13 years) = 0,000078, while 1,42 battery / (1233 cycles · 15 years) = 0,000078. Both arguments mentioned above only apply since scaling in LCA is linear. It does not matter whether a battery with a 1 MWh energy capacity is modelled or one with an energy capacity of 10 MWh. However, in practice the scaling of batteries might not necessarily be linear due to economies of scale. Moreover, in case of an RFB for example, the power and energy capacity can be scaled independently from each other. This implies that LCI data should correspond to the defined power and energy capacity which should be transparently defined in the goal and scope section.

The challenge when it comes to the stacking of applications are the questions how the limited energy and power capacities of the battery system are allocated to the different applications and which applications are compatible when they are served concurrently. The actual implementation of multi-use by batteries is the most relevant challenge, since combining applications is not as simple as stacking different application requirements. In case of combining a *power application* with an *energy storage application* this can be described as if a certain response power capacity needs to be preserved, which is a potential to deliver a certain amount of power during a period of time. If the battery does not have to serve this additional application, the total battery energy capacity could be available for the energy storage application. There is a competition between applications for the energy capacity potential of the battery. However, it doesn't trade-off freely in itself; the power application needs a minimum amount of power available which imposes a limitation on the energy storage capacity for the energy storage application since it restricts how much electric energy can be flowing through the battery. In the case study an arbitrary battery energy capacity is assumed based on available LCI data. Even though this does not affect the results due since this is corrected for by the battery input equation (Equation 6) and due to the fact that LCA is based on linear scaling, future research could investigate how the battery energy capacity in case of multiple applications is determined in practice and whether an optimum battery energy capacity can be defined that leads to the lowest environmental impacts. In the case study, for reasons of simplicity it is assumed that the battery operates at the same DoD for each application as it does in case of serving a single application. However, whether this is the case in reality and how this affects the modelling is a topic that requires further research. Moreover, it is assumed that the round-trip efficiency losses remain the same when the battery serves multiple applications compared to when it serves a single application. But this might not be the case in practice since fade in the round-trip efficiency might increase as a result of higher utilisation which increases the electricity losses during use. This is recommended to be investigated in further research. Moreover, only one variable of the battery fraction formula is adjusted at a time, while, for example, an increase of the cycle frequency might reduce the round-trip efficiency. Modelling the required battery fraction could be improved in future research by reflecting this interdependency. Finally, existing results of the optimisation of applications for a lithium-ion battery from Englberger et al. (2020) are used due to a lack of such results for a redox flow battery. Their results are assumed to be representative to illustrate the philosophy of value stacking, although using optimisation results for a redox flow battery would be more appropriate. In the illustrative case study, the stacking of applications is simply assumed to correspond to the sum of the required equivalent full cycles for each application reduced by a fixed percentage because the applications are served less due to operational constraints when combining applications. Assuming a reduction in how much of each application is served compared to serving single applications is quite a simplistic approach.

Since the aim of this case study was to gain a first impression of the effect of value stacking on the environmental impact scores of a battery system and the intention was not to model value stacking as accurate as possible this was considered an adequate approach that fitted to the aim of this study. However, future research could look further into these issues. Perhaps Equation 6 is not appropriate at all in case of modelling value stacking. To define the total amount of delivered electricity, the battery energy capacity is multiplied by the DoD and the total number of cycles. However, in case of value stacking, values for these parameters are difficult to determine. The modelling of the stacking of applications by a more advanced approach was outside the scope of the current study, but requires attention in future research. It might be a more adequate approach to derive the total delivered amount of electricity for each application from an application optimisation tool such as StorageVET (Electric Power Research Institute, n.d.), REopt (National Renewable Energy Laboratory, n.d.), the model developed by Arteaga and Zareipour (2019), the control framework by Namor et al. (2019) or mu_opt (Englberger et al., 2021). The sum of these amounts is the total delivered amount of electricity which can be used to calculate the required battery fraction, but it is also clear how much electricity is delivered for each application and therefore this could also be used as the applications' allocation factor in case allocation is applied.

These tools focus on optimising the allocation of battery power or energy capacity to different applications based on the prediction of certain variables like market prices, peak demand and renewable energy production (Marchgraber & Gawlik, 2021). An operational planning of how the battery could best be operated to maximise revenues is what results from these optimisation models. According to Namor et al. (2019), a distinction should be made between this operational planning phase and a real-time operation. During the real-time phase, the allocation relies on real time behaviour which is based on variables that are measured in real-time. There appears to be a gap to actually implementing by applying the results of an operational planning phase and the real-time phase; specifically the question how to deal with unpredictable input variables in real-time operation. (Marchgraber & Gawlik, 2021). Therefore, the method developed by Marchgraber and Gawlik (2021) to implement real-time multi-use operation including the novel concept of dynamic prioritisation that handles conflicts between applications based on priorities that are assigned to each application could be applied in future LCA studies that aim at assessing the effects of value stacking in a more advanced way. Furthermore, the aforementioned tools are economic optimisation methods since the combination of applications is generally optimised for profit. Even though the environmental impacts of the battery system are estimated in an LCA, i.e., are an outcome of the LCA, future research might focus on determining the optimal combination of applications not only maximising profit, but also minimising environmental impacts using multi-objective optimisation.

Care should be taken that it does not become the aim in itself to use such advanced optimisation models, but that these models add value and are also provided transparently. For example, Schulz-Mönninghoff et al. (2021) use an energy flow modelling tool to simulate the effects of implementing a battery system in a small energy system combining different battery storage applications in multi-use cases. It is not clear though which assumptions have been made and how this tool works. Therefore, it is complicated to judge the usefulness of the results. Highly advanced quantitative methods can be used even including datamining, but when the parameters, assumptions and mechanisms of a method are not specified it might as well be stated that this is the tool and the result is 42. Without this information it is impossible to judge the usefulness of the results.

Another difficulty arises in defining the FU in case of battery versus battery comparisons of batteries that are utilised for multiple applications because the system becomes multifunctional. Since battery parameters are different for distinct battery technologies, the optimisation and therefore the optimal way how and to what extent each application is served resulting from an optimisation algorithm is likely to vary between battery technologies. Therefore, in case of battery versus battery comparisons, it is difficult to define the FU in the goal and scope section since it results from an optimisation model and might be different for both battery technologies, even though they serve the same set of applications. In a way, the FU depends on the optimisation of the stacking of applications, which determines how much of each application is actually served by the battery. Therefore, the FU could perhaps be defined by including something along the line 'the operational profile based on economic optimisation of serving [define applications] over the lifetime of the battery'. Another option to solve this is defining the FU including a fixed extent to which each of the applications is served. In the case study this approach is applied in which the alternative product system is extended with a single-function battery to complement the missing degree of serving an application based on the number of EFCs. However, this approach does not necessarily reflect the philosophy of value stacking. The principle of value stacking is to utilise the capacity of the battery system as optimal as possible. The optimal operational profile for a LIB can diverge from the one for an RFB due to different battery characteristics, even though both batteries are submitted to serving the same applications. Moreover, a practical problem occurs at defining the degree of serving applications. How could this be defined and what is a suitable unit to express this? This issue requires attention in future research.

The case study results show that per delivered MWh of electricity, less battery fraction is required and therefore the total impacts per delivered MWh decrease in case of value stacking. However, the absolute impacts actually increase due to increased total round-trip efficiency losses. Whether total environmental impacts are higher or lower compared to the current situation is a different question and requires a different comparison that should be assessed in future research. This is related to the goal and scope definition and the selection of equivalent product systems. Which systems have to be compared and should be modelled is directly linked to the aim of the study. If the aim is to compare environmental impacts of multi-use of a specific battery to single-use of the same battery, then two product systems with batteries have to be compared. However, it might as well be the aim to compare the utilisation of a battery for multiple applications to the current situation in which one or more of these applications is/are served by conventional electricity generating technologies. For example, a battery utilised for RET firming and frequency regulation can be compared to an alternative product system in which a battery is used for RET firming while frequency regulation is served by a natural gas power plant. However, a difficulty in case of the latter is that frequency regulation is an additional application provided by natural gas plants which means that part of its emissions have to be allocated to the frequency regulation application. Moreover, in order to define the current situation and for which applications battery systems will be used in a certain region or country, the transmission network operator has to be involved in the discussion. Their expertise is required in order to define for which situation(s) and application(s) battery systems will or should be utilised in specific networks, but also how these applications are provided in the current situation and how this is expected to change towards the future when building new smart networks.

The case study results show that value stacking results in environmental benefits, especially when a battery is used for an RET firming application for which it is charged by renewable energy sources and this electricity can be used simultaneously to serve the other application(s) (e.g., frequency regulation). This indicates that utilising batteries with the aim of storing renewable electricity contributes to sustainability ambitions and emphasises the argument of Jongsma et al. (2021). The main justification for encouraging battery storage is the contribution to the energy transition. The aim of the energy transition is to reduce CO_2 emissions as quickly as possible at the lowest possible costs. Faster CO_2 reduction is achieved by accelerating the execution of renewable energy generation projects and delivering the generated electricity at the hours when the electricity mix is most polluting. The current optimisation of multiple applications is focused on maximising revenues or minimising costs. From the results of the study by Jongsma et al. (2021) it appears that an optimisation of the day-ahead, FCR, aFRR, and the congestion market, which correspond to wholesale arbitrage, area and frequency regulation and T&D investment deferral applications in the current study, results in the greatest economic benefits for grid connected batteries. Moreover, the currently most served applications by stationary battery systems are arbitrage applications and frequency regulation (Malhotra et al., 2016). In 2019, even 73% of battery storage power capacity in the United States provided frequency regulation applications (U.S. Energy Information Administration, 2021). These are not applications that are directly linked to the integration of renewables. Actually, batteries came into play due to the integration of renewable energy by storing excessive and otherwise curtailed energy. Next to this direct link to renewable energy, they can also provide ancillary applications such as frequency regulation which is indirectly linked to supporting the integration of renewables since these cause more deviations in the grid frequency due to their intermittent nature. However, batteries are also used for other applications that do not necessarily contribute to the energy transition. It is debatable whether batteries should be used for such applications for economic reasons since it might in practice result in increased environmental burdens. From the perspective of the current energy transition it could be argued that batteries should only be applied for applications that directly or indirectly support the integration of renewables.

However, it is a bit more nuanced. Drawing conclusions regarding this requires the comparison of using a battery for applications to how these applications are provided in the current situation. When the total implemented battery energy storage capacity is large enough, batteries might even eliminate a conventional generator. For example, if enough battery capacity is available, peak electricity demand that is supplied by gas power plants could theoretically be replaced by electricity from batteries charged with electricity from cheaper generation sources (Chowdhury et al., 2020). Whether or not this is economically feasible is another question. The effect of batteries on the electricity mix, however, depends on the application of the battery. For example, a battery used for frequency regulation substitutes frequency regulation commonly provided by fast-response gas power plants which run at higher operational costs (Pareis & Hittinger, 2021) because the battery can provide this function while being charged with more economic electricity. The use of batteries for frequency regulation therefore facilitates the replacement of expensive peak-loader (gas) generators with electricity from a battery charged with cheap base-loaders such as coal generators (Lee & Kim, 2019). In total, this could induce an increase or a decrease of environmental impacts compared to the current situation. Therefore, it is required to make such comparisons in future research which require modelling with future scenarios including an increased amount of renewables and as a result of that an increased required amount of batteries and frequency regulation. However this is quite complex since it comes with questions such as how much frequency regulation is required at different levels of renewable energy integration and how much of that is provided by gas plants and how much can be provided by battery systems. Such comparisons can be very insightful for policy makers and transmission network operators and are recommended to be assessed in further research. Even though this is basically a temporary transition problem as the aim is to provide most electricity by sustainable energy sources in the upcoming decades, it is still important to make these comparative assessments since an interim increase of environmental impacts is unfavourable for reaching the sustainability ambitions. Therefore, such applications could better be prevented and discouraged. With regard to the sustainability ambitions as defined by the European Commission in the Green Deal (European Commission, 2019b), battery applications that lead to a reduction in environmental impacts should be promoted. In that sense, a general incentive policy for all batteries does not seem appropriate. General policy stimulates all battery applications, also applications that make a negative contribution to CO_2 reduction and especially batteries that were already profitable without incentives.

Scientific relevance

Even though the use phase of a stationary battery can be a major contributor to the environmental impacts of a battery (Pellow et al., 2020) it is oftentimes excluded in LCA studies for reasons of complexity of modelling battery behaviour and a lack of real-word performance data of battery applications (Porzio & Scown, 2021). The current research responded to this by gaining insight into how the use phase is incorporated in existing LCA and footprinting studies and related methodological guidelines of stationary battery systems. To the best of the author's knowledge this is the first systematic review of the use phase of batteries which reveals what is already known, challenges and topics that require attention in future studies. The current research assists LCA practitioners by providing recommendations on how to model the use phase in future battery LCA studies. Additionally, a concise but constructive description of the working principle of a battery, terminology and battery applications is included which provides LCA practitioners with the necessary prior knowledge to perform battery LCA studies.

Societal relevance

The market for stationary batteries is expected to grow exceptionally (IRENA, 2017), not least owing to the bloom of renewable energy which requires energy storage to effectively integrate the generated electricity (European Commission, 2019a). This is reflected by the ambitious goals on energy storage development set in the recent Green Deal published by the European Commission (2019b). Therefore, it is important to critically assess the modelling of the use phase and provide recommendations for future battery LCA studies in order to perform adequate LCAs. These LCAs are used to provide the industry with information to improve their battery technologies to decrease environmental impacts. Moreover, these studies are required to provide policy makers with adequate information to make well-considered choices to stimulate the integration of battery technologies in society for certain applications to support and accelerate the energy transition. From the current research results it is carefully argued that battery systems should exclusively be utilised for applications directly or indirectly linked to the integration of renewables, however this requires further research. Moreover, this research gained a first impression of the effect of using a battery for multiple applications, i.e. value stacking, compared to using it for a single application on the environmental impact scores of a battery system. It appears to have a considerable positive effect since the battery is utilised more intensively and therefore utilises more of its maximum cycle life. Therefore, this is a strategy that the industry and battery operators should focus on, especially for batteries with a high cycle life.

Industrial Ecology relevance

This research is conducted as a Master’s thesis for the Master of Industrial Ecology. It provides an in-depth look on the use phase of stationary batteries in LCA which is an important and widely used quantitative framework as part of the environmental perspective of Industrial Ecology. Even though LCA is mainly focused on environmental impacts, it requires thinking about technical and economic aspects as well. In this research this is reflected by gaining knowledge on the working principle of a battery and terminology that is required to understand the modelling of the use phase and provide recommendations about this. This research also links value stacking as new and emerging operational strategy of batteries for economic reasons to battery LCA studies by qualitatively discussing the implications of modelling value stacking in battery LCA studies. Finally, this study provides the field of Industrial Ecology with knowledge on modelling the use phase in battery LCA studies which is relevant due to the increasing interest in batteries to enable the energy transition by storing renewable energy, even though batteries are currently used for other applications as well.

8

Conclusions and recommendations

This research aimed to gain insight into how the use phase is incorporated in existing LCA and footprinting studies and related methodological guidelines of stationary battery systems in order to provide guidance for LCA practitioners for the execution of stationary battery LCA studies. This chapter provides conclusions to the research questions and presents recommendations for future battery LCA studies.

8.1. Conclusions

The main research question investigated in this study is: *What are important considerations and how can these be included when modelling the use phase of a stationary battery system in a life cycle assessment?* By answering the sub-questions defined in section 1.2, this chapter provides the conclusions on the main research question.

1. How is the use phase modelled for different applications in existing life cycle assessment and footprinting studies and related methodological guidelines of stationary battery systems, what are their key characteristics and methodological principles and which challenges can be identified?

26 papers, Annex II of Regulation (EU) No 2019/1020 and the PEFCRs for High Specific Energy Rechargeable Batteries for Mobile Applications were reviewed. Key differences where found in the FU and system boundaries. Using battery energy capacity is not an accurate metric because electricity delivery always is the product that is obtained from the battery and therefore electricity output of a battery is a more meaningful metric. Even though the application of a battery does not correspond to the function, the application is closely connected to the function and puts certain requirements to the battery system and defines the operation of the battery. Different applications are modelled by assuming different power and energy capacities of the battery and different cycle frequencies required for the specific application, but these are oftentimes not defined which abates transparency.

Multiple elements are identified that are ambiguous that relate to harmonising system boundaries and require attention when performing a battery LCA. Annex II prescribes that the electricity input during use should not be included in the product system. However, environmental impact scores depend on the efficiency of the battery. Therefore, electricity consumption during use should be included in a battery LCA, certainly in case of comparative LCA studies. Some studies include only lost electricity during use, while others include total electricity throughput. The current research argues that only electricity that is lost due to efficiency losses and electricity for the operation of the battery system should be attributed to the battery system. Including total electricity throughput is appropriate for a study aimed at comparing electricity systems with and without battery, but not for LCA studies assessing a battery or comparing batteries. Making this distinction and stating the goal clearly in the goal and scope section of the LCA is important and the modelling of the use process in the LCI should be in line with the goal. The term round-trip efficiency is used differently in different studies where some studies include inverter efficiency and/or operational energy consumption while others do not. Transparency about whether or not inverters are included in the product system and thus which efficiency is included and how this efficiency is defined or even consensus about a definition of the round-trip efficiency that should be used would be beneficial. Finally, some studies subtract electricity from the (adjusted) electricity grid mix since the battery electricity output displaces otherwise curtailed electricity. This can lead to misleading negative impact scores. Even though such assessments do not fit to assessing (a) battery system(s) but to assessing the effects of a policy that specifies the integration of a total energy storage capacity in the electric power system and not of a battery system, a more proper way is making a comparative LCA study.

Even though some studies include advanced quantitative models, it is not always clear what happens in between and for which function and/or application the results apply because the FU is not clearly defined, the application is not defined, the application characteristics are not specified or modelling assumptions or complete LCI data are not included. Therefore, it is complicated to judge the usefulness of the results and it might as well be stated that the result is 42 (Adams, 2004). Overall, the degree of transparency of many battery LCA studies is mediocre and should be improved to improve judging the usefulness but also to improve reproducibility and comparability.

2. How could the use phase be modelled in life cycle assessments of stationary battery systems, which operational parameters and application characteristics are relevant and how do they interact when performing an application?

Five operational parameters and application characteristics were identified to be relevant to model the electricity and battery system input of the use process; the battery's nominal energy capacity, depth of discharge (DoD), round-trip efficiency, lifetime and annual cycle frequency for the application. How these parameters and application characteristics interact is described by Equation 5 and 6 in the recommended modelling guidelines in section 8.2.1.

3. What is the effect of incorporating alternative use cases consisting of multiple applications on the modelling of the use phase in a life cycle assessment of a stationary battery system, which challenges arise and which solutions can be identified to deal with these challenges?

A battery system that serves multiple applications simultaneously, i.e., value stacking, becomes a multifunctional product system. Two solutions are identified as appropriate to deal with this: allocation and system expansion. A challenge when it comes to the allocation approach is to determine an adequate indicator as a basis for the allocation between applications. An option might be to allocate based on the electricity output for each application, but this requires an advanced application optimisation model. The second solution is taking on a system expansion approach by defining the FU including a fixed extent to which each of the applications is served. The multi-use battery system is extended with additional battery system to complement the missing degree of serving an application compared to the alternative system. However, a challenge is deciding on a suitable unit to express the degree of serving an application. Second, the selection of alternative product systems requires attention and depends on the goal of the study. A battery utilised for multiple applications can be compared to a product system with one or multiple batteries serving one application. However, it could also be compared to a product system including a battery serving one application while another energy generating technology serves the other application.

Finally, the value of the parameters in Equation 6 to determine the required battery system fraction is affected in case of value stacking. How the energy capacity of the battery is determined for a battery serving multiple applications is questionable. The size can be based on the sum of required energy capacities for the different applications or on optimising the battery for a primary application like of Stephan et al. (2016) did. The average DoD at which the battery system operates might be different in case of multi-use. When the battery is utilised more intensively, the number of cycles increases.

Installing a larger battery results in cycles at a lower DoD and therefore cycle lifetime reduces less, however investment costs increase. This, again, relates to the question how the battery size of a battery serving multiple applications should be determined or optimised. Moreover, it is difficult to define an average DoD when the battery cycles at different DoDs for each application. A challenge when it comes to the stacking of applications are the questions how the limited energy and power capacities of the battery system are allocated to the different applications and which applications are compatible when they are served concurrently. As result, the cycle frequency for each application and how this compares to when each application is served by a single battery is difficult to determine and is something that might be obtained from an application optimisation tool. The cycle frequency increases when a battery is used for multiple applications, however, in case of serving multiple applications it is lower than the sum of cycle frequencies when single batteries serve the individual applications. In case of comparing batteries used for a single and for multiple applications this is something that should be corrected for in such a way that both product systems deliver the same number of cycles and thus the same total electricity output. Finally, value stacking increases battery utilisation and therefore potentially decreases the battery's lifetime, which depends on the battery technology and its related cycle life. This is only the case if the battery's lifetime based on the cycle lifetime becomes shorter than it's calendar lifetime due to the increased cycle frequency.

4. What implications do the issues identified in the literature review have on the environmental impact scores of a battery system?

The assumed cycle frequency for an application has a considerable effect on the LCIA scores of a battery system, in particular for impact categories in which the C2G and EOL impacts are the largest contributors. A reduction of the lifetime from 15 to 10 years appeared to result in considerably higher impacts, especially for freshwater ecotoxicity, human toxicity and ozone layer depletion impact categories. It appeared that any change in lifetime did not considerably affect climate change and acidification impacts due to the fact that the C2G and EOL phases contribute relatively little to these categories. LCIA scores depend strongly on the round-trip efficiency input data used in the LCA model. Particularly climate change and acidification scores are affected by a change in round-trip efficiency since the use phase is a large contributor to these impacts. Value stacking decreases the LCIA scores of a battery system since the battery system is more intensively utilised making more use of its maximum cycle life. Value stacking is particularly or only interesting for battery technologies that have a high cycle life such as RFBs and some lithium-ion technologies, since this offers the ability to increase battery utilisation without decreasing the battery's lifetime resulting from the constraining calendar lifetime. Especially when a battery is used for an application for which it is charged by renewable electricity sources and this electricity can be used to serve the other application(s) as well, the benefits of value stacking are high compared to a situation in which two batteries are serving these distinct applications.

All of the above provides relevant insides into important considerations when modelling the use phase of a battery system. Key recommendations for future LCA studies were produced which are provided in the next section.

8.2. Recommendations

Recommendations for practitioners of future battery LCA studies:

- Include a discussion about the function and from that clearly define the FU in order to improve transparency and reproducibility.
- Electricity delivery is what results from the battery use process and therefore this is argued to be the function of a battery. Therefore, electricity delivery of a battery in Wh is the metric that should always be used in the FU and not the battery energy storage capacity in Wh.
- A stationary battery should always be considered as part of the bigger electricity system in which it operates because a battery is used for (a) specific application(s) in this system which defines what is expected from the battery in terms of power and energy storage capacity and operation which is reflected by the cycle frequency, but also which electricity is used to charge the battery.
- The current study proposes two FUs for two subgroups of battery applications: *energy storage applications* and *power applications*.
  FU for energy storage applications: *delivering one MWh electricity of the total electricity delivered over the battery's lifetime from a battery used for [specify application]*.
  FU for power applications: *delivering one MWh of electricity of the total electricity delivered over the battery's lifetime in order to provide X MW of power capacity from a battery used for [specify application].*
- Specify the characteristics of the specific battery's application(s) that is/are assessed including the required battery power, discharge duration, battery energy capacity and the cycle frequency to improve transparency and potential comparability between studies. This can be included in the form of a table after the FU. Defining these requirements exclude battery technologies that are not able to fulfil these requirements and therefore prevents these from being included as alternative. This might be a recommendation that applies to LCAs in general since this is the case for other products as well such as vehicles and white goods such as washing machines.
- The FU in Regulation (EU) No 2019/1020 Annex II and the PEFCRs for High Specific Energy Rechargeable Batteries for Mobile Applications ('one kWh (kilowatt-hour) of the total energy provided over the service life by the battery system, measured in kWh') is proposed to be adapted to the FUs as defined above.
- The reference flow in Regulation (EU) No 2019/1020 Annex II and the PEFCRs for High Specific Energy Rechargeable Batteries for Mobile Applications is proposed to be adapted to the format as suggested by Guinée et al. (2002) where the reference flow is an output of the use process and results from the combination of the FU and the alternative.
- In case of value stacking, the FU is proposed to be defined as: *delivering one MWh electricity of the total electricity delivered over the battery's lifetime from a battery used for [specify applications].*
- Depicting the LCIA scores of different battery applications in one figure is discouraged. Even though it is not incorrect and prevents inefficient use of space, it is prudent to explicitly note under the figure that applications should not be cross compared.
- Transparently report about the electricity and battery inputs of the use process and which battery efficiency is used to be able to judge the pertinence of the model and the results, but also to improve the ability to consider the comparability of the results of LCA studies. Calculations, or at least equations, of the electricity input and the total delivered electricity that is used to determine the required battery fraction should be specified.

- The use process of a battery interacts with the electricity input and battery system input and output, as depicted in Figure 13 The relevant operational parameters and application characteristics and their interaction are captured in proposed modelling guidelines for both inputs, which are provided in section 8.2.1. Equation 6 also applies to define the battery system fraction output flow.
- Use the AC-AC round-trip efficiency to define efficiency losses. This is the efficiency from the point of interconnection to the electricity system which includes the efficiency of inverters.
- Include the cycle frequency required for the application as range combined with uncertainty analysis, or at least sensitivity analyses, to evaluate the effect of altering the cycle frequency on LCIA scores.
- Include the round-trip efficiency as range combined with uncertainty analysis, or at least sensitivity analyses, to evaluate the effect of altering the round-trip efficiency on LCIA scores.
- Since battery lifetime has a considerable effect on LCIA scores, future work should focus on developing cycle life models including DoD, charge/discharge rate, average SoC and operating temperature stress factors for different battery technologies. The outcomes of such models should be used in LCA models in order to improve the battery lifetime estimation and thus the modelling of the required battery fraction. For example like the cycle life model by Jenu et al. (2020) for NMC batteries with different combinations of DoD, operating temperature and average SoC. Other models such as a physical-chemical ageing model or semi-empirical model might be adopted for this (Silvera Diaz et al., 2021).
- Future battery LCA studies should consider defining replacement activities of battery systems and their components for battery technologies of which components can be replaced. Replacement activities can be reflected in the modelling by defining the total battery system's economic lifetime and considering which and how often components might have to be replaced during this lifetime which is reflected in the LCI of the battery system production processes. This might be complex since determining when a component or battery system is EOL is ambiguous. Besides technical aspects, economic considerations and innovation might be involved in determining the optimal time to replace (parts of) the battery system. A method like Sodhi et al. (2022) developed to define the optimal replacement time for solar panels can be adopted.
- It is debatable whether batteries should be used for renewable energy storage applications only and not for ancillary applications as these might (temporarily) increase environmental impacts. Therefore, future battery LCA studies should compare serving other applications to how these applications are served in the current situation. This requires modelling with future scenarios including an increased amount of renewable energy but also by accounting for the change in the electricity system as a result of an increased amount batteries. This requires involvement of the network operator to define the applications for which batteries are expected to be used in a certain region or country.

8.2.1. Modelling guidelines for electricity and battery system fraction inputs

Electricity

It is recommended to model the electricity lost due to efficiency losses as:

$$Electricity\ lost\ due\ to\ efficiency\ losses\ = \frac{100}{\eta} - 1 \qquad [MWh/MWh_{delivered}] \qquad (5)$$

where:

η = AC-AC round-trip efficiency of a battery system (%)

Electricity required for the operation of the battery system is recommended to be modelled as a separate input to the use process since it enables the LCA practitioner to separately assess the effects of a change in the round-trip efficiency and operational energy use on the overall environmental impact scores. The operational electricity consumption per delivered MWh should be obtained from the battery producer.

Battery system

For a FU that considers the total delivered electricity over the battery's lifetime, as recommended in this study, the included battery fraction should be based on the total electricity delivered over the battery's lifetime. The battery fraction that is required to deliver one MWh of electricity is recommended to be modelled as:

$$\frac{1}{C_{bat}\,[MWh] \cdot DoD\,[\%] \cdot annual\ cycle\ frequency\,[number] \cdot \eta^{0,5}\,[\%] \cdot \text{battery lifetime}\,[\text{y}]} \qquad (6)$$

where:

- **C_{bat}**

  Is the nominal installed battery energy capacity (MWh) that is required to ensure the rated power and discharge duration for a specific application, as defined in the goal and scope section, are met over the battery's lifetime. LCI data should correspond to the nominal installed battery energy capacity used in the formula. The nominal energy capacity is defined by:

$$C_{bat} = \frac{C_{app}}{DoD_{app} \cdot \eta^{0,5} \cdot \mathrm{CR}_{EOL}} \qquad [MWh] \qquad (7)$$

where:

- C_{bat} = nominal installed battery capacity of the battery system (MWh)
- C_{app} = required energy capacity for the application defined as the energy delivered per cycle (MWh). The energy delivered per cycle is defined by multiplying the required power (MW) per cycle by the discharge duration (h).
- DoD_{app} = depth of discharge at which the battery operates on average for the specific application as a percentage of the nominal capacity (%).
- $\eta^{0,5}$ = discharge efficiency based on the round-trip efficiency η (%). The charge and discharge efficiency are assumed to be equal and therefore the discharge efficiency is the square root of the round-trip efficiency.
- CR_{EOL} = energy capacity at EOL as a percentage of the nominal capacity (%).

Depending on the requirements regarding the EOL capacity, i.e., should the required capacity still be reached at EOL or only when the battery is new, the nominal energy capacity should be defined. The DoD at which the battery operates is determined by the combination of the application and the battery technology to optimise the trade-off between investment and replacement costs, or by the battery technology only in order to prevent damage to the battery system. This should be determined in consultation with the battery developers and the battery operator.

- **Annual cycle frequency**
  Is the number of annual charge-discharge cycles to provide the application for which the battery is utilised expressed in EFCs of the required amount of electricity for the application.
- **DoD**
  Is the depth of discharge at which the battery operates as a percentage of the nominal installed energy capacity. The value used here should correspond to the value used in the nominal installed battery energy capacity Equation 6.
- **$\eta^{0,5}$**
  Is the discharge efficiency which is considered to be half of the round-trip efficiency because the efficiency is assumed to be the same in the charge and discharge direction (Bordin et al., 2017). Therefore it is estimated as the square root of the round-trip efficiency η. It is proposed to use the AC-AC round-trip efficiency which includes the efficiency of inverters because that is the efficiency from the point of interconnection to the electricity system. The AC-AC roundtrip-efficiency can be obtained by multiplying the DC-DC round-trip efficiency by the AC-DC and DC-AC inverter efficiencies respectively.
- **Battery lifetime**
  Battery lifetime reflects how long the battery can be utilised until it is EOL. The lifetime to be included in Equation 6 is the minimum of the battery's calendar lifetime and cycle lifetime. In this study the cycle lifetime is defined as the equivalent number of years that the battery can operate according to the operating conditions of the application, which is calculated by:

$$Cycle\ lifetime = \frac{cycle\ life}{annual\ cycle\ frequency_{app}} \qquad [years] \tag{8}$$

References

Abraham, K. M. (2015). Prospects and limits of energy storage in batteries. In *Journal of Physical Chemistry Letters* (Vol. 6, Issue 5, pp. 830–844). American Chemical Society. https://doi.org/10.1021/jz5026273

Adams, D. (2004). *The Hitchhiker's Guide to the Galaxy*. Crown Pub.

Agusdinata, D. B., Liu, W., Eakin, H., & Romero, H. (2018). Socio-environmental impacts of lithium mineral extraction: Towards a research agenda. *Environmental Research Letters*, *13*(12), 123001. https://doi.org/10.1088/1748-9326/aae9b1

Ahmadi, L., Young, S. B., Fowler, M., Fraser, R. A., & Achachlouei, M. A. (2017). A cascaded life cycle: reuse of electric vehicle lithium-ion battery packs in energy storage systems. *International Journal of Life Cycle Assessment*, *22*(1), 111–124. https://doi.org/10.1007/S11367-015-0959-7/FIGURES/5

Akhil, A. A., Huff, G., Currier, A. B., Kaun, B. C., Rastler, D. M., Chen, S. B., Cotter, A. L., Bradshaw, D. T., & Gauntlett, W. D. (2015). DOE/EPRI Electricity Storage Handbook in Collaboration with NRECA. In *Sandia National Laboratories* (No. SAND2015-1002). https://www.sandia.gov/ess-ssl/publications/SAND2015-1002.pdf

Alipour, M., Ziebert, C., Conte, F. V., & Kizilel, R. (2020). A Review on Temperature-Dependent Electrochemical Properties, Aging, and Performance of Lithium-Ion Cells. *Batteries 2020, Vol. 6, Page 35*, *6*(3), 35. https://doi.org/10.3390/BATTERIES6030035

Alotto, P., Guarnieri, M., Moro, F., & Stella, A. (2013). Large scale energy storage with redox flow batteries. *COMPEL - The International Journal for Computation and Mathematics in Electrical and Electronic Engineering*, *32*(5), 1459–1470. https://doi.org/10.1108/COMPEL-04-2013-0133

Aneke, M., & Wang, M. (2016). Energy storage technologies and real life applications – A state of the art review. *Applied Energy*, *179*, 350–377. https://doi.org/10.1016/j.apenergy.2016.06.097

Appunn, K. (2015). *Setting the power price: the merit order effect*. Clean Energy Wire. https://www.cleanenergywire.org/factsheets/setting-power-price-merit-order-effect

Arbabzadeh, M., Johnson, J. X., & Keoleian, G. A. (2017). Parameters driving environmental performance of energy storage systems across grid applications. *Journal of Energy Storage*, *12*, 11–28. https://doi.org/10.1016/j.est.2017.03.011

Argus Metals. (2021). *VRFB applications to boost China's V demand: Correction* [Press release]. https://www.argusmedia.com/en/news/2196733-vrfb-applications-to-boost-chinas-v-demand-correction

Armand, M., & Tarascon, J. M. (2008). Building better batteries. In *Nature* (Vol. 451, Issue 7179, pp. 652–657). Nature Publishing Group. https://doi.org/10.1038/451652a

Arteaga, J., & Zareipour, H. (2019). A Price-maker / Price-taker model for the Operation of Battery Storage Systems in Electricity Markets. *Institute of Electrical and Electronics Engineers*, *10*(6). https://doi.org/10.1109/TSG.2019.2913818

Bae, H., Tsuji, T., Oyama, T., & Uchida, K. (2016). Frequency regulation method with congestion management using renewable energy curtailment. *2016 IEEE Power and Energy Society General Meeting (PESGM)*, 1–5.

Bahar, H., & Sauvage, J. (2013). Cross-Border Trade in Electricity and the Development of Renewables-Based Electric Power. In *OECD Trade and Environment Working Papers* (Issue 2013/02). https://doi.org/10.1787/5K4869CDWNZR-EN

Banza Lubaba Nkulu, C., Casas, L., Haufroid, V., De Putter, T., Saenen, N. D., Kayembe-Kitenge, T., Musa Obadia, P., Kyanika Wa Mukoma, D., Lunda Ilunga, J. M., Nawrot, T. S., Luboya Numbi, O., Smolders, E., & Nemery, B. (2018). Sustainability of artisanal mining of cobalt in DR Congo. *Nature Sustainability*, *1*(9), 495–504. https://doi.org/10.1038/s41893-018-0139-4

Barnhart, C. J., & Benson, S. M. (2013). On the importance of reducing the energetic and material demands of electrical energy storage. *Energy and Environmental Science*, *6*(4), 1083–1092. https://doi.org/10.1039/c3ee24040a

Battke, B., & Schmidt, T. S. (2015). Cost-efficient demand-pull policies for multi-purpose technologies-The case of stationary electricity storage. *Applied Energy*, *155*, 334–348. https://doi.org/10.1016/j.apenergy.2015.06.010

Battke, B., Schmidt, T. S., Grosspietsch, D., & Hoffmann, V. H. (2013). A review and probabilistic model of lifecycle costs of stationary batteries in multiple applications. *Renewable and Sustainable Energy Reviews*, *25*, 240–250. https://doi.org/10.1016/j.rser.2013.04.023

Baumann, M., Peters, J. F., Weil, M., & Grunwald, A. (2017). CO2 Footprint and Life-Cycle Costs of Electrochemical Energy Storage for Stationary Grid Applications. *Energy Technology*, *5*(7), 1071–1083. https://doi.org/10.1002/ENTE.201600622

Baumann, M., Salzinger, M., Remppis, S., Schober, B., Held, M., & Graf, R. (2019). Reducing the Environmental Impacts of Electric Vehicles and Electricity Supply: How Hourly Defined Life Cycle Assessment and Smart Charging Can Contribute. *World Electric Vehicle Journal 2019, Vol. 10, Page 13*, *10*(1), 13. https://doi.org/10.3390/WEVJ10010013

Behrens, P. (2020). *The Best of Times, the Worst of Times: Futures from the Frontiers of Climate Science*. The Indigo Press.

Bhatnagar, D., Currier, A., Hernandez, Jacquelynne Ma, O., & Kirby, B. (2013). *Market and policy barriers to energy storage deployment* (No. SAND2013-7606). Sandia National Laboratories. http://consultkirby.com/files/SAND2013-7606_Market_and_Policy_Barriers_to_Energy _Storage_Development_September_2013.pdf

Bhatt, A., Forsyth, M., Wang, G., & Withers, R. (2016). *How a battery works*. Australian Academy of Science. https://www.science.org.au/curious/technology-future/batteries

BloombergNEF. (2019). *Energy Storage Investments Boom As Battery Costs Halve in the Next Decade* [Press release]. https://about.bnef.com/blog/energy-storage-investments-boom-battery-costs-halve-next-decade/#_ftn1

Bordin, C., Anuta, H. O., Crossland, A., Gutierrez, I. L., Dent, C. J., & Vigo, D. (2017). A linear programming approach for battery degradation analysis and optimization in offgrid power systems with solar energy integration. *Renewable Energy*, *101*, 417–430. https://doi.org /10.1016/J.RENENE.2016.08.066

Bowen, T., Chernyakhovskiy, I., & Denholm, P. (2019). *Grid-scale battery storage - Frequently asked questions* (NREL/TP-6A20-74426). National Renewable Energy Laboratory. https://www.nrel .gov/docs/fy19osti/74426.pdf

Bradbury, K., Pratson, L., & Patiño-Echeverri, D. (2014). Economic viability of energy storage systems based on price arbitrage potential in real-time U.S. electricity markets. *Applied Energy*, *114*, 512–519. https://doi.org/10.1016/j.apenergy.2013.10.010

Braff, W. A., Mueller, J. M., & Trancik, J. E. (2016). Value of storage technologies for wind and solar energy. *Nature Climate Change*, *6*(10), 964–969. https://doi.org/10.1038/nclimate3045

Brogan, P. V., Best, R., Morrow, J., Duncan, R., & Kubik, M. (2020). Stacking battery energy storage revenues with enhanced service provision. *IET Smart Grid*, *3*(4), 520–529. https://doi.org /10.1049/iet-stg.2018.0255

Bucher, C. (2014). Analysis and Simulation of Distribution Grids with Photovoltaics [Doctoral dissertation, Swiss Federal Institute of Technology in Zürich]. In *ETH Zürich Research Collection*. https://doi.org/https://doi.org/10.3929/ethz-a-010204387

Carvalho, M. L., Temporelli, A., & Girardi, P. (2021). Life cycle assessment of stationary storage systems within the italian electric network. *Energies*, *14*(8), 2047. https://doi.org/10.3390 /EN14082047/S1

Casals, L. C., García, B. A., Aguesse, F., & Iturrondobeitia, A. (2017). Second life of electric vehicle batteries: relation between materials degradation and environmental impact. *International Journal of Life Cycle Assessment*, *22*(1), 82–93. https://doi.org/10.1007/S11367-015-0918-3/TABLES/4

Chen, H., Cong, G., & Lu, Y. C. (2018). Recent progress in organic redox flow batteries: Active materials, electrolytes and membranes. In *Journal of Energy Chemistry* (Vol. 27, Issue 5, pp. 1304–1325). Elsevier B.V. https://doi.org/10.1016/j.jechem.2018.02.009

Choi, J. W., & Aurbach, D. (2016). Promise and reality of post-lithium-ion batteries with high energy densities. *Nature Reviews Materials*, *1*(4), 1–16. https://doi.org/10.1038/natrevmats.2016.13

Chowdhury, J. I., Balta-Ozkan, N., Goglio, P., Hu, Y., Varga, L., & McCabe, L. (2020). Techno-environmental analysis of battery storage for grid level energy services. *Renewable and Sustainable Energy Reviews*, *131*, 110018. https://doi.org/10.1016/J.RSER.2020.110018

Clarivate Analytics. (n.d.). *Web of Science*. http://webofknowledge.com/

Clemente, A., & Costa-Castelló, R. (2020). Redox Flow Batteries: A Literature Review Oriented to Automatic Control. *Energies*, *13*(17). https://doi.org/10.3390/en13174514

Colthorpe, A. (2021). *German startup launches software aimed at balancing battery degradation versus system revenues*. Energy Storage. https://www.energy-storage.news/news/german-startup-launches-software-aimed-at-balancing-battery-degradation-ver

Consequential-LCA. (2021). *Why and when?* https://consequential-lca.org/clca/why-and-when/

Cucurachi, S., Van Der Giesen, C., & Guinée, J. (2018). Ex-ante LCA of Emerging Technologies. *Procedia CIRP*, *69*, 463–468. https://doi.org/10.1016/j.procir.2017.11.005

da Silva Lima, L., Quartier, M., Buchmayr, A., Sanjuan-Delmás, D., Laget, H., Corbisier, D., Mertens, J., & Dewulf, J. (2021). Life cycle assessment of lithium-ion batteries and vanadium redox flow batteries-based renewable energy storage systems. *Sustainable Energy Technologies and Assessments*, *46*, 101286. https://doi.org/10.1016/j.seta.2021.101286

de Sisternes, F. J., Jenkins, J. D., & Botterud, A. (2016). The value of energy storage in decarbonizing the electricity sector. *Applied Energy*, *175*, 368–379. https://doi.org/10.1016/j.apenergy.2016.05.014

Delgado, M. A. S., Usai, L., Pan, Q., & Strømman, A. H. (2019). Comparative Life Cycle Assessment of a Novel Al-Ion and a Li-Ion Battery for Stationary Applications. *Materials 2019, Vol. 12, Page 3270*, *12*(19), 3270. https://doi.org/10.3390/MA12193270

Denholm, P., Ela, E., Kirby, B., & Milligan, M. (2010). *Role of Energy Storage with Renewable Electricity Generation* (NREL/TP-6A2-47187). https://doi.org/10.2172/972169

Divya, K. C., & Østergaard, J. (2009). Battery energy storage technology for power systems—An overview. *Electric Power Systems Research*, *79*(4), 511–520. https://doi.org/https://doi.org/10.1016/j.epsr.2008.09.017

Doets Reizen. (2023). *Canada Moraine Lake*. https://www.doetsreizen.nl/vakantie/canada/alberta/moraine-lake/

Dunn, B., Kamath, H., & Tarascon, J. M. (2011). Electrical energy storage for the grid: A battery of choices. *Science*, *334*(6058), 928–935. https://doi.org/10.1126/science.1212741

Eindhoven University of Technology. (2021, March 2). *"Honeycomb" electrode makes redox flow battery more efficient* [Press release]. https://www.tue.nl/en/news/news-overview/02-03-2021-honeycomb-electrode-makes-redox-flow-battery-more-efficient/#:~:text=NASA developed the redox-flow,their smaller size and weight.

Electric Power Research Institute. (n.d.). *StorageVET 2.1 Storage Value Estimation Tool*. https://www.storagevet.com/home/

Electric Power Research Institute. (2018). *StorageVET 2.0 User Guide: End User and Technical Documentation for the Storage Value Estimation Tool in Python* (v1.0.2). https://www.storagevet.com/files/StorageVET User Guide 2v102.pdf

Eller, A., & Gauntlett, D. (2017). *Energy Storage Trends and Opportunities in Emerging Markets*. https://esmap.org/sites/default/files/esmap-files/7151-IFC-EnergyStorage-report.pdf

Elsen, M., van Giesen, R., van den Akker, K., & Dunne, A. (2019). *Consumer testing of alternatives for communicating the Environmental Footprint profile of products*. https://ec.europa.eu /environment/eussd/smgp/pdf/2019_EF_commtest_report.pdf

Elzein, H., Dandres, T., Levasseur, A., & Samson, R. (2019). How can an optimized life cycle assessment method help evaluate the use phase of energy storage systems? *Journal of Cleaner Production*, *209*, 1624–1636. https://doi.org/10.1016/j.jclepro.2018.11.076

Englberger, S., Hesse, H., Hanselmann, N., & Jossen, A. (2019). SimSES Multi-Use: A simulation tool for multiple storage system applications. *International Conference on the European Energy Market, EEM*, *2019-Septe*. https://doi.org/10.1109/EEM.2019.8916568

Englberger, S., Jossen, A., & Hesse, H. (2020). Unlocking the Potential of Battery Storage with the Dynamic Stacking of Multiple Applications. *Cell Reports Physical Science*, *1*(11), 100238. https://doi.org/10.1016/j.xcrp.2020.100238

Englberger, S., Jossen, A., & Hesse, H. (2021). *Multi-use optimization tool for energy storage systems (mu_opt)*. https://gitlab.lrz.de/open-ees-ses/mu_opt/-/tree/master

Er, S., Suh, C., Marshak, M. P., & Aspuru-Guzik, A. (2015). Computational design of molecules for an all-quinone redox flow battery. *Chemical Science*, *6*(2), 885–893. https://doi.org/10.1039 /c4sc03030c

Eto, J. H., Undrill, J., Mackin, P., Daschmans, R., Williams, B., Haney, B., Hunt, R., Ellis, J., Illian, H. F., Martinez, C. A., O'Malley, M., & Coughlin, K. (2010). *Use of frequency response metrics to assess the planning and operating requirements for reliable integration of variable renewable generation* (LBNL-4142E). Lawrence Berkeley National Laboratory. https://doi.org/10.2172 /1003830

Eurometaux. (2021). *Batteries legislative proposal Comments from the European metals industry*. https://eurometaux.eu/media/3tuc1cpz/2021-03-01-batteries_eurometaux_comments-on-the-legislative-proposal_2021-03-01_final.pdf

European Association for Storage of Energy. (2018). *EASE Study on Energy Storage Demand*. https://ease-storage.eu/wp-content/uploads/2018/06/2018.06_EASE_Study_on_Storage _Demand.pdf

European Commission. (2011). *EC Directorate-General for Energy: Standardization Mandate to European Standardisation Organisations (ESOs) to support European Smart Grid deployment.* https://ec.europa.eu/growth/tools-databases/mandates/index.cfm?fuseaction=search.detail&id=475#

European Commission. (2013). *Commission recommendation of 9 April 2013 on the use of common methods to measure and communicate the life cycle environmental performance of products and organisations* (2013/179/EU). https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32013H0179&from=EN

European Commission. (2016). *Energy, transport and GHG emissions - Trends to 2050, EU Reference Scenario*. https://ec.europa.eu/energy/sites/ener/files/documents/20160713 draft_publication_REF2016_v13.pdf

European Commission. (2017). *PEFCR Guidance document - Guidance for the development of Product Environmental Footprint Category Rules (PEFCRs)* (6.3). https://ec.europa.eu/environment/eussd/smgp/pdf/PEFCR_guidance_v6.3.pdf

European Commission. (2018a). *A Clean Planet for all - A European strategic long-term vision for a prosperous, modern, competitive and climate neutral economy* (COM(2018) 773 final). https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52018DC0773

European Commission. (2018b). *PEFCR - Product Environmental Footprint Category Rules for High Specific Energy Rechargeable Batteries for Mobile Applications*. https://ec.europa.eu/environment/eussd/smgp/pdf/PEFCR_Batteries.pdf

European Commission. (2019a). *Report on the Implementation of the Strategic Action Plan on Batteries: Building a Strategic Battery Value Chain in Europe* (COM(2019) 176 final). https://eur-lex.europa.eu/legal-content/en/TXT/?uri=CELEX%3A52019DC0176

European Commission. (2019b). *The European Green Deal* (COM(2019) 640 final). https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=COM%3A2019%3A640%3AFIN

European Commission. (2020a). *ANNEXES to the Proposal for a Regulation of the European Parliament and of the Council concerning batteries and waste batteries, repealing Directive 2006/66/EC and amending Regulation (EU) No 2019/1020* (COM(2020) 798 final). https://eur-lex.europa.eu/resource.html?uri=cellar:4b5d88a6-3ad8-11eb-b27b-01aa75ed71a1.0001.02/DOC_2&format=PDF

European Commission. (2020b). *Proposal for a Regulation of the European Parliament and of the Council concerning batteries and waste batteries, repealing Directive 2006/66/EC and amending Regulation (EU) No 2019/1020*. https://eur-lex.europa.eu/resource.html?uri=cellar:4b5d88a6-3ad8-11eb-b27b-01aa75ed71a1.0001.02/DOC_1&format=PDF

European Commission. (2020c). *Study on the EU's list of Critical Raw Materials – Final Report (2020)*

(ET-01-20-491-EN-N). https://ec.europa.eu/docsroom/documents/42883/attachments/1/translations/en/renditions/native

European Commission. (2020d). *Study on the EU's list of Critical Raw Materials (2020), Factsheets on Critical Raw Materials* (ET-03-20-530-EN-N). https://ec.europa.eu/docsroom/documents/42883/attachments/2/translations/en/renditions/native

European Commission. (2021). *Environmental footprint methods*. https://ec.europa.eu/environment/news/environmental-footprint-methods-2021-12-16_en

European Network of Transmission System Operators for Electricity. (2014). *ENTSO-E Member Companies*. https://www.entsoe.eu/about/inside-entsoe/members/

European Parliament Council of the European Union. (n.d.). *Batteries and accumulators and waste batteries and accumulators and repealing Directive 91/157/EEC*. https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX%3A32006L0066

Eyer, J., & Corey, G. (2010). Energy storage for the electricity grid: Benefits and market potential assessment guides. In *Sandia National Laboratories* (No. SAND2010-0815). https://downloads.regulations.gov/EPA-HQ-OAR-2010-0799-0030/content.pdf

Faessler, B., Schuler, M., Preißinger, M., & Kepplinger, P. (2017). Battery storage systems as grid-balancing measure in low-voltage distribution grids with distributed generation. *Energies*, *10*(12), 2161. https://doi.org/10.3390/en10122161

Faria, R., Marques, P., Garcia, R., Moura, P., Freire, F., Delgado, J., & de Almeida, A. T. (2014). Primary and secondary use of electric mobility batteries from a life cycle perspective. *Journal of Power Sources*, *262*, 169–177. https://doi.org/10.1016/j.jpowsour.2014.03.092

Fitzgerald, G., Mandel, J., Morris, J., & Hervé, T. (2015). *The Economics of Battery Energy Storage: How Multi-use, Customer- Sited Batteries Deliver the Most Services and Value to Customers and the Grid*. Rocky Mountain Institute. https://rmi.org/wp-content/uploads/2017/03/RMI-TheEconomicsOfBatteryEnergyStorage-FullReport-FINAL.pdf

Frischknecht, R. (2000). Allocation in Life Cycle Inventory Analysis for Joint Production. *The International Journal of Life Cycle Assessment*, *5*(2). https://doi.org/10.1065/lca2000.02.013

Gallo, A. B., Simões-Moreira, J. R., Costa, H. K. M., Santos, M. M., & Moutinho dos Santos, E. (2016). Energy storage in the energy transition context: A technology review. *Renewable and Sustainable Energy Reviews*, *65*, 800–822. https://doi.org/10.1016/j.rser.2016.07.028

Gentil, S., Reynard, D., & Girault, H. H. (2020). Aqueous organic and redox-mediated redox flow batteries: a review. In *Current Opinion in Electrochemistry* (Vol. 21, pp. 7–13). Elsevier B.V. https://doi.org/10.1016/j.coelec.2019.12.006

Ghosh, S. K., Saha, R., & Saha, B. (2015). Toxicity of inorganic vanadium compounds. *Research on Chemical Intermediates*, *41*(7), 4873–4897. https://doi.org/10.1007/s11164-014-1573-1

Greim, P., Solomon, A. A., & Breyer, C. (2020). Assessment of lithium criticality in the global energy transition and addressing policy gaps in transportation. *Nature Communications*, *11*(1), 1–11. https://doi.org/10.1038/s41467-020-18402-y

Guinée, J. B., Gorrée, M., Heijungs, R., Huppes, G., Kleijn, R., de Koning, A., van Oers, L., Wegener Sleeswijk, A., Suh, A., Udo de Haes, A. H., de Bruijn, H., van Duin, R., & Huijbregts, M. A. J. (2002). *Handbook on life cycle assessment. Operational guide to the ISO standards.* Kluwer Academic Publishers.

Guney, M. S., & Tepe, Y. (2017). Classification and assessment of energy storage systems. *Renewable and Sustainable Energy Reviews*, *75*, 1187–1197. https://doi.org/10.1016/j.rser.2016.11.102

Hesse, H. C., Schimpe, M., Kucevic, D., & Jossen, A. (2017). Lithium-ion battery storage for the grid - A review of stationary battery storage system design tailored for applications in modern power grids. *Energies*, *10*(12), 2107. https://doi.org/10.3390/en10122107

Hiremath, M., Derendorf, K., & Vogt, T. (2015). Comparative Life Cycle Assessment of Battery Storage Systems for Stationary Applications. *Environmental Science & Technology*, *49*(8), 4825–4833. https://doi.org/10.1021/es504572q

Holguin, J. P., & Ramos, G. (2020). Reverse Power Flow (RPF) Detection and Impact on Protection Coordination of Distribution Systems. *IEEE Transactions on Industry Applications*, *56*(3), 2393–2401. https://doi.org/10.1109/TIA.2020.2969640

Hollas, A., Wei, X., Murugesan, V., Nie, Z., Li, B., Reed, D., Liu, J., Sprenkle, V., & Wang, W. (2018). A biomimetic high-capacity phenazine-based anolyte for aqueous organic redox flow batteries. *Nature Energy*. https://doi.org/10.1038/s41560-018-0167-3

Hopkins, A. S., Takahashi, K., & Lis, D. (2018). Challenges and Opportunities for Deep Decarbonization through Strategic Electrification under the Utility Regulatory Structures of the Northeast. *American Council for an Energy-Efficient Economy Summer Study on Energy Efficiency in Buildings*, 1–6. https://www.synapse-energy.com/sites/default/files/ACEEE-Deep-Decarbonization-Paper.pdf

Hu, B., Tang, Y., Luo, J., Grove, G., Guo, Y., & Liu, T. L. (2018). Improved radical stability of viologen anolytes in aqueous organic redox flow batteries. *Chemical Communications*, *54*(50), 6871–6874. https://doi.org/10.1039/c8cc02336k

Immendoerfer, A., Tietze, I., Hottenroth, H., & Viere, T. (2017). Life-cycle impacts of pumped hydropower storage and battery storage. *International Journal of Energy and Environmental Engineering*, *8*(3), 231–245. https://doi.org/10.1007/S40095-017-0237-5/FIGURES/7

Intergovernmental Panel on Climate Change. (2014). *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* (R. K. Pachauri & L. A. Meyer (eds.)).

https://www.ipcc.ch/site/assets/uploads/2018/02/SYR_AR5_FINAL_full.pdf

International Energy Agency. (2019). *Offshore Wind Outlook 2019*. https://www.iea.org/reports/offshore-wind-outlook-2019

International Energy Agency. (2020a). *Electricity Market Report - December 2020*. https://iea.blob.core.windows.net/assets/a695ae98-cec1-43ce-9cab-c37bb0143a05/Electricity_Market_Report_December_2020.pdf

International Energy Agency. (2020b). *Outlook for electricity - World Energy Outlook 2020*. International Energy Agency. https://www.iea.org/reports/world-energy-outlook-2020/outlook-for-electricity

International Labour Organization. (2019). *Child Labour in Mining and Global Supply Chains*. https://www.ilo.org/wcmsp5/groups/public/---asia/---ro-bangkok/---ilo-manila/documents/publication/wcms_720743.pdf

International Organization for Standardization. (2006). *Environmental management: life cycle assessment; Principles and Framework* (No. 14040). https://www.iso.org/standard/37456.html

International Renewable Energy Agency. (2017). *Electricity Storage and Renewables: Costs and Markets to 2030*. https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2017/Oct/IRENA_Electricity_Storage_Costs_2017.pdf

International Renewable Energy Agency. (2019). Innovation landscape brief: Utility-scale batteries. In *International Renewable Energy Agency*. http://ktn-csbs-media.s3.amazonaws.com/8d1e03c0-d749-4ff0-93e0-d4ee7de5b07e/IRENA_Utility-scale-batteries_2019.pdf

Janoschka, T., Martin, N., Martin, U., Friebe, C., Morgenstern, S., Hiller, H., Hager, M. D., & Schubert, U. S. (2015). An aqueous, polymer-based redox-flow battery using non-corrosive, safe, and low-cost materials. *Nature*, *527*(7576), 78–81. https://doi.org/10.1038/nature15746

JenaBatteries GmbH. (n.d.). *The flow battery in practice*. Retrieved May 21, 2021, from https://jenabatteries.de/en/technology#c204

Jenu, S., Deviatkin, I., Hentunen, A., Myllysilta, M., Viik, S., & Pihlatie, M. (2020). Reducing the climate change impacts of lithium-ion batteries by their cautious management through integration of stress factors and life cycle assessment. *Journal of Energy Storage*, *27*, 101023. https://doi.org/10.1016/J.EST.2019.101023

Jones, C., Gilbert, P., & Stamford, L. (2019). Assessing the Climate Change Mitigation Potential of Stationary Energy Storage for Electricity Grid Services. *Environmental Science and Technology*, *54*(1), 67–75. https://doi.org/10.1021/ACS.EST.9B06231/SUPPL_FILE/ES9B06231_SI_001.PDF

Jongsma, C., van Cappellen, L., & Vendrik, J. (2021). Omslagpunt grootschalige batterijopslag. In *CE Delft* (21.210361.169a). https://ce.nl/wp-content/uploads/2022/01/CE_Delft_210361_Omslagpunt_grootschalige_batterijopslag_Hoofdrapport_Def.pdf

Kamath, D., Shukla, S., Arsenault, R., Kim, H. C., & Anctil, A. (2020). Evaluating the cost and carbon footprint of second-life electric vehicle batteries in residential and utility-level applications. *Waste Management*, *113*, 497–507. https://doi.org/10.1016/j.wasman.2020.05.034

Keil, P., Schuster, S. F., Wilhelm, J., Travi, J., Hauser, A., Karl, R. C., & Jossen, A. (2016). Calendar Aging of Lithium-Ion Batteries. *Journal of The Electrochemical Society*, *163*(9), A1872. https://doi.org /10.1149/2.0411609JES

Khan Academy. (n.d.). *Oxidation-reduction (redox) reactions*. Retrieved June 8, 2021, from https://www.khanacademy.org/science/ap-chemistry-beta/x2eef969c74e0d802:chemical-reactions/x2eef969c74e0d802:oxidation-reduction-redox-reactions/a/oxidation-number

Kim, H. C., Wallington, T. J., Arsenault, R., Bae, C., Ahn, S., & Lee, J. (2016). Cradle-to-Gate Emissions from a Commercial Electric Vehicle Li-Ion Battery: A Comparative Analysis. *Environmental Science and Technology*, *50*(14), 7715–7722. https://doi.org/10.1021/ACS.EST.6B00830 /SUPPL_FILE/ES6B00830_SI_001.PDF

Kim, J. H., Kim, K. J., Park, M. S., Lee, N. J., Hwang, U., Kim, H., & Kim, Y. J. (2011). Development of metal-based electrodes for non-aqueous redox flow batteries. *Electrochemistry Communications*, *13*(9), 997–1000. https://doi.org/10.1016/j.elecom.2011.06.022

Klausen, M., Resch, M., & Bühler, J. (2016). Analyis of a Potential Single and Combined Business Model for Stationary Battery Storage Systems. *Energy Procedia*, *99*, 321–331. https://doi.org /10.1016/j.egypro.2016.10.122

Koffler, C. (2018). *Why Attributional LCA Doesn't Care What You Didn't Do*. https://www.linkedin .com/pulse/why-attributional-lca-doesnt-care-what-you-didnt-do-christoph-koffler

Koj, J. C., Stenzel, P., Schreiber, A., Hennings, W., Zapp, P., Wrede, G., & Hahndorf, I. (2015). Life Cycle Assessment of Primary Control Provision by Battery Storage Systems and Fossil Power Plants. *Energy Procedia*, *73*, 69–78. https://doi.org/10.1016/j.egypro.2015.07.563

Kowalski, J. A., Su, L., Milshtein, J. D., & Brushett, F. R. (2016). Recent advances in molecular engineering of redox active organic molecules for nonaqueous flow batteries. *Current Opinion in Chemical Engineering*, *13*, 45–52. https://doi.org/10.1016/j.coche.2016.08.002

Krishan, O., & Suhag, S. (2019). An updated review of energy storage systems: Classification and applications in distributed generation power systems incorporating renewable energy resources. *International Journal of Energy Research*, *43*(12), 6171–6210. https://doi.org /10.1002/ER.4285

Kwabi, D. G., Ji, Y., & Aziz, M. J. (2020). Electrolyte Lifetime in Aqueous Organic Redox Flow Batteries: A Critical Review. *Chemical Reviews*, *120*(14), 6467–6489. https://doi.org/10.1021/acs.chemrev .9b00599

Lai, Q., Zhang, H., Li, X., Zhang, L., & Cheng, Y. (2013). A novel single flow zinc-bromine battery with improved energy density. *Journal of Power Sources*, *235*, 1–4. https://doi.org/10.1016/j.jpowsour.2013.01.193

Lee, E., & Kim, J. (2019). Assessing the Benefits of Battery Energy Storage Systems for Frequency Regulation, Based on Electricity Market Price Forecasting. *Applied Sciences*, *9*(10), 1–13. https://doi.org/10.3390/app9102147

Litjens, G. B. M. A., Worrell, E., & van Sark, W. G. J. H. M. (2018a). Economic benefits of combining self-consumption enhancement with frequency restoration reserves provision by photovoltaic-battery systems. *Applied Energy*, *223*, 172–187. https://doi.org/10.1016/J.APENERGY.2018.04.018

Litjens, G. B. M. A., Worrell, E., & van Sark, W. G. J. H. M. (2018b). Lowering greenhouse gas emissions in the built environment by combining ground source heat pumps, photovoltaics and battery storage. *Energy and Buildings*, *180*, 51–71. https://doi.org/10.1016/J.ENBUILD.2018.09.026

Lombardi, P., & Schwabe, F. (2017). Sharing economy as a new business model for energy storage systems. *Applied Energy*, *188*, 485–496. https://doi.org/10.1016/J.APENERGY.2016.12.016

Longson, M. (2021, April 13). *Strong growth ahead for battery storage*. Pv Magazine. https://www.pv-magazine.com/2021/04/13/strong-growth-ahead-for-battery-storage/

Lopes, J. A. P., Hatziargyriou, N., Mutale, J., Djapic, P., & Jenkins, N. (2007). Integrating distributed generation into electric power systems: A review of drivers, challenges and opportunities. *Electric Power Systems Research*, *77*(9), 1189–1203. https://doi.org/10.1016/j.epsr.2006.08.016

Luo, J., Hu, B., Hu, M., Zhao, Y., & Liu, T. L. (2019). Status and Prospects of Organic Redox Flow Batteries toward Sustainable Energy Storage [Article]. *ACS Energy Letters*, *4*(9), 2220–2240. https://doi.org/10.1021/acsenergylett.9b01332

Ma, C. T. (2020). A Novel State of Charge Estimating Scheme Based on an Air-Gap Fiber Interferometer Sensor for the Vanadium Redox Flow Battery. *Energies*, *13*(2), 13. https://doi.org/10.3390/en13020291

Mai, H. J. (2019). *WoodMac: Energy storage will move toward value stacking as industry matures*. Utility Dive. https://www.utilitydive.com/news/woodmac-energy-storage-will-move-toward-value-stacking-as-industry-matures/555021/

Malhotra, A., Battke, B., Beuse, M., Stephan, A., & Schmidt, T. (2016). Use cases for stationary battery technologies: A review of the literature and existing projects. *Renewable and Sustainable Energy Reviews*, *56*, 705–721. https://doi.org/10.1016/j.rser.2015.11.085

Mallapragada, D. S., Sepulveda, N. A., & Jenkins, J. D. (2020). Long-run system value of battery energy storage in future grids with increasing wind and solar generation. *Applied Energy*, *275*, 115390. https://doi.org/10.1016/J.APENERGY.2020.115390

Manz, D., Jeffrey, K., & Miller, N. (2011). Value propositions for utility-scale energy storage. *IEEE/PES Power Systems Conference and Exposition*, 1–10. https://doi.org/10.1109/PSCE.2011.5772524

Marchgraber, J., & Gawlik, W. (2021). Dynamic Prioritization of Functions during Real-Time Multi-Use Operation of Battery Energy Storage Systems. *Energies 2021, Vol. 14, Page 655*, *14*(3), 655. https://doi.org/10.3390/EN14030655

Mattson, N., Unger, T., & Ekvall, T. (2008). *Effects of perturbations in a dynamic system – The case of Nordic power production*. https://research.chalmers.se/publication/514508/file/514508_Fulltext.pdf

Mey, A. (2021). *Utility-scale batteries and pumped storage return about 80% of the electricity they store*. U.S. Energy Information Administration. https://www.eia.gov/todayinenergy/detail.php?id=46756

Minke, C., Kunz, U., & Turek, T. (2017). Techno-economic assessment of novel vanadium redox flow batteries with large-area cells. *Journal of Power Sources*, *361*, 105–114. https://doi.org/10.1016/j.jpowsour.2017.06.066

MIT Electric Vehicle Team. (2008, December). *A Guide to Understanding Battery Specifications*. https://web.mit.edu/evt/summary_battery_specifications.pdf

Mooney, D. (2015). Large-Scale Energy Storage. *Global Climate and Energy Project Tutorial Series*. https://gcep.stanford.edu/pdfs/symposium2015/Presentations/Mooney_GCEPSymposium2015_EnergyStorage101.pdf

Moore, M., Robert, C., Js, W., Az, T., Sun, C.-N., & Engineering, B. (2016). An Analysis of the Contributions of Current Density and Voltage Efficiency to the Capital Costs of an All Vanadium Redox-Flow Battery. *J Chem Eng Process Technol*, *7*(2), 288. https://doi.org/10.4172/2157-7048.1000288

Mostert, C., Ostrander, B., Bringezu, S., & Kneiske, T. M. (2018). Comparing Electrical Energy Storage Technologies Regarding Their Material and Carbon Footprint. *Energies 2018, Vol. 11, Page 3386*, *11*(12), 3386. https://doi.org/10.3390/EN11123386

Muelaner, J. (2021). *What is an electrolyte? - Battery Power Tips*. https://www.batterypowertips.com/what-is-an-electrolyte-faq/

Namor, E., Sossan, F., Cherkaoui, R., & Paolone, M. (2019). Control of Battery Storage Systems for the Simultaneous Provision of Multiple Services. *IEEE Transactions on Smart Grid*, *10*(3), 2799–2808. https://doi.org/10.1109/TSG.2018.2810781

Narayan, S. R., Nirmalchandar, A., Murali, A., Yang, B., Hoober-Burkhardt, L., Krishnamoorthy, S., & Prakash, G. K. S. (2019). Next-generation aqueous flow battery chemistries. In *Current Opinion in Electrochemistry* (Vol. 18, pp. 72–80). Elsevier B.V. https://doi.org/10.1016/j.coelec.2019.10.010

National Agency for Research and Development. (2019). *Building a Low-Carbon, Climate Resilient Future: Next-Generation Batteries (H2020-LC-BAT-2019-2020)*. http://www.h2020.md/en /building-low-carbon-climate-resilient-future-next-generation-batteries-h2020-lc-bat-2019-2020

National Renewable Energy Laboratory. (n.d.). *REopt: Renewable Energy Integration & Optimization*. https://reopt.nrel.gov/

National Research Council. (2008). *The National Academies Summit on America's Energy Future: Summary of a Meeting*. The National Academies Press. https://doi.org/https://doi.org /10.17226/12450

Next Kraftwerke GmbH. (2021). *What is Frequency Containment Reserve (FCR)?* https://www.next-kraftwerke.com/knowledge/frequency-containment-reserve-fcr

Noack, J., Roznyatovskaya, N., Herr, T., & Fischer, P. (2015). The Chemistry of Redox-Flow Batteries. *Angewandte Chemie - International Edition*, *54*(34), 9776–9809. https://doi.org/10.1002 /anie.201410823

Nykvist, B., & Nilsson, M. (2015). Rapidly falling costs of battery packs for electric vehicles. *Nature Climate Change*, *5*(4), 329–332. https://doi.org/10.1038/nclimate2564

Oliveira, L., Messagie, M., Mertens, J., Laget, H., Coosemans, T., & Van Mierlo, J. (2015). Environmental performance of electricity storage systems for grid applications, a life cycle approach. *Energy Conversion and Management*, *101*, 326–335. https://doi.org/10.1016 /J.ENCONMAN.2015.05.063

Olk, C., Sauer, D. U., & Merten, M. (2019). *Bidding strategy for a battery storage in the German secondary balancing power market*. https://doi.org/10.1016/j.est.2019.01.019

Panchal, S., Mathewson, S., Fraser, R., Richard, C., & Michael, F. (2015). Thermal management of lithium-ion pouch cell with indirect liquid cooling using dual cold plates approach. *SAE International Journal of Alternative Powertrains*, *4*(2), 293–307. https://doi.org/10.4271/2015-01-1184

Pareis, E., & Hittinger, E. (2021). Emissions Effects of Energy Storage for Frequency Regulation: Comparing Battery and Flywheel Storage to Natural Gas. *Energies*, *14*(3), 549–568. https://doi .org/10.3390/EN14030549

Park, M., Ryu, J., Wang, W., & Cho, J. (2016). Material design and engineering of next-generation flow-battery technologies. *Nature Reviews Materials*, *2*(1), 1–18. https://doi.org/10.1038 /natrevmats.2016.80

Pellow, M. A., Ambrose, H., Mulvaney, D., Betita, R., & Shaw, S. (2020). Research gaps in environmental life cycle assessments of lithium ion batteries for grid-scale stationary energy storage systems: End-of-life options and other issues. *Sustainable Materials and Technologies*, *23*, e00120. https://doi.org/10.1016/j.susmat.2019.e00120

Peng, J., Meng, J., Chen, D., Liu, H., Hao, S., Sui, X., & Du, X. (2022). A Review of Lithium-Ion Battery Capacity Estimation Methods for Onboard Battery Management Systems: Recent Progress and Perspectives. *Batteries*, *8*(11), 229. https://doi.org/10.3390/BATTERIES8110229

Penn State College of Earth and Mineral Sciences. (2017). *Frequency Regulation*. https://www.e-education.psu.edu/ebf483/node/705

Peters, J. F., Buchholz, D., Passerini, S., & Weil, M. (2016). Life cycle assessment of sodium-ion batteries. *Energy & Environmental Science*, *9*(5), 1744–1751. https://doi.org/10.1039/C6EE00640J

Peters, J. F., & Weil, M. (2017). Aqueous hybrid ion batteries – An environmentally friendly alternative for stationary energy storage? *Journal of Power Sources*, *364*, 258–265. https://doi.org/10.1016/j.jpowsour.2017.08.041

Poplavskaya, K. (2018). *Impact of balancing market design on business case for storage*. https://horizon2020-story.eu/wp-content/uploads/Session-III-_-KseniaPoplavskayaK_final.pdf

Porzio, J., & Scown, C. D. (2021). Life-Cycle Assessment Considerations for Batteries and Battery Materials. *Advanced Energy Materials*, *11*(33), 2100771. https://doi.org/10.1002/AENM.202100771

Poza, R. F. (n.d.). *Redox flow batteries: a sustainable technology* [Blog post]. CIC EnergiGUNE. https://cicenergigune.com/en/blog/redox-flow-batteries-sustainable-technology

Pucker-Singer, J., Aichberger, C., Zupančič, J., Neumann, C., Bird, D. N., Jungmeier, G., Gubina, A., & Tuerk, A. (2021). Greenhouse Gas Emissions of Stationary Battery Installations in Two Renewable Energy Projects. *Sustainability 2021, Vol. 13, Page 6330*, *13*(11), 6330. https://doi.org/10.3390/SU13116330

Puiu, T. (2020, April 2). *The Future is Bright for Lithium-Ion Batteries* [Blog post]. Lindau Nobel Laureate Meetings. https://www.lindau-nobel.org/blog-the-future-is-bright-for-lithium-ion-batteries/

Quan, H., Teo, J. K., Trivedi, A., & Srinivasan, D. (2019). Optimal Energy Management of Vanadium Redox Flow Batteries Energy Storage System for Frequency Regulation and Peak Shaving in an Islanded Microgrid. *2019 IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia)*, 4053–4058. https://doi.org/10.1109/ISGT-Asia.2019.8880902

Rahman, M. M., Gemechu, E., Oni, A. O., & Kumar, A. (2021). The greenhouse gas emissions' footprint and net energy ratio of utility-scale electro-chemical energy storage systems. *Energy Conversion and Management*, *244*, 114497. https://doi.org/10.1016/j.enconman.2021.114497

Rebours, Y. G., Kirschen, D. S., Trotignon, M., & Rossignol, S. (2007). A survey of frequency and voltage control ancillary services - Part I: Technical features. *IEEE Transactions on Power*

Systems, *22*(1), 350–357. https://doi.org/10.1109/TPWRS.2006.888963

RELiON Battery. (2019). *Tech Tuesday: Depth Of Discharge, State Of Charge & Capacity* [Blog post]. https://relionbattery.com/blog/tech-tuesday-depth-of-discharge

Reynard, D., Dennison, C. R., Battistel, A., & Girault, H. H. (2018). Efficiency improvement of an all-vanadium redox flow battery by harvesting low-grade heat. *Journal of Power Sources*, *390*, 30–37. https://doi.org/10.1016/j.jpowsour.2018.03.074

Richa, K., Babbitt, C. W., Nenadic, N. G., & Gaustad, G. (2017). Environmental trade-offs across cascading lithium-ion battery life cycles. *International Journal of Life Cycle Assessment*, *22*(1), 66–81. https://doi.org/10.1007/S11367-015-0942-3/FIGURES/7

Robson, P., & Bonomi, D. (2020). *Growing The Battery Storage Market 2020: Exploring Four Key issues*. https://energystorageforum.com/files/ESWF_Whitepaper_-_Growing_the_battery_storage_market.pdf

Romero, H., Méndez, M., & Smith, P. (2012). Mining development and environmental injustice in the atacama desert of Northern Chile. *Environmental Justice*, *5*(2), 70–76. https://doi.org/10.1089/env.2011.0017

Roser, M. (2020, December 12). *Why did renewables become so cheap so fast? And what can we do to use this global opportunity for green growth?* Our World in Data. https://ourworldindata.org/cheap-renewables-growth

Roux, C., Schalbart, P., & Peuportier, B. (2017). Development of an electricity system model allowing dynamic and marginal approaches in LCA—tested in the French context of space heating in buildings. *International Journal of Life Cycle Assessment*, *22*(8), 1177–1190. https://doi.org/10.1007/S11367-016-1229-Z/FIGURES/4

Ryan, N. A., Lin, Y., Mitchell-Ward, N., Mathieu, J. L., & Johnson, J. X. (2018). Use-Phase Drives Lithium-Ion Battery Life Cycle Environmental Impacts When Used for Frequency Regulation. *Environmental Science & Technology*, *52*(17), 10163–10174. https://doi.org/10.1021/acs.est.8b02171

Rydh, C. J. (1999). Environmental assessment of vanadium redox and lead-acid batteries for stationary energy storage. *Journal of Power Sources*, *80*, 21–29.

Sánchez-Díez, E., Ventosa, E., Guarnieri, M., Trovò, A., Flox, C., Marcilla, R., Soavi, F., Mazur, P., Aranzabe, E., & Ferret, R. (2021). Redox flow batteries: Status and perspective towards sustainable stationary energy storage. *Journal of Power Sources*, *481*, 228804. https://doi.org/10.1016/j.jpowsour.2020.228804

Schmidt, O., Hawkes, A., Gambhir, A., & Staffell, I. (2017). The future cost of electrical energy storage based on experience rates. *Nature Energy*, *2*(8), 1–8. https://doi.org/10.1038/nenergy.2017.110

Schmidt, T. S., Beuse, M., Zhang, X., Steffen, B., Schneider, S. F., Pena-Bello, A., Bauer, C., & Parra, D.

(2019). Additional Emissions and Cost from Storing Electricity in Stationary Battery Systems. *Environmental Science and Technology*, *53*(7), 3379–3390. https://doi.org/10.1021/ACS.EST.8B05313/SUPPL_FILE/ES8B05313_SI_002.ZIP

Schram, W., Louwen, A., Lampropoulos, I., & Van Sark, W. (2019). Comparison of the Greenhouse Gas Emission Reduction Potential of Energy Communities. *Energies 2019, Vol. 12, Page 4440*, *12*(23), 4440. https://doi.org/10.3390/EN12234440

Schulz-Mönninghoff, M., Bey, N., Nørregaard, P. U., & Niero, M. (2021). Integration of energy flow modelling in life cycle assessment of electric vehicle battery repurposing: Evaluation of multi-use cases and comparison of circular business models. *Resources, Conservation and Recycling*, *174*, 105773. https://doi.org/10.1016/j.resconrec.2021.105773

Shafiul Alam, M., Al-Ismail, F. S., Salem, A., & Abido, M. A. (2020). High-level penetration of renewable energy sources into grid utility: Challenges and solutions. *IEEE Access*, *8*, 190277–190299. https://doi.org/10.1109/ACCESS.2020.3031481

Shah, H. (2005). Harmonics - A power quality problem. In *Industry Watch*. https://www.mecoinst.com/media-releases/documents/harmonics.pdf

Silvera Diaz, V., Cantane, D. A., Quites, A., Santos, O., Hideo, O., & Junior, A. (2021). Comparative Analysis of Degradation Assessment of Battery Energy Storage Systems in PV Smoothing Application. *Energies 2021, Vol. 14, Page 3600*, *14*(12), 3600. https://doi.org/10.3390/EN14123600

Singh, V., Kim, S., Kang, J., & Byon, H. R. (2019). Aqueous organic redox flow batteries. In *Nano Research* (Vol. 12, Issue 9, pp. 1988–2001). Tsinghua University Press. https://doi.org/10.1007/s12274-019-2355-2

Sodhi, M., Banaszek, L., Magee, C., & Rivero-Hudec, M. (2022). Economic Lifetimes of Solar Panels. *Procedia CIRP*, *105*, 782–787. https://doi.org/10.1016/J.PROCIR.2022.02.130

Solomon, B. D., & Krishna, K. (2011). The coming sustainable energy transition: History, strategies, and outlook. *Energy Policy*, *39*(11), 7422–7431. https://doi.org/10.1016/j.enpol.2011.09.009

Soloveichik, G. L. (2015). Flow Batteries: Current Status and Trends. In *Chemical Reviews* (Vol. 115, Issue 20, pp. 11533–11558). American Chemical Society. https://doi.org/10.1021/cr500720t

Solovev, A., & Petrova, A. (2021). *Efficient Energy Management and Energy Saving with a BESS (Battery Energy Storage System)*. Integra Sources. https://www.integrasources.com/blog/energy-management-and-energy-saving-bess/

Soskin, P. (2019). *Every charge cycle counts when it comes to battery degradation*. Energy Storage News. https://www.energy-storage.news/every-charge-cycle-counts-when-it-comes-to-battery-degradation/

Spanos, C., Turney, D. E., & Fthenakis, V. (2015). Life-cycle analysis of flow-assisted nickel zinc-, manganese dioxide-, and valve-regulated lead-acid batteries designed for demand-charge reduction. *Renewable and Sustainable Energy Reviews*, *43*, 478–494. https://doi.org/10.1016 /j.rser.2014.10.072

Stephan, A., Battke, B., Beuse, M. D., Clausdeinken, J. H., & Schmidt, T. S. (2016). Limiting the public cost of stationary battery deployment by combining applications. *Nature Energy*, *1*(7), 1–9. https://doi.org/10.1038/nenergy.2016.79

Telaretti, E., & Dusonchet, L. (2017). Stationary battery technologies in the U.S.: Development Trends and prospects. *Renewable and Sustainable Energy Reviews*, *75*, 380–392. https://doi.org /10.1016/j.rser.2016.11.003

Teng, F., & Strbac, G. (2016). Business cases for energy storage with multiple service provision. *Journal of Modern Power Systems and Clean Energy*, *4*(4), 615–625. https://doi.org/10.1007 /S40565-016-0244-1

Tennet. (2020). *Annual Market Update 2019: Electricity market insights*. https://www.tennet.eu/fileadmin/user_upload/Company/Publications/Technical_Publications/ TenneT_Annual_Market_Update_2019.pdf

Terlouw, T., AlSkaif, T., Bauer, C., & van Sark, W. (2019). Multi-objective optimization of energy arbitrage in community energy storage systems using different battery technologies. *Applied Energy*, *239*, 356–372. https://doi.org/10.1016/J.APENERGY.2019.01.227

Thaller, L. H. (1976). *Electrically rechargeable REDOX flow cell* (Patent No. US3996064A). https://patents.google.com/patent/US3996064A/en

Thoubboron, K. (2021). *Depth of discharge (DoD): What does it mean for your battery, and why is it important?* EnergySage. https://news.energysage.com/depth-discharge-dod-mean-battery-important/

Truong, C. N., Schimpe, M., Bürger, U., Hesse, H. C., & Jossen, A. (2018). Multi-Use of Stationary Battery Storage Systems with Blockchain Based Markets. *Energy Procedia*, *155*, 3–16. https://doi.org/10.1016/J.EGYPRO.2018.11.070

U.S. Energy Information Administration. (n.d.). *Electricity explained How electricity is delivered to consumers*. https://www.eia.gov/energyexplained/electricity/delivery-to-consumers.php

U.S. Energy Information Administration. (2020). *What is the difference between electricity generation capacity and electricity generation?* https://www.eia.gov/tools/faqs/faq.php?id=101&t=3

U.S. Energy Information Administration. (2021). *Battery Storage in the United States: An Update on Market Trends*. https://www.eia.gov/analysis/studies/electricity/batterystorage/pdf/battery _storage_2021.pdf

United Nations Environment Programme. (2011). Global guidance principles for Life Cycle Assessment (LCA) databases: a basis for greener processes and products. In *UNEP/SETAC*.

https://www.lifecycleinitiative.org/wp-content/uploads/2012/12/2011 - Global Guidance Principles.pdf

Van Gastel, E., & De Jonge Baas, M. (2019). *Staatssecretaris Snel: problematiek dubbele belasting bij energieopslag per 2021 oplossen door wetswijziging*. Smart Storage Magazine. https://smartstoragemagazine.nl/nieuws/i18940/staatssecretaris-snel-problematiek-dubbele-belasting-bij-energieopslag-per-2021-oplossen-door-wetswijziging

Vandepaer, L., Cloutier, J., Bauer, C., & Amor, B. (2019). Integrating Batteries in the Future Swiss Electricity Supply System: A Consequential Environmental Assessment. *Journal of Industrial Ecology*, *23*(3), 709–725. https://doi.org/10.1111/jiec.12774

Vanitec Transforming Possibilities. (n.d.). *Vanadium redox flow battery companies*. Retrieved May 20, 2021, from http://www.vanitec.org/vanadium-redox-flow-battery-vrfb-companies

Vanitec Transforming Possibilities. (2019, April 30). *Vanadium Redox Flow Battery (VRFB) technology is increasingly being tested or deployed across the globe*. https://willigan.digital/pr/bold-editorial/vanitec/v3/

Vuarnoz, D., Cozza, S., Jusselme, T., Magnin, G., Schafer, T., Couty, P., & Niederhauser, E. L. (2018). Integrating hourly life-cycle energy and carbon emissions of energy supply in buildings. *Sustainable Cities and Society*, *43*, 305–316. https://doi.org/10.1016/J.SCS.2018.08.026

Vuarnoz, Didier, & Jusselme, T. (2018). Temporal variations in the primary energy use and greenhouse gas emissions of electricity provided by the Swiss grid. *Energy*, *161*, 573–582. https://doi.org/10.1016/J.ENERGY.2018.07.087

Wang, W., & Sprenkle, V. (2016). Energy storage: Redox flow batteries go organic. In *Nature Chemistry* (Vol. 8, Issue 3, pp. 204–206). Nature Publishing Group. https://doi.org/10.1038/nchem.2466

Wanner, B., & Cozzi, L. (2020). *Electricity security in tomorrow's power systems*. International Energy Agency. https://www.iea.org/articles/electricity-security-in-tomorrow-s-power-systems

Weber, S., Peters, J. F., Baumann, M., & Weil, M. (2018). Life Cycle Assessment of a Vanadium Redox Flow Battery. *Environmental Science and Technology*, *52*(18), 10864–10873. https://doi.org/10.1021/acs.est.8b02073

Wedege, K., Dražević, E., Konya, D., & Bentien, A. (2016). Organic Redox Species in Aqueous Flow Batteries: Redox Potentials, Chemical Stability and Solubility. *Scientific Reports*, *6*(1), 1–13. https://doi.org/10.1038/srep39101

Wei, X., Pan, W., Duan, W., Hollas, A., Yang, Z., Li, B., Nie, Z., Liu, J., Reed, D., Wang, W., & Sprenkle, V. (2017). Materials and Systems for Organic Redox Flow Batteries: Status and Challenges. *ACS Energy Letters*, *2*(9), 2187–2204. https://doi.org/10.1021/acsenergylett.7b00650

Wei, X., Xu, W., Vijayakumar, M., Cosimbescu, L., Liu, T., Sprenkle, V., & Wang, W. (2014). TEMPO-based catholyte for high-energy density nonaqueous redox flow batteries. *Advanced Materials*, *26*(45), 7649–7653. https://doi.org/10.1002/adma.201403746

Weitzel, T., & Glock, C. H. (2018). Energy management for stationary electric energy storage systems: A systematic literature review. *European Journal of Operational Research*, *264*(2), 582–606. https://doi.org/10.1016/j.ejor.2017.06.052

Wernet, G., Bauer, C., Steubing, B., Reinhard, J., Moreno-Ruiz, E., & Weidema, B. (2016). The ecoinvent database version 3 (part I): overview and methodology. *International Journal of Life Cycle Assessment*, *21*(9), 1218–1230. https://doi.org/10.1007/S11367-016-1087-8/FIGURES/7

Winsberg, J., Hagemann, T., Janoschka, T., Hager, M. D., & Schubert, U. S. (2017). Redox-Flow Batteries: From Metals to Organic Redox-Active Materials. In *Angewandte Chemie - International Edition* (Vol. 56, Issue 3, pp. 686–711). Wiley-VCH Verlag. https://doi.org/10.1002/anie.201604925

Winsberg, J., Janoschka, T., Morgenstern, S., Hagemann, T., Muench, S., Hauffman, G., Gohy, J. F., Hager, M. D., & Schubert, U. S. (2016). Poly(TEMPO)/Zinc Hybrid-Flow Battery: A Novel, “green,” High Voltage, and Safe Energy Storage System. *Advanced Materials*, *28*(11), 2238–2243. https://doi.org/10.1002/adma.201505000

Xu, Y., Wen, Y.-H., Cheng, J., Cao, G.-P., & Yang, Y.-S. (2010). A study of tiron in aqueous solutions for redox flow battery application. *Electrochimica Acta*, *55*, 715–720. https://doi.org/10.1016/j.electacta.2009.09.031

Zhong, F., Yang, M., Ding, M., & Jia, C. (2020). Organic Electroactive Molecule-Based Electrolytes for Redox Flow Batteries: Status and Challenges of Molecular Design. *Frontiers in Chemistry*, *8*. https://doi.org/10.3389/FCHEM.2020.00451

Appendix A

Concise explanation of life cycle assessment

Life cycle assessment

To assess the environmental impacts of a product system and compare it to other systems, life cycle assessments are performed. The trade-offs in life cycles, complexity of the life cycle of products and of the impacts they have on the environment requires a comprehensive assessment method in order to evaluate the environmental burdens. An appropriate method that provides an interpretation throughout the whole life cycle of a product system is life cycle assessment (LCA). This is a tool to analyse the potential environmental burden of products at all stages of their life cycle; from extraction of resources through the use to final disposal, i.e., from cradle to grave (Guinée et al., 2002). In the International Organization for Standardization (ISO) 14040 standard it is defined as the "compilation and evaluation of the inputs, outputs and potential environmental impacts of a product system throughout its life cycle" (ISO, 1997, as cited in Guinée et al., 2002). Product can refer here to an actual product as well as a service.

A general methodological framework has been defined by the ISO, as shown in Figure A1, depicting the four phases of an LCA:

1. Goal and scope definition
2. Inventory analysis
3. Life cycle impact assessment
4. Interpretation

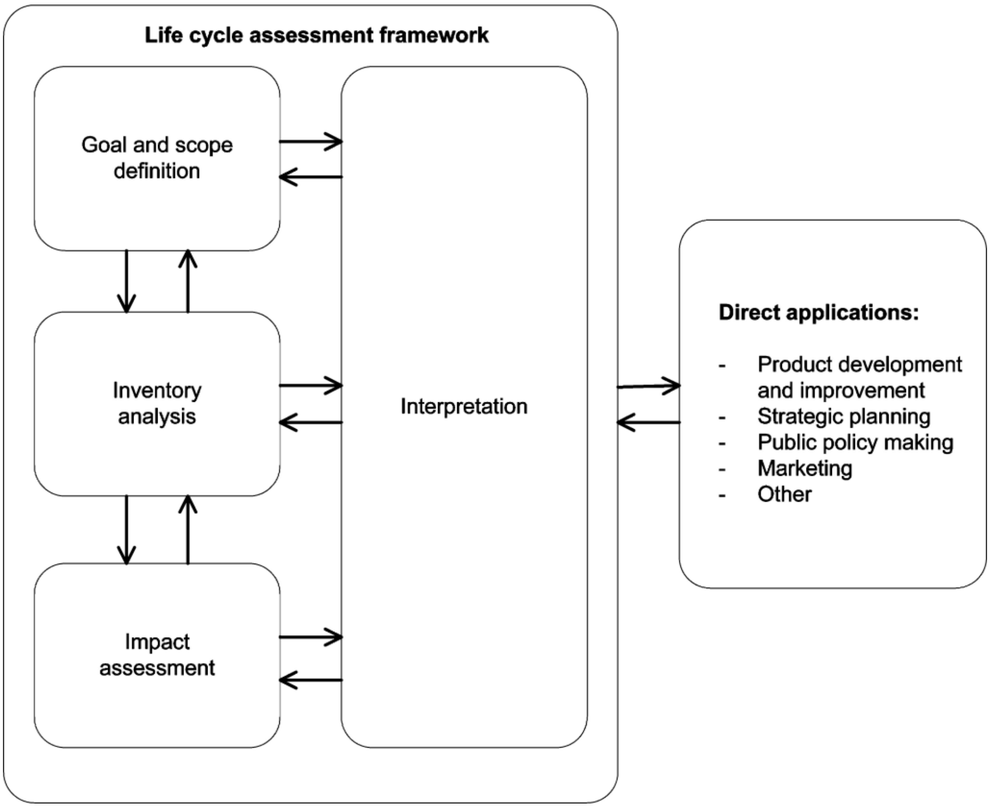
LCA is an iterative process which means that each of the four phases is performed iteratively, continuously adapting and improving the LCA.

Goal and scope definition

The goal and scope definition is the phase in which the aims and initial choices which determine the working plan of the whole LCA are made. In this phase the exact question, target audience and the intended application are formulated (Guinée et al., 2002). Moreover, the scope is defined in terms of the temporal, geographical and technological coverage and the level of sophistication is defined. Lastly, the product system(s) that is/are analysed in the study is/are described in terms of a function, FU, alternatives and reference flows. The FU is a description of the primary function(s) that are fulfilled by a product system and how much of this/these function(s) is/are considered in the LCA. The FU offers a basis to select one or more alternative product systems that are functionally equivalent and reference flows are determined for these alternatives. The reference flow is a measure of the outputs from the processes in an alternative product system which are required to fulfil the FU. How much product is required for the function is not part of the reference flow but rather of the unit process data which is part of the data collection in the inventory analysis phase (Guinée et al., 2002).

Figure A1

Phases of a life cycle assessment



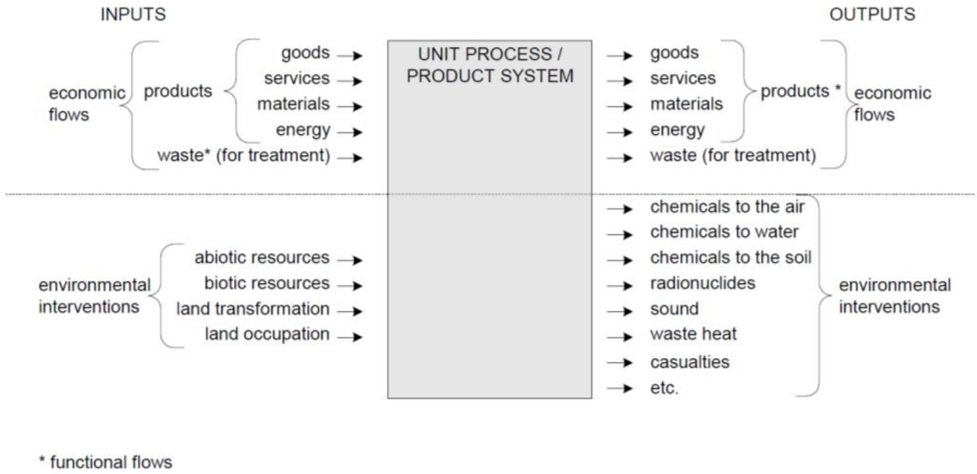
Note. Methodological framework of LCA: phases of an LCA (ISO 14040). From *Handbook on life cycle assessment. Operational guide to the ISO standards.* (p. 404), J. B. Guinée, M. Gorrée, R. Heijungs, G. Huppes, R. Kleijn, A. de Koning, L. van Oers, A. Wegener Sleeswijk, A. Suh, A. H. Udo de Haes, H. de Bruijn, R. van Duin, and M. A. J. Huijbregts, 2002, Kluwer Academic.

Inventory analysis

In this phase, the product system, or product systems in case alternatives are compared, is defined (Guinée et al., 2002). In an LCA, the world is split into biosphere (i.e., pristine environment) and Technosphere (i.e., economic activities) which is modelled by a series of connected unit processes, as depicted in Figure A2. This total system of unit processes is called the 'product system'. Defining the product system comprises setting the system boundaries, designing the flow diagrams representing the system in unit processes, collecting data for each of these processes, performing allocation for multifunctional processes and completing the final calculations to scale all flows to the FU. The latter is usually done by a model in a software program. The result of this phase is the life cycle inventory (LCI) which is an inventory table listing all emissions to the environment, resource extractions and land use.

Figure A2

Basic structure of a unit process (or product system) in terms of its inputs and outputs



Note. From *Handbook on life cycle assessment. Operational guide to the ISO standards.* (p. 117), J. B. Guinée, M. Gorrée, R. Heijungs, G. Huppes, R. Kleijn, A. de Koning, L. van Oers, A. Wegener Sleeswijk, A. Suh, A. H. Udo de Haes, H. de Bruijn, R. van Duin, and M. A. J. Huijbregts, 2002, Kluwer Academic.

Life cycle impact assessment

The LCIA is the phase in which the results of the inventory table are further processed and interpreted with regard to the potential environmental impacts (Guinée et al., 2002). The environmental impact of the emissions, resource extractions and land use contribute to different impact categories, for example, climate change, acidification or eutrophication. Therefore, a list of impact categories is defined and different models are available to relate the environmental interventions to the different impact categories. This step is called the classification. In the characterisation step, characterisation models containing characterisation factors are used to calculate the score in the individual impact categories. Characterisation factors express the relative contribution of an environmental intervention to an impact category (e.g., the global warming potential of methane is 22 kg CO_2-eq./kg). Optionally, these results can be normalised which provides the share of the results compared to a worldwide or regional total reference value for each impact category. Optionally, the impact category results can be grouped and weighted to provide a single score, which is based on societal preferences of each impact category.

Interpretation

The fourth phase of an LCA is the overarching phase of interpretation in which the results of the analysis and all choices and use of data are evaluated on their soundness and robustness (Guinée et al., 2002). Moreover, overall conclusions are drawn. In fact, this phase should be adopted during the whole assessment, not just at the end. The main goal is to align all results of the previous steps and to evaluate the results in terms of consistency and completeness but also to analyse the results, for example with regard to the robustness. It should be verified that the LCI and LCIA phases should reflect the aim of the study as defined in the goal and scope section. When this is not the case, either the LCI and LCIA phase should be partially revised, or the goal and scope section should be adapted in order to match the results. Finally, conclusions and recommendations are formulated in this phase.

Appendix B

Discussion of other battery application classification schemes and the discrepancies between them

This appendix aims to illustrate the variation in number of distinguished applications and overlap of applications or grouped applications between different application classification schemes. Applications and services are used as synonyms in this section. Bowen et al. (2019) summarise potential applications of battery systems as: arbitrage; firm capacity or peaking capacity; operating reserves and ancillary services; transmission and distribution upgrade deferrals; and black start. Arbitrage concerns the charging of a battery when energy prices are low in order to discharge during peak hours when electricity prices are high. Peaking capacity refers to supplying peak electricity demand by a battery instead of higher-cost generators. Ancillary services are a group of services to ensure reliable power system operation such as frequency regulation and voltage regulation. The electricity transmission and distribution infrastructure must be dimensioned to be able to meet peak demand, which may only occur during a couple of hours of the year. Costly investments are required to upgrade the infrastructure in order to meet a growth in peak electricity demand. Instead of upgrading the infrastructure, battery systems can be applied to meet peak electricity demand with energy that is stored from low demand periods, thereby reducing congestion, which is referred to as transmission and distribution upgrade deferrals. Finally, black start is the use of electricity from a battery to start large conventional electricity generators after a system failure. In the classification of Bowen et al. (2019), reducing renewable energy curtailment, i.e., storing renewable energy that would otherwise be curtailed, is described as an extension of the energy arbitrage service, while in other classifications it is indicated as a separate service. Moreover, frequency regulation is included in ancillary services, while in other classifications, reserve capacity and frequency regulation are indicated as distinct services. Finally, this overview of applications does not distinguish any service regarding the integration of renewable energy sources, except from the extension of arbitrage.

Another classification by Akhil et al. (2015) distinguishes: bulk energy services; ancillary services; transmission and infrastructure services; distribution infrastructure services; and customer energy management services as shown in Table B1. Bulk energy services can be referred to as arbitrage as described before. In this classification scheme, power quality and power reliability are grouped under customer energy management services, but they are also included under ancillary services as separate services (regulation. Spinning, non-spinning and supplemental reserves and voltage support). Again, also this classification does not include any service specifically related to renewable energy. Moreover, a service like voltage support is even grouped under two application groups.

Hesse et al. (2017) have classified applications into four ‘application families’, distinguishing: ancillary service; behind-the-meter; energy trade; grid support and investment deferral; and combined applications, see Table B2. Here, peak shaving, as a specific application, is grouped under the behind-the-meter application family. However, the classification by Battke & Schmidt (2015) includes this in transmission and distribution investment deferral services. The former is about reducing peak tariff for the consumer, while the goal of the latter is avoiding investments in the distribution and infrastructure network.

Table B1

Electric grid energy storage services

Bulk Energy Services
Electric Energy Time-Shift (Arbitrage)
Electric Supply Capacity
Ancillary Services
Regulation
Spinning, Non-Spinning and Supplemental Reserves
Voltage Support
Black Start
Other Related Uses

Transmission Infrastructure Services
Transmission Upgrade Deferral
Transmission Congestion Relief
Distribution Infrastructure Services
Distribution Upgrade Deferral
Voltage Support
Customer Energy Management Services
Power Quality
Power Reliability
Retail Electric Energy Time-Shift
Demand Charge Management

Note. From *DOE/EPRI Electricity Storage Handbook in Collaboration with NRECA* (p. 2), by A. A. Akhil, G. Huff, A. B. Currier, B. C. Kaun, D. M. Rastler, S. B. Chen, A. L. Cotter, D. T. Bradshaw, and W. D. Gauntlett, 2015, Sandia National Laboratories.

Table B2

Applications of storage systems classified to application families

Application Family	Application
Ancillary Service (A)	Frequency Regulation
	Black-Start
	Droop control
Behind-the-Meter (B)	PV-BESS
	Peak-Shaving UPS
	Ramping
Energy Trade (T)	Arbitrage
Grid Support and Investment Deferral (G)	Voltage Support
	EV-Grid Integration
	Balance Management
Combined Applications	Multiple Applications
	Island-/Micro-Grid
	Vehicle-to-Grid

Note. Droop control refers to controlling the rate of power that is produced by an electrical power generator according to the grid frequency. Adapted from "Lithium-ion battery storage for the grid - A review of stationary battery storage system design tailored for applications in modern power grids," by H. C. Hesse, M. Schimpe, D. Kucevic and A. Jossen, 2017, *Energies, 10*(12), p. 18.

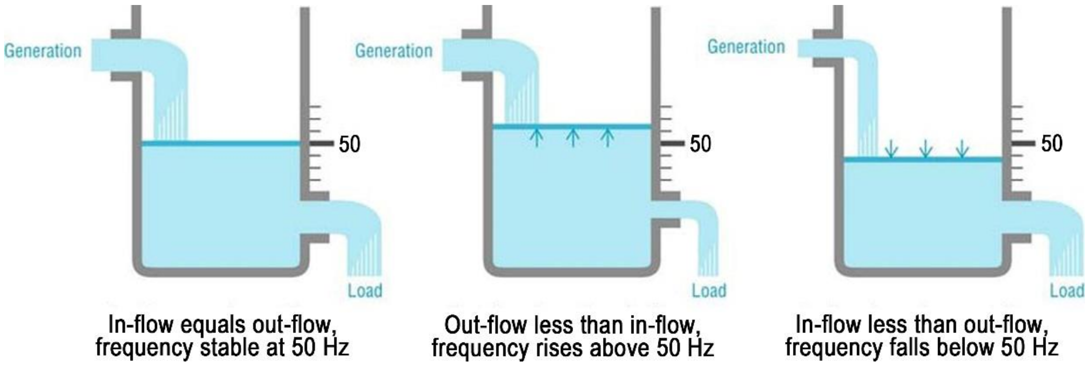
Appendix C

Explanation of the frequency balancing principle and how batteries are utilised for balancing the frequency

The frequency of the power grid could be thought of as the level of water in a bathtub including a tap and a drain, as depicted in Figure C1. If the amount of water tapped is much larger than the amount leaving through the drain, the water level will rise. Similarly, if supply of electricity suddenly becomes much larger than demand, e.g., due to a sudden increase in wind energy, or demand drops, the frequency will rise.

Figure C1

Explanation of power system frequency by using the analogy of water level in a bathtub

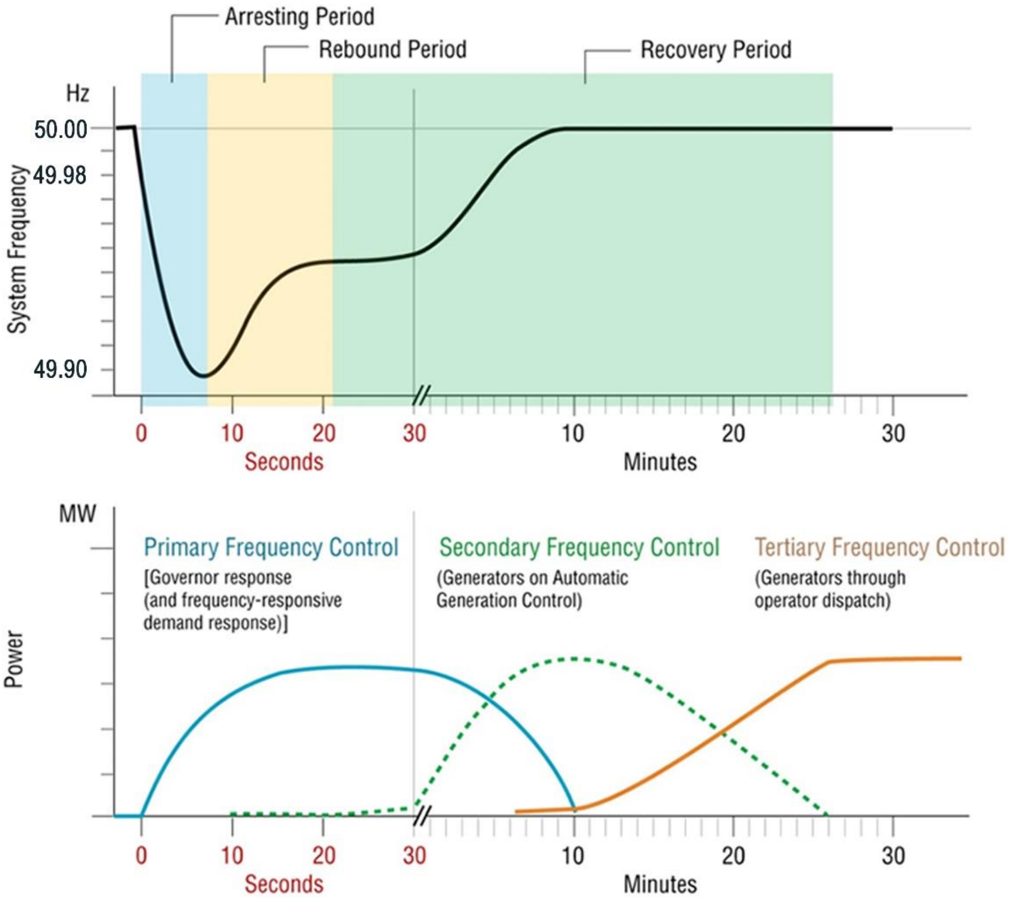


Note. Adapted from *Use of frequency response metrics to assess the planning and operating requirements for reliable integration of variable renewable generation* (No. LBNL-4142E) (p. 8), by J.H. Eto, J. Undrill, P. Mackin, R. Daschmans, B. Williams, B. Haney, R. Hunt, J. Ellis, H.F. Illian, C. Martinez, M. OMalley, and K. Coughlin, 2010, Lawrence Berkeley National Laboratory.

Over-frequency events (i.e., frequency rises above 50 Hz), are easier to handle than under-frequency events (i.e., frequency falls below 50 Hz). In case of over-frequency, which typically happens slowly, grid operators reduce output from some electricity generators (Penn State College of Earth and Mineral Sciences, 2017). Under-frequency events are often unexpected and faster. In case of under-frequency, recovery to 50 Hertz involves three phases, together known as frequency regulation or frequency control, as depicted in Figure C2.

Figure C2

The sequential actions of primary, secondary and tertiary frequency regulation



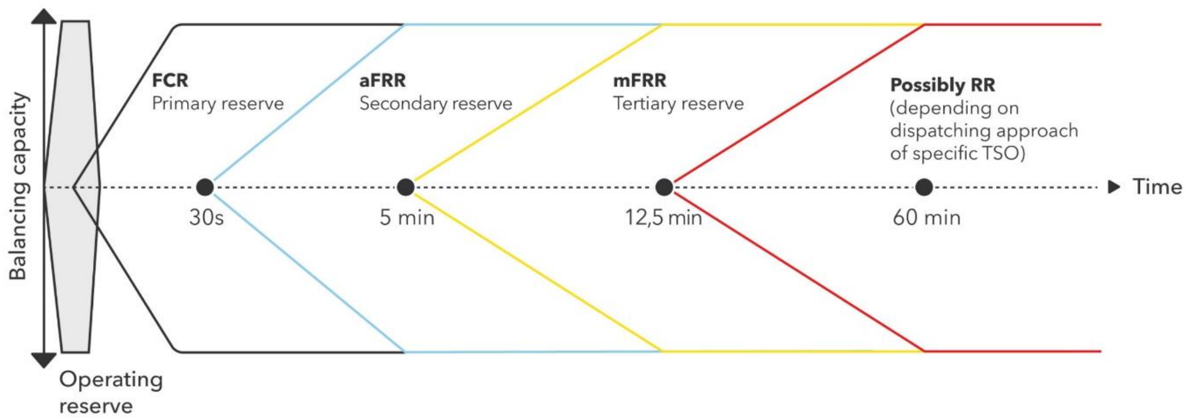
Note. Adapted from *Use of frequency response metrics to assess the planning and operating requirements for reliable integration of variable renewable generation* (No. LBNL-4142E) (p. 15), by J.H. Eto, J. Undrill, P. Mackin, R. Daschmans, B. Williams, B. Haney, R. Hunt, J. Ellis, H.F. Illian, C. Martinez, M. OMalley, and K. Coughlin, 2010, Lawrence Berkeley National Laboratory.

Frequency is balanced by the frequency regulation market. In a system without batteries, electricity generators offering frequency regulation commit to increasing or decreasing output by some amount (regulation up and regulation down) in exchange for a financial compensation. Directly after an under-frequency event, primary frequency control is triggered automatically (Penn State College of Earth and Mineral Sciences, 2017). Generators automatically adjust (increase) their output based on frequency sensors. If the frequency is not corrected to 50 Hz, secondary frequency control is triggered within tens of seconds, which is also an automatic response. Finally, tertiary frequency control is activated within a couple of minutes if primary and secondary frequency regulation does not correct the frequency. This is typically effectuated by manually adjusting the output of some power plants. In case of over-frequency, the frequency can be balanced by decreasing supply of electricity generators (which is uneconomical for power plants because they do not run optimally), but also by simulating an increase in demand by drawing electricity from the grid and store it in a battery. Likewise, when the frequency is too low, a battery could increase supply by discharging which increases frequency again. Balancing frequency by (dis-)charging is a mechanism that conventional plants are unable to provide. Even though the application of such a battery is frequency regulation, the electricity (i.e., the energy) that is discharged from the battery for frequency regulation is just electricity that is used for all kinds of devices. In that sense such a battery always offers multiple applications. Moreover, frequency regulation is also related to the energy market; a fluctuation in demand can cause a fluctuation in frequency and thus demand for regulation.

In the European Network of Transmission System Operators (ENTSO-E), which represents 42 electricity transmission system operators (TSOs) from 35 countries in Europe (ENTSO-E, 2014), three products for frequency balancing exist: frequency containment reserve (FCR), automatic and manual frequency restoration reserve (aFRR and mFRR) and replacement reserve (RR). FCR is the first response to frequency deviations and intervenes within a couple of seconds. aFRR and later on mFRR replace FCR when the deviation persists, as depicted in Figure C3 (Next Kraftwerke GmbH, 2021). Because prices are high for FCR balancing, this is the most economically interesting market for battery systems in central Europe. The price for FCR on the Dutch daily auction market was about €15/MWh in 2019, while it was only €2,50/MWh and €4/MWh for mFRR downward and upward respectively (Tennet, 2020). Because the frequency regulation provider also receives a regulation capability fee for the capacity dedicated to providing frequency regulation, the total revenues of providing frequency regulation oftentimes exceed the revenues of providing energy on the real-time market (arbitrage). Of course, this depends on the exact prices for energy and regulation, which differ per region. Furthermore, in Germany for example, batteries have the potential to cover about 90% of the demand for FCR in the German balancing market (Poplavskaya, 2018). The market for FCR is symmetric, which means that providers of FCR must procure the same volume of positive as well as negative FCR (Next Kraftwerke GmbH, 2021). With regard to a battery this means that the amount of discharged electricity for FCR is similar to the amount of charged electricity.

Figure C3

Balancing services according to ENTSO-E energy system



Note. From *What is Frequency Containment Reserve (FCR)?,* by Next Kraftwerke, 2021 (https://www.next-kraftwerke.com/knowledge/frequency-containment-reserve-fcr).

Appendix D

Working principle of a redox flow battery

To get a better understanding of the battery technology that is assessed in the illustrative case study in this research, this appendix provides a short description of the components and working mechanism of a redox flow battery.

The principle behind an RFB is the reduction-oxidation (redox) reaction of two redox couples (Alotto et al., 2013). A redox reaction is a chemical reaction in which electrons transfer between two species (atoms, ions, or molecules) (Khan Academy, n.d.). Oxidized species are the species that lose electrons, while the ones that gain electrons are reduced species (Clemente & Costa-Castelló, 2020). Whether an element loses or gains an electron is equivalent to the change in the oxidation state of the element. Redox reactions always exist of two parts; a reduced half and an oxidized half. During reduction (red) electrons are bound, while during oxidation (ox) electrons are released. This is what the RFB owes its name to, where 'flow' refers to the liquid storage medium that is pumped trough the cell.

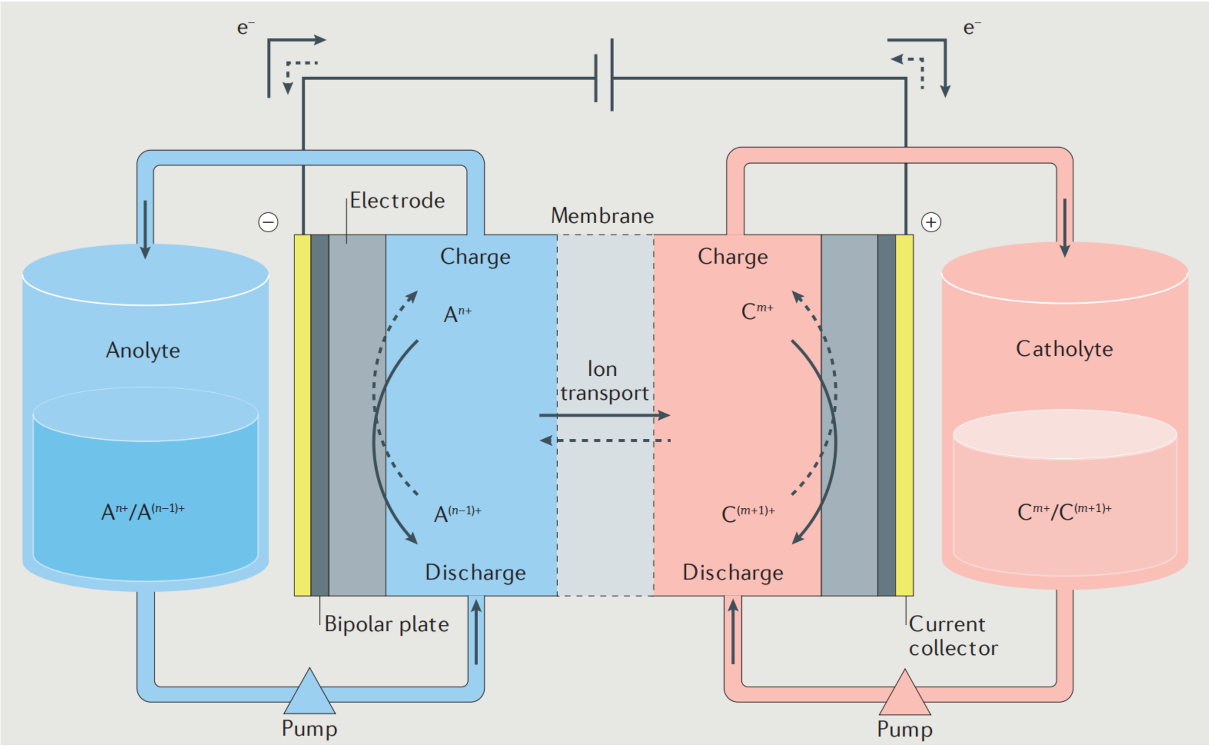
An RFB is composed of three core elements: storage tanks, cell stack and the flow or peripherical system, as shown in Figure D1. The redox active species are dissolved in a solution in a specific concentration. This solution is defined as electrolyte and has a certain energy density. One tank contains the anodic redox active materials dissolved in an electrolyte solution which is referred to as the positive electrolyte (catholyte or posolyte), while the other tank contains the dissolved anodic redox active materials which is the negative electrolyte (anolyte or negolyte) (Park et al., 2016). Both electrolytes are pumped into two closed circuits through the stack, which is composed of several cells that are stacked together and connected in series. A cell comprises electrodes, bipolar plates, current collectors and membranes.

The electrochemical conversion (redox reaction) occurs at the surface of the corresponding electrodes (Sánchez-Díez et al., 2021). At one electrode the reduction half-reaction is performed of one electrolyte that releases one electron and one ion (Alotto et al., 2013). The oxidation half-reaction is performed at the other electrode which recombines them into the other electrolyte. The ions migrate from one electrode to the other through the membrane, while electrons are forced to pass through the electrical circuit via the current collectors and therefore exchange electric energy. This way, chemical energy is converted into electric energy in case of discharging the battery and vice versa in case of charging the battery. The membrane has two functions; it separates the electrolytes and therefore prevents them from mixing with the redox species, while it allows ions to transfer to keep the system electroneutral (Clemente & Costa-Castelló, 2020).

Several cells are connected in series and form a stack (Sánchez-Díez et al., 2021). The size of the active area inside the stack, or in other words, the size of the stack determines the total power output (W) of the battery system. The amount of electrolyte that is stored in the tanks on the other hand determines the total energy capacity (Wh) of the battery. For this reason, high-solubility electrolytes are preferred to achieve high volumetric energy densities (Park et al., 2016).

Figure D1

Basic principle of a redox flow battery



Note. From "Material design and engineering of next-generation flow-battery technologies," by M. Park, J. Ryu, W. Wang, and J. Cho, 2016, *Nature Reviews Materials, 2*(1), p. 2.

Appendix E

Details of the analysis of the reviewed LCA studies

Table E1

Overview of the application, functional unit, alternatives and modelling of the use process in reviewed stationary battery LCA studies

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
Ahmadi et al. (2017)	Not specified.	One kilowatt-hour (kWh) delivered by the battery pack over its full life.	None. Only lithium-ion (Li-ion) batteries that are recovered from end-of-life electric vehicles (EV) are assessed.	**Electricity** Total electricity consumption is modelled instead of only efficiency losses because the battery system is compared to electricity delivered by natural gas peaking power plants. It is assumed that every day one cycle (charging/discharging) per day is assumed, so the total number of the battery cycling would be 3650 cycles in ten years. Daily peaking power energy delivery by a repurposed battery: 6079 kWh Use time: 10 years (3650 cycles) Round-trip efficiency: 85% Transmission efficiency: 90% $Total\ electricity\ delivered = 6079\ kWh \cdot 3650\ cycles = 22188\ kWh$ $Total\ electricity\ required = \frac{22188\ kWh}{0{,}85 \cdot 0{,}9} = 29004\ kWh$ **Battery system** Repurposed EV battery packs with an energy capacity of 6.079 kWh. It is not clearly defined in the LCI, but the amount of battery is assumed to be divided by the total electricity delivered as calculated above.	Full life exists of 8 years use in an electric vehicle and 10 years as stationary battery. Only the 10 years stationary use modelling is reviewed.

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
Baumann et al. (2017)	Wholesale arbitrage (electric time shift), increase of self-consumption (increase of photovoltaics self-consumption), frequency regulation (primary regulation) and RET firming (renewables support).	Not specified	8 different battery technologies: valve regulated lead acid (VRLA), lithium iron phosphate (LFP), lithium titanate (LTO), lithium manganese oxide (LMO), nickel cobalt manganese oxide (NCM), nickel cobalt alumina oxide (NCA), sodium nickel chloride (NaNiCl) and vanadium redox flow battery (VRFB).	**Electricity** Electricity that is lost during charge/discharge caused by internal inefficiencies of the battery system which is called energy consumption in the article. For this the DC-DC efficiency of the battery is used. A minimum, maximum and media value for the efficiency included by means of a sensitivity analysis. No further calculations are provided on how the electricity input is calculated. **Battery system** Fraction of battery per kWh of energy storage capacity. No calculation included.	
Carvalho et al. (2021)	Wholesale arbitrage (generic use scenario) and RET firming	1 kWh of energy released	Lithium-iron-phosphate (LFP), nickel-manganese-cobalt (NMC) 532 and NMC	Two scenarios were included. *Scenario A:* a generic use where the battery is charged by the grid and released energy avoids electricity from the grid in a generic moment. *Scenario B:* the battery is used to control overproduction from non-programmable renewable power plants below 1 TWh in 2030. The released	The battery-released energy avoids energy production from the grid and natural gas

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
	(Italian INECP scenario)		622 battery technologies.	energy avoids energy production from a natural gas combined-cycle power plant. **Electricity** The battery is assumed to consume 10% of its input energy, based on data by the cell manufacturer, releasing heat. Wasted electricity is accounted for as a requirement. Therefore, 0,1 kWh/kWh$_{delivered}$ is included in the use process. **Battery system** The battery is capable of delivering 83,3 kWh/kWh$_{installed}$. Therefore, the quantity of battery that was used for each kWh released by the battery is $\frac{1}{83{,}3}$ = 1,20E-03 in scenario B. In scenario A, the quantity of battery included is 2,00E-04, but a clarification of this amount is lacking.	combined-cycle power plant in scenario A and B respectively, which indicates that this is a CLCA.
Casals et al. (2017)	Wholesale arbitrage (energy arbitrage), increase of self-consumption (island installations) and RET firming (autonomous use)	1 functional kWh received by the consumer directly from the battery.	Second use of an electric vehicle battery versus a lead-acid battery.	**Electricity** Electricity lost due to efficiency losses. Not clear how this is modelled. **Battery system** Battery fraction in kg required for 1 functional kWh. However, no further calculations are included.	
Chowdhury et al. (2020)	RET firming. During periods of low demand wind and solar energy is stored, which	1 kWh of electricity generated	Lithium-manganese battery versus combined cycle gas turbine (CCGT) plants	**Electricity** Self-consumption: 0,379 MWh/MWh$_{generated}$ (Electricity uses for operation, control and management systems including losses from battery manufacturer WEMAG) This was copied from Immendoerfer et al. (2017) where it is included as “total losses per MWh$_{generated}$”	

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
	is used during peak demand.		that deliver peak demand.	0,379 MWh/$MWh_{generated}$ is derived from the efficiency of 72,5% by: $\frac{1}{0{,}725} - 1 = 0{,}379$ **Battery system** 1 lithium-manganese-oxide battery with 9,6 GW/9,6 GWh rated power and nominal energy capacity respectively The battery fraction is included to normalise to 1 kWh generated by calculating the total generated electricity over 20 years: $$1855\ GWh/year\ \cdot 20\ years = 37100\ GWh =\ 37100000000\ kWh$$ $\frac{1}{37100000000}$ battery fraction is required per $kWh_{generated}$	
da Silva Lima et al. (2021)	RET firming. Not clearly defined, but the battery is charged with renewable electricity*, which indicates an RET firming application.	The provision of 1 MWh of electricity (AC) over 20 years, with electricity from renewable sources.	Lithium-ion battery (LIB) versus vanadium redox flow battery (VRB).	**Electricity** Included electricity use during the use phase exists of efficiency losses and operational energy. Equations below are derived from the calculations made in this study. Example calculations are for the VRB. *Efficiency losses* $Efficiency\ losses = \frac{dischargable\ energy\ capacity\ [MWh] \cdot \#\ of\ annual\ cycles \cdot years\ of\ operation}{overall\ efficiency} - (dischargable\ energy\ capacity\ [MWh] \cdot \#\ of\ annual\ cycles \cdot years\ of\ operation)$ where: $Dischargable\ energy\ capacity = nominal\ battery\ energy\ capacity\ [MWh] \cdot round\text{-}trip\ efficiency \cdot DC\text{-}AC\ converter\ efficiency \cdot DoD$	* In the introduction the authors mention that the excess of energy generated at moments of low demand should be stored to balance supply and demand.

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
				Overall efficiency consists of round-trip efficiency and AC to DC and DC to AC power converter efficiency. This results in: $Dischargable\ energy\ capacity = 0{,}375 \cdot 83\% \cdot 96{,}5\% \cdot 100\% = 0{,}30\ MWh$ The authors assumed 300 cycles per year, which is based on 1 cycle per day, which is adjusted downwards to 300 cycles as a more realistic estimate due to weather conditions since the battery is charge with PV energy. $Efficiency\ losses = \frac{0{,}30\ MWh \cdot 300 \cdot 20}{83\% \cdot 96{,}5\% \cdot 96{,}5\%} - (0{,}30\ MWh \cdot 300 \cdot 20) = \frac{180\ MWh}{77{,}29\%} - 180\ MWh = 52{,}88\ MWh$ *Operational energy* Operational energy exists of the sum of electricity use for the pumps, fan, inverter, etc. This is calculated by: $Operational\ energy = hours\ of\ electricty\ consumption\ per\ cycle \cdot power\ of\ components\ for\ operation\ [W] \cdot \#\ of\ annual\ cycles \cdot years\ of\ operation$ Which results in: $Operational\ energy = 9\ hours \cdot 500\ W \cdot 300\ cycles \cdot 20\ years = 27\ MWh$ Both electricity inputs are normalised to 1 $MWh_{delivered}$ by dividing by the total of energy delivered over 20 years. Total delivered energy is calculated by: $Total\ energy\ delivered = dischargable\ energy\ capacity \cdot \#\ of\ annual\ cycles \cdot years\ of\ operation$	

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
				This results in: $Total\ energy\ delivered = 0{,}30\ MWh \cdot 300 \cdot 20 = 180\ MWh$ Therefore, 0,29 and 0,15 MWh/$MWh_{delivered}$ are included for efficiency losses and operational energy respectively. **Battery system** The battery input is normalised to 1 $MWh_{delivered}$. For example, the 7,5 kW / 37,5 kWh VRB is assumed to deliver 180 MWh over 20 years (as calculated above). Therefore $\frac{1}{180} = 0{,}056$ battery fraction and battery disposal fraction is included to deliver 1 MWh over 20 years.	
Delgado et al. (2019)	Increase of self-consumption (the battery is charged with electricity from a 3 kW PV installation, but the exact application is not defined).	No clearly defined FU. The authors mention that they chose to express the results in two FUs. First, using a per-Wh of storage capacity basis and second, a per-cell basis.	Aluminium-ion battery versus lithium-ion with NMC chemistry.	**Electricity** Environmental impacts stemming from the extra electrical energy that is required to cover charge and discharge losses is included. No clarification is included on how the electricity input is calculated. It is only mentioned that a 95% Coulombic efficiency and a cyclability of 5000 cycles was used for the Al-ion battery, while a 95% Coulombic efficiency and a cyclability of 3000 cycles was used for the Li-ion battery. **Battery system** Battery cell manufacturing and EOL for 1 Wh battery capacity	
Elzein et al. (2019)	RET firming. Not clearly defined, but the optimisation algorithm first supplies	Fulfil local consumer demand for electricity and the demand of neighbouring regions	Norman grid (France) including exports to other regions without batteries	Supply and demand are matched on a 30 minute basis where renewable energy sources are utilised as much as possible and the remainder of the demand is supplied by dispatchable technologies namely nuclear, coal and natural gas, in a way that grid operating costs are minimalised. Once for a system without battery and once with battery, the difference is assigned to the battery.	This study is a CLCA. The discharged electricity from the battery is assumed to

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
	consumer demand by renewable RESs first. The remainder of demand is supplied by batteries (if charged) and other dispatchable technologies.	retrospectively, as they were in 2017, in MWh, every 30 min, over the entire year.	versus Norman grid with batteries.	The total number of batteries (N_s) is included in the cost minimisation function. However the total number of batteries is not mentioned.	replace coal and natural gas and the marginal electricity mix is adjusted correspondingly based on an optimal operation of the battery minimising power grid operating costs for grid operators. This results in lower emissions factors of grid mix electricity. The use of a battery is stated to result in negative (i.e., saved) emissions. Moreover, temporal variability is included in the modelling of

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
Faria et al. (2014)	T&D investment deferral (peak shaving) and end-consumer arbitrage (load shifting).	Not specified for stationary use.	None, only secondary use of an end-of-life lithium-ion electric vehicle battery is assessed.	**Electricity** Efficiency losses during battery charge and discharge are included. No further calculations are included, the authors only mention 22% efficiency losses. **Battery system** For the stationary use, electric vehicle lithium-ion batteries that are no longer suitable for electric mobility are used with a nominal capacity of 13,3 kWh.	Not clear how the results for the stationary use of the battery are expressed.
Hiremath et al. (2015)	End-consumer arbitrage (energy management at community scale); increase of self-consumption; area and frequency regulation; support of voltage regulation; T&D investment deferral; and wholesale arbitrage (utility energy time-shift).	One megawatt-hour of electricity delivery (1 MWh_d).	Lithium-ion, lead-acid, sodium–sulfur and vanadium-redox-flow battery technologies.	**Electricity** The authors notice that batteries don't have independent existence in the electricity network. Batteries always exist as conjugated systems with power sources. "Hence, a decision to install batteries will directly influence the impacts of associated power source which in conjunction will govern the overall impacts arising from taking such a decision." (Hiremath et al., 2015, p. S4). Therefore, the total impacts arising from the battery manufacturing and power source conjugate system is accounted for. They state that accounting for just the electricity losses due to the battery does not help in comparing batteries with competitors, but also even to get an idea of the overall environmental impacts of delivering electricity via a battery system. So, not just efficiency losses but all electricity going through the battery (i.e., throughput energy) is included. The total electricity throughput is calculated for each application, which differs in terms of the required power rating (MW), energy capacity (MWh) and the cycle frequency. This data is based on Battke et al. (2013). $Total\ electricity\ troughput = required\ energy\ storage\ capacity\ rating\ for\ specific\ application\ [kWh] \cdot \#\ of\ cycles\ required\ for\ the\ application\ for\ 20\ years\ of\ service$ For example, for the VRFB that is utilised for the wholesale arbitrage application:	The German national electricity mix at distribution grid level was assumed to charge the batteries for all applications except increase of self-consumption. Solar PV electricity mix in Germany is used for modelling the increase of self-consumption application. This mix is also used in a sensitivity analysis to

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
				$Required\ energy\ storage\ capacity\ rating\ for\ specific\ application =$ $100\ MW \cdot 8\ hours = 800\ MWh$ $Total\ electricty\ troughput\ [MWh]$ = $800\ MWh \cdot 1\ cycle\ per\ day \cdot 365\ days \cdot 20\ years =\ 5{,}84E^6\ MWh$ Then the electricity input is calculated as: $Total\ electricity\ input = \frac{total\ electricity\ throughput\ [MWh]}{round\text{-}trip\ efficiency\ [\%]}$ For example, for the VRFB: $Total\ electricity\ input = \frac{5{,}84E^6\ MWh}{75\%} = 7{,}79\ E^6\ MWh$ Then, the electricity input per MWh delivery is: $Electricity\ input = \frac{7{,}79\ E^6\ MWh}{5{,}84E^6\ MWh} = 1{,}33\ MWh/MWh_d$ They assume X MWh required energy capacity rating for a specific application that is withdrawn from the battery. For example, for increase of self-consumption, the required power rating is 0,0025 MW and the discharge duration is 4 hours. This results in a required battery energy rating of 0,01 MWh. For this application the battery has a cycle frequency of 0,6 cycles per day and thus 4380 cycles over the 20 years lifetime, which is based on the data of Battke et al. (2013) as shown in Table 3. For a LIB with an average round-trip efficiency of 90% and operation at 80% DoD this results in 0,01 MWh · 4380 cycles · 80% DoD / 0,9 = 38,93 MWh of electricity consumption. **Battery system** The required battery energy capacity depends on the specific application and is determined as follows:	assess the effect of charging the batteries with electricity from solar only and from solar and wind only (50/50). However, for which application this is modelled is not clarified. In the Supporting Information the authors mention that the impacts from electricity losses and associated power sources during the use stage are added to the cradle-to-gate impacts. However, earlier on in the text they state

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
				$Battery\ energy\ capacity\ [MWh] = \frac{required\ energy\ capacity\ for\ application\ [MWh]}{round\text{-}trip\ efficiency^{0,5} \cdot DoD}$ The number of batteries required for 20 years of service is: $\#\ of\ batteries = \frac{20}{calendrical\ life}$ if the required number of cycles for the application is less than the battery cycle life within its calendrical lifetime. Or: $\#\ of\ batteries = \frac{\#\ of\ cycles\ for\ application}{cycle\ life\ at\ 80\%\ DoD}$ if the required number of cycles for the application is more than the battery cycle life within its calendrical lifetime. The fraction of battery included for 1 MWh electricity delivery is then calculated by: $Battery\ fraction\ per\ MWh_d = \frac{1}{total\ electrcity\ throughput\ [MWh]} \cdot number\ of\ batteries$	that the impacts of the total electricity throughput are included, which also appears from the results, since these include impacts due to electricity losses from battery use as well as impacts from the power-grid mix of all electricity used to charge the batteries.
Jenu et al. (2020)	RET firming. The battery is stated to store solar electricity which substitutes electricity from the grid.	25,3 MWh of electricity delivered with one nickel manganese cobalt oxide (NMC) lithium-ion battery.	Electricity from the battery versus electricity from the grid mix.	**Electricity** The total electricity throughput of the battery is calculated, which is assumed to replace electricity from the grid. The battery is charged by PV electricity. $Total\ electricity\ throughput =$ $nominal\ battery\ energy\ capacity\ [kWh] \cdot round\text{-}trip\ efficiency\ [\%] \cdot$ $lifetime\ full\ cycle\ equivalents$ The total electricity input from the PV system is then:	This study is a CLCA. The electricity output of the battery which is charged by PV electricity replaces

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
				$Total\ electricity\ input = \frac{total\ electricity\ throughput}{round\text{-}trip\ efficiency\ [\%]}$ *E.g., for the baseline scenario:* Equivalent full cycles are based on one full charge-discharge cycle per day over the lifetime of the battery. The lifetime of the battery results from a cycle life model which estimates the cycle life of the battery expressed in full cycle equivalents (FCE) for different combinations of DoD, average SoC during operation and operating temperature. The reference scenario (1 charge-discharge cycle per day) at a DoD of 90%, average SoC of 50% and temperature of 25 °C results in a battery lifetime of 7,7 years. Therefore, 2810 (365 · 7,7) full equivalent cycles are modelled. $Total\ electricity\ throughput = 10\ kWh \cdot 90\% \cdot 2810 = 25{,}3\ MWh$ $Total\ electricity\ input = \frac{25{,}3\ MWh}{90\%} = 28{,}11\ MWh$ **Battery system** One 10 kWh lithium-ion NMC battery.	electricity from the grid. Because the alternatives are energy systems the total electricity throughput of the battery is accounted for. However, the results are not provided for both systems, but the impacts of the electricity from the grid mix are subtracted from those of the electricity from the battery system.
Jones et al. (2019)	Not specified. A range of utilisation rates (how often storage is used) is included which represents	1 MWh of electricity output to the electricity system.	Lithium iron phosphate (LFP) battery, vanadium redox flow battery (VRFB) and liquid air energy	**Electricity** Only electricity losses based on round-trip efficiency are included in the use process modelling. Round-trip efficiency is defined here as electricity output to the grid relative to electricity input. This includes all losses of the total battery system, so also losses due to efficiency losses of the inverters, transformers and cooling. The lost electricity during use is calculated as: $Electricity\ lost\ [MWh/MWh_{delivered}] = \frac{1}{round\text{-}trip\ efficiency} - 1$	The effect of the increased utilisation rate probably has an effect on the battery cycle lifetime, which does not seem to be reflected

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
	different applications.		storage (LAES).	For the round-trip efficiency a lower and upper bound is included, which is shown in the results by means of an error bar reflecting the range in environmental impacts. **Battery system** The impacts of the production of one battery system including replacement of certain parts over a total lifetime of 30 years is normalised to 1 MWh electricity output over the total lifetime. In other words, the fraction of battery required to deliver 1 MWh of electricity is included by dividing the cradle-to-gate impacts of the battery by the total delivered electricity over the lifetime. This is explained and becomes clear from the results, however, no further calculations are shown. A range of technically and economically feasible use scenarios (i.e., applications) is represented in the modelling by using different utilisation rates. The utilisation rate refers here to the proportion of time that the battery is discharging electricity. The typical use of energy storage systems is assumed to be 5%, which corresponds to an average of one full charge-discharge cycle every three days. A higher use case is included in which the utilisation rate is set to 15%, which corresponds to an average of one full charge-discharge cycle per day. Increased utilisation increases the total electricity delivered over the lifetime of the battery and therefore decreases environmental impacts per MWh electricity output to the grid. The cradle-to-gate impacts are divided by a larger number compared to the base case because the total electricity delivered increases. But the lost electricity per MWh output remains the same since the round-trip efficiency remains the same. So the total environmental impacts per MWh output decreases.	in the modelling of battery input. The lifetime of the battery systems is solely based on calendar lifetime.
Kamath et al. (2020)	Increase of self-consumption (residential	One FU for each application:	Second-life electric vehicle battery (SLB)	**Electricity** PV generation data were used to simulate the minute by minute change in the PV generation. This was matched to hourly household appliance electricity consumption modelled with BEopt software (Building Energy Optimization	

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
	energy storage), RET firming (utility-level PV firming) and T&D investment deferral (peak shaving).	1.Delivery of electricity to meet the demand of the house with or without electric vehicle charging over the project lifetime of 10 years. 2. Delivery of one kWh of firmed PV output over 10 years, 3. Delivery of electricity to meet one kWh of peak demand over 10 years.	versus a new lithium-ion battery and SLB versus a natural gas power plant for the peak shaving scenario.	Tool). For the peak shaving application hourly net generation data were obtained from which the peak demand is determined (peak demand is denoted as any demand above 80% of the annual peak). The peak demand is modelled to be met by the battery. The baseload electricity generation used to charge the battery was assumed to be the present electricity generation without the peaking power capacity by natural gas plants. Energy losses due to round-trip efficiency losses are included in the modelling. **Battery system** Second-life battery and new lithium-ion battery cradle-to-gate GWP data were obtained from Kim et al. (2016) and Ahmadi et al. (2017). Data are normalised to 1 kWh delivered.	
Koj et al. (2015)	Frequency regulation (primary control provision).	Total primary control power demand of 551 MW which has to be provided permanently for the period of 20 years.	Battery energy systems versus coal power plants.	**Electricity** To provide primary control, the BESS requires energy from the electricity grid which is summarised as the battery's *self-consumption* of electricity. Self-consumption = 0,206 $MWh/MWh_{provided}$ (positive and negative) This value includes: additional energy required from the grid to balance the difference between positive and negative frequency regulation; cycling	The attributable must-run electricity generation of coal power plants shifts as a consequence

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
				efficiency losses (charging/discharging); consumption of auxiliary systems (e.g. battery management systems; ventilation and air conditioning of the BESS buildings); and performance-related losses by transformers etc. This is stated to be used for further calculations. Most likely the value is used to calculate the total electricity input required to deliver 551 MW over 20 years, however, further calculations are not included. The battery is assumed to be charged by an average electricity mix for the period 2015-2034 for Germany which is based on expected changes in the electricity mix. **Battery system** The production of 111 5 MW/5 MWh lithium-ion batteries is used as an input.	of providing frequency regulation which influences the environmental performance of these plants. Therefore, in the alternative product system, in which frequency regulation is provided by coal power plants, different scenarios are analysed by varying sensitive parameters like efficiency loss due to frequency regulation and required must-run capacity for the plants.
Mostert et al. (2018)	RET firming. Energy storage is	No specific FU defined, but an FU for each	Lead-acid, lithium-ion, sodium-	**Electricity** Example for the vanadium redox flow battery: $Total\ discharged\ energy =$	No FU is defined, but the FU is an

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
	used to store electrical excess energy from a renewable energy power plant.	storage technology is defined based on an equation. See comment.	sulphur, vanadium redox flow batteries and two power-to-gas plants storing synthetic natural gas and hydrogen in the gas grid and a new underwater compressed air energy storage system.	$2{,}5\ MWh\ nominal\ capacity \cdot 80\%\ DoD \cdot 1\ cycle\ per\ day \cdot 77\%\ efficiency * 365\ days \cdot 20\ years = 11240\ MWh$ $Total\ charged\ energy = \frac{11240\ MWh}{77\%} = 14600\ MWh$ However, the electricity fed-in for the use process is excess electricity of renewable sources, which is made usable only by the storage system. Therefore, it is not bearing any impacts and is considered burden free. **Battery system** One battery for which LCI data is taken from existing studies and scaled to a nominal storage energy capacity of 2,5 MWh. A DoD of 80% is assumed, so the useable capacity is 2 MWh. The included battery fraction is normalised to 1 MWh_{output} based on the total output as calculated above.	equation is included to calculate the amount of usable electricity, considering that the amount of electrical energy delivered varies from storage to storage technology according to the efficiency of the storage with the same amount of loading cycles and energy being stored. An energy input of 2 MWh, one loading cycle per day and a period of 20 years is considered. FU = 2 MWh/day · 365

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
					days · 20 years · η_{EEST} [%] where: η_{EEST} = efficiency of energy storage technology $\eta_{EEST} = \frac{electricity_{out}}{electricity_{in}}$
Oliveira et al. (2015)	Not specified.	One kilowatt hour of electricity stored and delivered from the storage system back to the grid.	Pumped hydro storage, compressed air storage, advanced lead acid, sodium sulfur, lithium-ion and nickel–sodium-chloride batteries.	**Electricity** The electricity input is stated to be directly tied to the charge/discharge efficiency of the technology. The total lifetime energy delivered for each storage technology is calculated by taking into account the expected life time, capacity factor and capacity of the installation. The power rating, total capacity and energy capacity factors were combined to determine the number of cycles and life time. However, the authors refrained from providing any calculations. **Battery system** The total mass of a battery system to provide 1 kWh of electricity is calculated based on the specific energy (Wh/kg) of each technology. Again, no further calculations are provided.	
Peters & Weil (2017)	Increase of self-consumption. The battery stores electricity from a rooftop PV panel over daytime and	1 kWh of storage capacity	Aqueous hybrid ion battery (AHIB), lithium-iron phosphate with graphite anode (LFP-C), lithium-iron	**Electricity** The impacts due to using the battery are assumed to be caused by the impacts related to the electricity loss caused by internal inefficiencies of the battery, i.e., efficiency losses. A simplified approach based on average load assumptions (i.e., average number of cycles per day) is used to obtain an idea of the potential use phase impacts.	The stated FU is 1 kWh of storage capacity. However, the use phase impacts are provided per $MWh_{delivered}$.

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
	discharges during night-time.		phosphate with lithium-titanate anode (LFP-LTO) and a sodium ion battery (SIB)	It is assumed that one full charge-discharge cycle is required per day for both applications, resulting in a total of 7200 cycles over the assumed lifetime of the application of 20 years. Exact calculations are not included. The example calculation given below is based on the statement that only efficiency losses are included and the battery parameters provided in the Supplementary Information. *Example calculation of electricity input for the AHIB:* The AHIB battery with a nominal energy capacity of 26 kWh operates at 83% efficiency under the circumstances of the modelled application and shows an effectively available capacity of 80% DoD, which means 20,8 kWh. All batteries are assumed to be operated at 80% DoD. $MWh_{delivered} = nominal\ battery\ energy\ capacity\ [kWh] \cdot DoD \cdot round\text{-}trip\ efficiency \cdot \#\ of\ cycles$ $MWh_{required} = nominal\ battery\ energy\ capacity \cdot DoD * \#\ of\ cycles$ $Electricity\ lost\ [MWh/MWh_{delivered}] = \frac{MWh_{required} - MWh_{delivered}}{MWh_{delivered}}$ $MWh_{delivered} = 26\ kWh\ \cdot 80\% \cdot 83\% \cdot 7200\ cycles = 124\ MWh$ $MWh_{required} = 26\ kWh \cdot 80\% \cdot 7200\ cycles = 150\ kWh$ $Electricity\ lost = \frac{150-124}{124}\ = 0{,}21\ MWh/MWh_{delivered}$ **Battery system** The lifetime of the battery is assumed to be limited by the cycle lifetime only, the calendric lifetime is not considered. The batteries will be limited by their cycle life and require therefore one or more battery replacements are required over the lifetime of the application (20 years). However, exact calculations are not included. The example calculation given below is based on the battery parameters provided in the Supplementary Information.	Therefore the calculations for the use phase are based on the latter. 7200 cycles instead of 7300 (1 cycle per day · 165 days · 20 years = 7300 cycles) is not explained. The authors mention that proper modelling of battery operation would require the optimisation of the battery system configurations for typical load profiles for different applications and under consideration of specific dynamic load

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
				Example calculation of battery fraction for the AHIB: $Number\ of\ batteries\ required = \frac{7200\ cycles}{4000\ cycle\ life} = 1{,}8\ batteries$ $Required\ battery\ fraction = \frac{1{,}8}{124301\ kWh_{delivered}} = 1{,}45E^{-05}\ battery/kWh_{delivered}$	profiles. However, this was out of the scope of this study.
Pucker-Singer et al. (2021)	Increase of self-consumption from photovoltaics and wholesale arbitrage.	1 kWh of battery capacity	Use cases (UC) with and without Li-ion batteries (NMC 111 and NCA) are compared. Pilot project 1: UC1: Electricity consumption of a village in Slovenia with grid and PV energy without battery versus UC2: grid and PV energy with battery system.	**Electricity** Battery and PV system data and monitoring data from their operation from the pilot projects were collected and implemented in a technical grid simulation (which is not publicly available) to calculate the annual energy balance for the different UCs. Total energy losses are included, which are based on round-trip efficiency, but also auxiliary energy demand for cooling and heating of the battery container and the operation strategy of the battery. No detailed calculations are included. **Battery system** Case 1: 150 kW/552 kWh lithium-ion battery Case 2: 50 kW/222 kWh lithium-ion battery The included battery fraction is scaled to 1 kWh battery capacity.	Hourly data for consumed and replaced grid mix electricity emission factors is used to reflect generation mix changes over the year and during daytime. The performed LCA is a CLCA since the electricity supplied to the grid by the battery is assumed to replace electricity from the grid and therefore the

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
			Pilot project 2: Electricity consumption of a factory in Spain. The following use cases are compared: UC0: no PV, no battery UC1: PV UC2: PV + battery (without charging from grid) UC3: PV + battery (with charging from grid at low-tariff times) UC = use case PV = photovoltaics		emissions are included as negative emissions.
Rahman et al. (2021)	Wholesale arbitrage (bulk energy storage), T&D investment deferral, frequency	1 MWh electricity delivered from the energy storage system	Sodium-sulfur, lithium-ion, valve-regulated lead-acid, nickel–	**Electricity** Electricity charged during use phase, which is calculated as follows: $Electricity\ delivered = rated\ power\ [MW] \cdot discharge\ duration\ [h] \cdot cycles\ per\ year * power\ conversion\ system\ efficiency\ [\%] \cdot lifetime\ [years]$	

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
	regulation and voltage regulation (support of voltage regulation).		cadmium and vanadium redox flow batteries.	The rated power, discharge duration and cycles per year are for a specific application. $Electricity\ charged = \frac{electricity\ delivered}{round\text{-}trip\ efficiency\ [\%] \cdot power\ conversion\ system\ efficiency\ [\%]}$ Example for the vanadium redox flow battery in the wholesale arbitrage scenario: $Electricity\ delivered = 50\ MW \cdot 5\ h \cdot 365\ cycles \cdot 95\% \cdot 20\ years = 1733750\ MWh_{delivered}$ $Electricity\ charged = \frac{1733750\ MWh}{75\% \cdot 95\%} = 2433333\ MWh$ **Battery system** Battery mass fraction required to deliver 1 MWh, which is calculated by: $m = \frac{E_I}{E_d}$ where: - m = total mass of battery (kg) - E_I = installed battery capacity (MWh) - E_d = energy density (MWh/kg) Different methods from literature were used to estimate the mass fractions for the redox flow battery because the power (MW) and energy capacity (MWh) can be scaled separately from each other.	
Richa et al. (2017)	Not specified	A stationary energy storage system, delivering 150 kWh of energy on a daily basis for 20 years	Lead-acid battery system.	**Electricity** Only the internal energy efficiency of the battery has been included in the calculation of the use phase losses. Other losses resulting from electricity transmission efficiency and efficiencies of charger and inverter are not included. The charge-discharge electricity losses from operation are estimated by:	Only case 2 has been considered. Case 1 reflects an expanded system to include the

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
				$E_{loss} = \sum_{k}^{l_c} (C_s \cdot PS_k \cdot (1 - \eta_k) \cdot DoD_k)/\eta_k$ where: - C_s = energy storage capacity of the battery at the start of stationary use - PS_k = percent residual capacity of the stationary battery at beginning of a given cycle k - η_k = round-trip efficiency of the battery at cycle k - DoD_k = depth-of-discharge of stationary battery during that cycle - l_c = cycle life of retired EV cells in stationary energy storage system - k = charge-discharge cycle Cycle life has been varied from 365 (1-year life span) to 3650 (10-year life span) charge–discharge cycles. The round-trip efficiency is assumed to be 80% at beginning of the stationary service life and declines linearly, reaching 65% at end-of-life. The depth of discharge of the battery lies in the range of 33% to 42%. For example for the first cycle: $E_{loss} = \frac{450\ kWh \cdot 100\% \cdot (1-0{,}8) \cdot 42\%}{80\%} = 47{,}25\ kWh$ **Battery system** Refurbished lithium-ion packs from a EOL electric vehicle to build a single stationary battery system storing 450 kWh energy, including steel casing and battery management system.	"avoided product system" for a lead-acid battery that provides equivalent functionality in the stationary energy storage use.
Schram et al. (2019)	Increase of self-consumption. Rooftop PV energy is stored in a battery system.	1 kWh	Three policy scenarios applied in eight different countries are compared: baseline; all-electric-no	The change in GHG emissions from battery operation in the scenarios with PV and battery storage is calculated by: $GHG_{batt,annual,j} \sum_{t=1}^{t=8760} (E_{charge,t,j} \cdot HEF_{con,t,j}) - \sum_{t=1}^{t=8760} (E_{discharge,t,k} \cdot HEF_{con,t,j}) + GHG_{batt,manufacture}$	Grid electricity is replaced by PV electricity from the battery, which indicates that this is a CLCA.

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
			sharing; and all-electric-sharing, which are applied to a typical EU community. Both all-electric scenarios include the application of batteries (type is not defined) for enhanced self-consumption of PV electricity.	where: - t = hour of the year - j = country - $E_{charge,t,j}$ = hourly electricity charge into the battery - $E_{discharge,t,k}$ = hourly electricity discharged from the battery - $HEF_{con,t,j}$ = hourly emission factors for electricity consumption - $GHG_{batt,manufacture}$ = total emissions resulting from manufacturing of the battery The first sum represents the emissions of grid electricity that would have been displaced by the PV electricity that is now charged into the battery. The second sum represents the avoided emissions from grid electricity due to discharging the battery. The third sum represents emissions from manufacturing the battery system, which are taken from Litjens et al. (2018b).	
Schulz-Mönninghoff et al. (2021)	Increase of self-consumption (renewable energy integration of PV (PV)), end-consumer arbitrage (peak shaving (PS)) and end-consumer power	The energy consumption of the DC micro-grid in the production facility over a period of 10 years.	Single use is compared to multi-use cases. Four use cases: 1. increase of self-consumption 2. increase of self-consumption	**Electricity** The use process includes efficiency losses and constant self-consumption which covers the energy demand for lighting, cooling and battery management system. Efficiency refers to the charge and discharge efficiency, which is assumed to be constant at 95%. This results in an overall efficiency of 90,3% (95% · 95% = 90,3%). 3 multi-use cases are assessed in which the battery system serves two or three applications simultaneously. This is reflected in the model by an adjustment of the available battery energy capacity for storage of PV electricity and of the number of cycles.	This is a CLCA because the output of electricity from the battery system that stores PV electricity is assumed to avoid grid mix electricity resulting in

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
	reliability (uninterrupted power supply (UPS)).		+ peak shaving 3. increase of self-consumption + uninterrupted power supply 4. increase of self-consumption + peak shaving + uninterrupted power supply	Energy flow simulation software TOP Energy is used to simulate when and how much of the electricity from the PV system is charged into the battery. The objective function is to minimise the overall system costs. This results in an operational profile of the battery for each specific use case from which the number of cycles is defined. Total efficiency losses are calculated by: $Total\ efficiency\ losses\ [kWh] = efficiency\ losses\ per\ cycle\ [\%] \cdot charging\ cycles\ per\ year \cdot available\ battery\ energy\ capacity\ [kWh] \cdot lifetime\ [years]$ The constant self-consumption is assumed to be 4 kW. *Example for the single-use case:* $Total\ efficiency\ losses = 9{,}7\% \cdot 123{,}2 \cdot 1113\ kWh \cdot 10\ years = 133008\ kWh$ $Total\ self\text{-}consumption = 4\ kW \cdot 24\ hours \cdot 365\ days \cdot 10\ years = 350400\ kWh$ **Battery system** 1 battery system consisting of 112 retired plug-in hybrid electric vehicle lithium-ion batteries with nickel manganese cobalt oxide (NMC) cells, which results in a 1230 kW/1113 kWh battery system.	negative emissions. The authors modelled a future German grid mix taking into account the degree of the expected decarbonisation of the grid mix by 2030. Only the electricity discharged from the storage capacity that is available for storing PV electricity (so the total energy storage capacity minus reserved capacity for the other one or two applications) is assumed to

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
					replace grid mix electricity. The benefits of electricity discharged for the other two applications are stated to occur outside the scope of the system and therefore are not included in the model as avoiding grid mix electricity. Both uninterrupted power supply and peak shaving are assumed to only improve economic profitability of the energy system, they do not lead to environmental benefits.
Spanos et al. (2015)	End-consumer arbitrage (demand	Not specified	Three battery technologies: valve-	**Electricity** Total electricity lost due to efficiency losses over the battery's lifetime is included as calculated by:	FU is not defined but is probably 1 kWh

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
	charge reduction for residential and commercial loads)		regulated lead-acid (VRLA); flow-assisted nickel–zinc (NiZn) and; non-flow manganese dioxide–zinc (MnO_2/Zn).	$Electricity\ lost\ (kWh) = throughput\ (kWh)\ (\frac{1}{\eta} - 1)$ where: - η = DC/DC round-trip efficiency Throughput refers here to total electricity delivered: $Throughput\ (kWh) = \frac{1}{N}\sum_{i=1}^{N} E_{Nom} \cdot DoD_i \cdot C_i)_{DoD_a}^{DoD_b}$ where: - E_{Nom} = nominal battery energy capacity (kWh) - DoD_i = specific depth of discharge being considered (%) - C_i = cycles to failure to the specific depth of discharge - DoD_i = discrete DoD measurement provided by battery manufacturer over the range of DoD_a to DoD_b **Battery** The required mass of the battery is calculated by: $m = \frac{E}{d\eta_{inverter}\frac{DoD}{100}}$ where: - *E* = required battery electricity output (Wh) - *d* = specific energy (Wh/kg) - $\eta_{inverter}$ = inverter's efficiency (%) - DoD = the depth of discharge (%) Battery mass must be sized to achieve 350 kWh electricity output under a 71,9% DoD of 8 h capacity (slow discharge condition), or equivalently, 100% DoD of 2 h capacity (fast discharge condition).	of electricity delivered since the authors state that environmental impact results are normalised by kWh of electricity throughput (total electricity delivered) over the battery's lifetime is a more meaningful metric of comparison than normalising per Wh of storage capacity.

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
T. S. Schmidt et al. (2019)	Wholesale arbitrage, area and frequency regulation, T&D investment deferral, end-consumer arbitrage (demand peak shaving) and increase of self-consumption.	Storing one kWh of electricity in the battery systems.	Vanadium redox flow (VRF), valve-regulated lead-acid (RLA) and lithium-ion batteries. Among lithium-ion batteries four chemistries were differentiated: lithium iron phosphate (LFP), lithium nickel manganese cobalt oxide (NMC), lithium nickel cobalt aluminum oxide (NCA) and lithium titanium oxide (LTO). Moreover, 3 different geographies are assessed.	**Electricity** Electricity losses associated with the battery systems' round-trip efficiency losses are included. The total electricity throughput and therefore the total losses over the lifetime are different per application. The total electricity throughput is calculated based on the number of equivalent full cycles for each application (see battery system section below). However, the efficiency losses per kWh delivered are the same for all applications and therefore the modelling is the same for all applications. $Efficiency\ losses\ [kWh/kWh_{delivered}] = \frac{1}{\eta} - 1$ where: - η = round-trip efficiency of battery system (%) **Battery system** In order to fulfil the application specifications throughout the entire lifetime a certain battery energy capacity (i.e., battery size) is required. The total required nominal battery energy storage capacity for each application is determined as: $C_{bat} = \frac{C_{app}}{DoD \cdot \eta^{0,5} \cdot CR_{eol}}$ where: - C_{bat} = the required installed energy capacity battery system (kWh) - C_{app} = storage energy capacity required for the application (kWh) as defined by the energy delivered per cycle (kWh) - DoD = depth of discharge as a percentage of installed capacity (%) - $\eta^{0,5}$ = discharge efficiency calculated based on round-trip efficiency η (%) - CR_{eol} = end-of-life energy capacity retention as a percentage of initially installed battery energy capacity (%). Then the required fraction of this battery to deliver 1 kWh over the lifetime is determined as:	Results are provided per $kWh_{delivered}$, which does not correspond to the FU of 1 kWh battery energy storage capacity. The example calculations included here are based on the former.

<table>
<tr><th>Authors</th><th>Battery system application[a]</th><th>FU</th><th>Alternatives</th><th>Use process modelling</th><th>Comments</th></tr>
<tr><td></td><td></td><td></td><td></td><td>$$Battery\ fraction\ for\ 1\ kWh_{delivered} = \frac{1}{kWh_{app} \cdot lifetime}$$
where:
- kWh_{app} = annual electricity delivered from battery (kWh/year)
- lifetime = lifetime of the battery system, which is held constant at 20 years in this study

The annual electricity delivered from the battery is calculated by:

$$kWh_{app} = energy\ delivered\ per\ cycle\ [kWh] \cdot equivalent\ full\ cycles\ per\ year$$</td><td></td></tr>
<tr><td>Vandepaer et al. (2019)</td><td>RET firming. Storage is used to store surplus electricity which is fed back into the electricity grid system when required.</td><td>The integration of surplus electricity from variable renewable energy sources (VRES) via batteries resulting in the supply of 1 megawatt-hour (MWh) of electricity for the 2030 Swiss electricity system.</td><td>2030 Swiss electricity grid with lithium metal polymer (LMP) batteries versus Swiss grid with lithium-ion (Li-ion) batteries.</td><td>Electricity
The electricity from variable renewable energy sources would be curtailed in the absence of batteries. Therefore, the production of the charging electricity is not included in the product system. 1 MWh electricity discharged from the battery is assumed to replace 1 MWh of electricity in a 1:1 ratio from and adjusted marginal electricity mix to 2030 and 2040 (without VRES and combined heat and power plants). Scenarios on future grid mixes are used from the Swiss TIMES Energy Model (STEM).

Cycle lifetime, calendric lifetime, efficiency and DoD are taken into account to define the output of the batteries. However, calculations or equations for total output are not specified. Moreover, these performance parameters are assumed to improve by 10% every 20 years

Battery system
6 MWh of total battery capacity is assumed to be included in the Swiss electricity grid with a total electricity supply of 64126 GWh and 65817 GWh in 2030 and 2040 respectively.</td><td>This study is a CLCA. Batteries enable the use of electricity that is otherwise curtailed, which is assumed to cause a decrease in the demand for electricity from alternative production sources. The electricity supplied by the batteries is assumed to displace grid mix electricity a</td></tr>
</table>

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
					1:1 substitution ratio.
Weber et al. (2018)	RET firming (renewables support)	The provision of 1 MWh of electricity by the battery over the 20 year lifetime of a hypothetical renewables support application.	Vanadium redox flow battery (VRFB) versus lithium-ion battery (lithium–iron-phosphate based cathode with lithium titanate anode, i.e., LFP-LTO).	**Electricity** Only the electricity lost (dissipated) due to internal inefficiencies is accounted for, not the impacts associated with the electricity discharged by the battery. Calculation of electricity lost based on the stated parameters: $MWh_{delivered} = nominal\ battery\ energy\ capacity\ [MWh] \cdot DoD \cdot round\text{-}trip\ efficiency$ $MWh_{required} = nominal\ battery\ energy\ capacity \cdot DoD$ $Electricity\ lost\ [MWh/MWh_{delivered}] = \frac{MWh_{required} - MWh_{delivered}}{MWh_{delivered}}$ For example for the VRFB: $MWh_{delivered} = 8{,}30\ MWh \cdot 95\% \cdot 75\% = 5{,}91\ MWh$ $MWh_{required} = 8{,}30\ MWh \cdot 95\% = 7{,}89\ MWh$ $Electricity\ lost = \frac{7{,}89 - 5{,}91}{5{,}91} = 0{,}33\ MWh/MWh_{delivered}$ **Battery system** To provide 6 MWh of energy storage capacity which is required for the RET firming application, a nominal capacity of 8,3 MWh and 7 MWh are required for the VRFB and LFP-LTO battery respectively (no further details on the required nominal capacity are provided). The RET firming application is assumed to require an average of 1,12 cycles per day over 20 years. This results means a total of 8176 charge-discharge cycles over the application lifetime of 20 years.	

Authors	Battery system application[a]	FU	Alternatives	Use process modelling	Comments
				VRFB The VRFB has a cycle life of 10000 cycles and a calendric life of 10 years, which only applies to the cell stack. Therefore one battery is required to serve the application over 20 years lifetime; only the cell stack is assumed to be replaced after 10 years due to its lifetime of 10 years. $MWh_{delivered}\ over\ 20\ years =$ $6\ MWh\ effective\ energy\ capacity \cdot 1{,}12\ cycles \cdot 365\ days \cdot 20\ years =$ $49056\ MWh$ 319948 kg battery mass is required for a 1 MW/8,3 MWh VRFB battery The required battery mass to deliver 1 MWh over 20 years: $\frac{319948\ kg}{49056\ MWh_{delivered}} = 6{,}52\ kg/MWh_{delivered}$ *LFP-LTO* Effective energy density = 37,9 Wh/kg = 3,79E^{-05} MWh/kg Required battery mass for a 1 MW/6,97 MWh LFP-LTO battery: $\frac{6{,}97\ MWh\ nominal\ energy\ capacity}{3{,}79E^{-05}\ MWh/kg} = 183905\ kg$ The required battery mass to deliver 1 MWh over 20 years: $\frac{183905\ kg}{49056\ MWh_{delivered}} = 3{,}75\ kg/MWh_{delivered}$ The calendric lifetime of the battery cells of 17,5 years. So part of the cells has to be replaced over the 20 years. For this 0,36 kg cells are assumed to be replaced per MWh delivered over 20 years.	

Note. [a] Translated to the application classification by Battke & Schmidt (2015). In case of translated applications the original application name as mentioned by the authors is included between brackets.

Appendix F

Lifetime versus specified period in FU

Instead of defining the FU in terms of electricity delivered “over the battery’s lifetime” another option would be to define a certain period over which the application has to be served, for example 20 years. However, this results in the same environmental impact results when these are expressed per MWh delivered. The battery lifetime determines how many batteries are required in the specified period of time, which depends on battery characteristics and is part of LCI phase. For example, if the lifetime of a 1 MWh battery system is 10 years and it cycles once a day, then this battery delivers 3650 MWh over its lifetime, assuming no losses and a DoD of 100%. To deliver 1 MWh of electricity for this application 1 / 3650 battery fraction is required. If a period of 20 years is defined over which the battery should serve the application this means that two battery systems are required based on the battery’s lifetime of 10 years. In 20 years these two batteries deliver 7300 MWh. To deliver 1 MWh of electricity 2 / 7300 = 1 / 3650 battery fraction is required. In conclusion, whether a fixed period is defined or “over the battery’s lifetime” is defined in the FU, eventually the results are the same when these are expressed per MWh delivered.

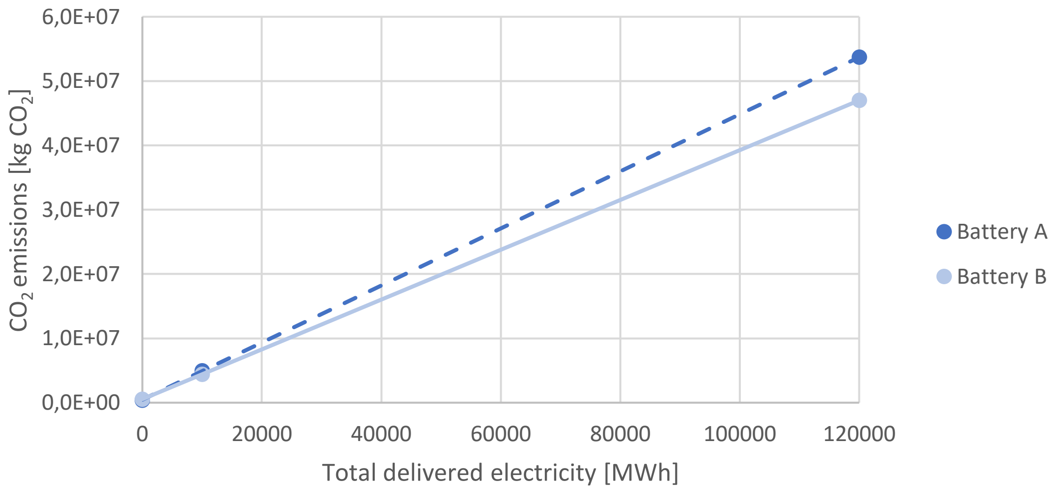
Appendix G

Expressing LCIA results per MWh

Most LCA studies express the environmental impact results for 1 MWh delivered electricity. This is perfectly fine to compare alternatives within the study, since these are assumed to provide the same application and have to provide the same total electricity output. However, expressing the results per MWh delivered electricity might give the impression that these results can be compared between studies that express the results per MWh. This way there is a risk that results of different LCA studies are compared in meta-analysis studies without putting attention to the conditions and assumptions for which the battery is assumed to be used. This oftentimes happens because it is not clearly stated what the product is used for and how this is modelled. The higher the amount of total electricity delivered, which depends on the application of the battery which requires a certain number of cycles, the lower the impacts per MWh, as shown in Figure G1. The numbers used in this figure are only illustrative. The emissions of the batteries being cycled 50 times per year and delivering 10000 MWh in total are 498 and 440 kg CO_2/MWh for battery A and B respectively which have different characteristics. When the batteries perform 600 cycles per year and deliver 120000 MWh in total the emissions are 448 and 392 kg CO_2/MWh. This is due to the fact that the C2G impacts are divided by a larger amount of total delivered electricity, while the impacts resulting from efficiency losses are constant per MWh delivered. Different cycle frequencies correspond to different applications. Therefore, next to properly defining the FU, it is also important to report the application characteristics for which the battery is used in the research since this defines the total electricity delivered. This increases the transparency and the ability to judge the comparability of studies which helps to prevent inappropriate comparisons between studies.

Figure G1

Illustrative CO_2 emissions of two battery technologies at different amounts of total delivered electricity as a result of different cycle frequencies



Appendix H

Temporal resolution in modelling charging electricity

The charging electricity in LCA studies is commonly modelled as if the battery is charged with electricity from an annual aggregated generation mix (e.g., market for electricity datasets in the ecoinvent database) or from renewable energy technologies only. Modelling the charging electricity by using an average electricity mix of a specific country or region might not be adequate. The marginal electricity mix, and the corresponding emissions, vary with time of day because the proportion of technologies that generate electricity varies. This means that each kWh electricity does not have the same environmental impacts over time. Since a battery charges at certain moments of the day, the frequency and duration of charging determine the exact electricity input. Therefore, using an average electricity mix might over- or underestimates the emissions of the charging electricity. This is similar to the case of electric vehicles (EVs), where the environmental impacts of charging (i.e., the use phase) strongly depend on the electricity mix during the charging session. Therefore, some scholars state that there is a need to overcome this issue and developed approaches to integrate a temporal resolution (e.g., hourly) into the modelling of electricity generation that is used as input for the use process of product systems in environmental assessments. However, this only matters for product systems where the use phase has a considerable or significant contribution to the overall impacts.

Vuarnoz et al. (2018) proposed two ways to integrate hourly life-cycle conversion factors in LCAs of energy systems in buildings. Moreover, Vuarnoz and Jusselme (2018) developed hourly GHG emission factors for the Swiss grid. They illustrate the over- and underestimation of climate change impacts and cumulative energy demand by using mean annual data compared to using hourly data with a case study of a building. Baumann et al. (2019) developed an hourly-defined LCA (HD-LCA) approach to capture the environmental profile of electricity supply in an hourly resolution, which they applied to the case of EVs. A charging session during hours when electricity generation causes high greenhouse gas emissions results in 138% higher impacts on global warming than a session during hours when more renewables are part of the mix.

However, an important difference between an EV and a grid-connected stationary battery system is that the moment of charging of an EV can be shifted, i.e., the moment of charging is a factor that can be in influenced by the user. This does not apply to the case of stationary batteries where the points in time of charging are determined by the operational profile required for a specific application. These cannot be adjusted because that would imply serving a different application. The precise modelling of electricity by integrating a time resolution is therefore only relevant when the aim is to model the environmental impacts of the use phase of a battery system as accurately as possible. To compare battery systems, which is commonly the aim of LCA studies, it is less relevant because the batteries are used for the same application and therefore have the same operational profile. Moreover, the exact timing of charging might be different on each day and therefore the marginal electricity mix at those moments might be different. Hence, for comparative LCA studies, using an average electricity mix background dataset is adequate since the variation in electricity generation sources that are in the electricity mix over time is averaged out.

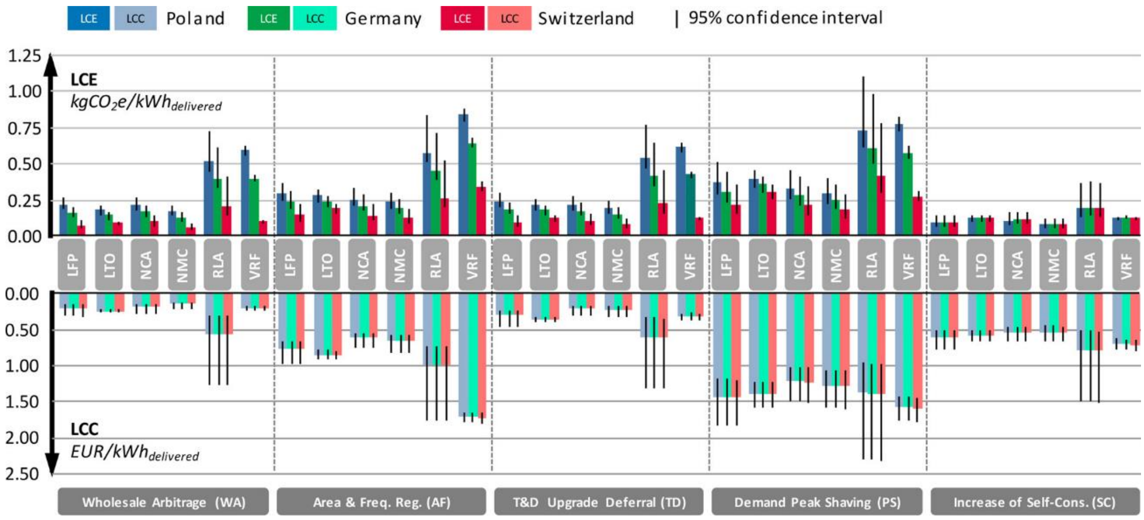
Appendix I

Explanation why applications should not be cross compared

Like Hiremath et al. (2015), T. S. Schmidt et al. (2019) show results of different applications next to each other as depicted in Figure I1. Moreover, Weber et al. (2018) show impact results of the assessed batteries charged with different electricity sources next to each other as shown in Figure I2. In their analysis, none of these authors compare the applications to each other but only compare different battery technologies within the application scenarios and conclude that the relative ranking of battery technologies is different for the different applications. For example, in the study by Weber et al. (2018), the vanadium redox flow battery (VRFB) scores better than the lithium-titanium-oxide (LTO) battery when it is charged with renewable electricity, since the emissions of renewable electricity are lower. The contribution of the C2G impacts becomes relatively higher and the contribution of the efficiency losses of the VRFB becomes relatively lower compared to charging the battery with grid mix electricity, despite the lower round-trip efficiency of the VRFB. When the batteries are charged with electricity with higher emissions, the relevance of efficiency losses increases and the LTO scores better than the VRFB. These figures may imply that the results can be compared across applications as if they are alternatives. From these figures it seems like one could conclude that batteries could better be charged with renewable electricity instead of electricity from the grid. However, they actually represent different applications. Batteries cannot be charged with renewable electricity for all applications; the application determines which electricity the battery is charged with. The rationale behind charging a battery with PV or wind energy is to store renewable electricity, either for RET firming, RET arbitrage, or RET smoothing. There is little reason to charge a battery with grid mix electricity to store this electricity for reasons of time-shifting, except from wholesale arbitrage. A battery charged with electricity from the grid is likely to be utilised for applications such as frequency regulation or T&D investment deferral because these applications provide revenue or decrease investment and therefore save money. However, in practice, renewable electricity is oftentimes also cheap electricity and therefore there is an overlap between applications; in this case wholesale arbitrage and RET arbitrage. Therefore, even though it is not incorrect to depict the results of different applications in one figure to prevent inefficient use of space, it is prudent to explicitly note under the figure that applications cannot be cross compared.

Figure I1

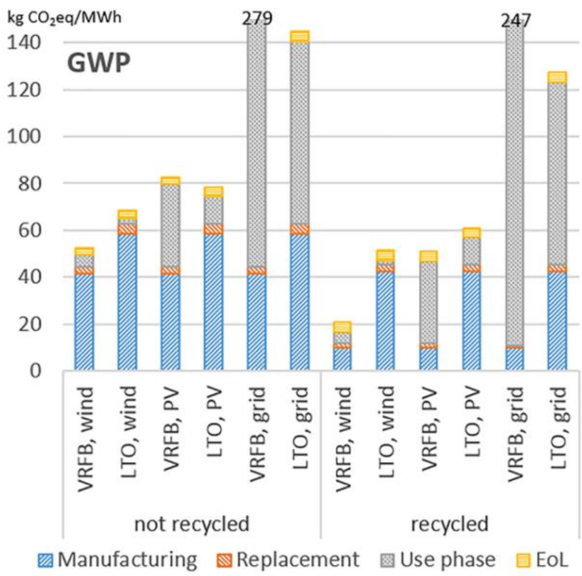
Life cycle emissions and costs by battery technology and application



Note. From "Additional Emissions and Cost from Storing Electricity in Stationary Battery Systems," by T. S. Schmidt, M. Beuse, X. Zhang, B. Steffen, A. Pena-Bello, C. Bauer and D. Parra, 2019, *Environmental Science and Technology, 53*(7), p. 3383.

Figure I2

Environmental impact scores per MWh of electricity provided over lifetime, broken down to life cycle stages



Note. From "Life Cycle Assessment of a Vanadium Redox Flow Battery," by S. Weber, J. Peters, M. Baumann and M. Weil, 2018, *Environmental Science and Technology, 52*(18), p. 10868.

Appendix J

Redox flow batteries, shift towards organic redox flow batteries and the BALIHT research consortium

Redox flow batteries

The battery energy storage market is dominated by lithium-ion batteries (LIBs), being ubiquitous in our society, due to the impressive energy density and rapidly declining battery pack costs (Choi & Aurbach, 2016; Nykvist & Nilsson, 2015; Puiu, 2020). Therefore, LIBs are particularly dominating the mobile application sector, e.g., portable devices and electric vehicles, although this technology is also steadily moving towards stationary storage (Hiremath et al., 2015). A 8,8 GWh stationary storage system was already installed in 2019 (Sánchez-Díez et al., 2021). However, LIBs are accompanied by some drawbacks such as high maintenance cost and safety limitations, but especially by the limited availability of lithium, which is already unable to meet lithium demand as a result of the electrification of vehicles and the related ramp-up in battery production (European Commission, 2020d; Greim et al., 2020). As a result, lithium is included in the European Union's list of Critical Raw Materials (European Commission, 2020c). Next to criticality, lithium mineral extraction is also accompanied by environmental justice issues (Romero et al., 2012). Mining of lithium requires the extraction of large quantities of groundwater, forcing local populations to migrate due to water scarcity. Moreover, these mining sites are increasingly being located near or in nature conservation areas which are experiencing ecosystem degradation as a result. Finally, there are potential health effects due to geochemically lithium being released into the environment, but these effects are still poorly understood (Agusdinata et al., 2018). LIBs also need cobalt. Likewise, the cobalt for LIBs is associated with issues such as adverse health effects and environmental pollution (Banza Lubaba Nkulu et al., 2018), but is also characterised by controversial child labour (International Labour Organization, 2019).

As for the use phase, the operating temperature of LIBs should stay below 50 °C to prevent significant degradation of the battery, which requires a cooling system that utilises energy and therefore lowers the overall efficiency (Panchal et al., 2015; Reynard et al., 2018). At the EOL of the battery, recycling of highly integrated battery cells such as lithium-ion requires complex processes which are energy intensive (Weber et al., 2018). Moreover, LIBs are challenging to scale up to larger applications, not only due to the aforementioned limited availability of lithium, but also because the power and capacity components cannot be decoupled from each other. Power and capacity cannot be dimensioned separately, i.e., increasing capacity means increasing the power, which is not necessarily desired and increases costs. Therefore, LIBs occasionally maintain discharge at peak power for stretches long enough to regulate power output from intermittent renewable sources (Abraham, 2015).

Exactly that is one of the key advantages of redox flow batteries, which makes them great candidates for grid-storage applications (Soloveichik, 2015). RFBs are a versatile means of storing electricity as they have an attractive characteristic that makes them a promising candidate for stationary large-scale storage. The electrolyte (storage) and electrode (cell) are separated, which makes the battery safer, but it also offers the capability to independently scale the energy and power outputs of the battery (Noack et al., 2015; Park et al., 2016).

Moreover, RFBs offer advantages like: flexible and modular design depending on the specific situation; good scalability; moderate maintenance costs; and cost-efficient storage media (Noack et al., 2015; Sánchez-Díez et al., 2021). RFBs especially diverge from other batteries by their long cycle life which is the result of the electrodes being spectators of the reaction so the soluble redox species are not consumed (Reynard et al., 2018). These are major advantages over solid electrode batteries (e.g., LIBs) to meet the requirements for large-scale applications and grid integration such as cyclability, lifetime, high round-trip efficiency and depth of discharge (Hollas et al., 2018; Sánchez-Díez et al., 2021). Some clear targets on requirements have already been set for 2030 in the Strategic Energy Technology (SET) Plan for stationary energy storage systems regarding cost (0,05 € kW/h/cycle) and lifetime (10.000 cycles and 20 years) (Sánchez-Díez et al., 2021).

The RFB was developed by the National Aeronautics and Space Administration (NASA) in 1976 for its space programme (Thaller, 1976). Due to the higher energy density of LIBs and thus smaller size and lower weight, these were more useful for our current (mobile) applications and therefore further development of RFBs halted (Eindhoven University of Technology, 2021). However, due to the challenging sustainable energy transition, particularly RFBs emerged as a promising solution for large-scale energy storage (Alotto et al., 2013) and research has experienced a significant upturn (Winsberg et al., 2017). The expiry of the patents held by the NASA in 2006 has sparked the industry and companies around the world to commercialize this technology towards large-scale applications (Eindhoven University of Technology, 2021). RFBs are now expected to play a significant role in any future energy storage development.

Organic RFBs

The vanadium redox flow battery and zinc-bromine redox flow battery can be defined as the state-of-the-art in terms of RFB technology, where the VRFB is most successful and the only one that reached commercial maturity by now (Alotto et al., 2013; Sánchez-Díez et al., 2021). Worldwide there are 32 companies producing this technology and several plants have actually been installed (Vanitec Transforming Possibilities, n.d., 2019). The largest installation is the Minami Hayakita Substation plant in Japan, which produces 15 MW and 60 MWh. At this moment a facility is being installed by Rongke Power in Dalian in the province of Liaoning in China, which is designed to produce 200MW and 800 MWh (Argus Metals, 2021). This will be by far the largest electrochemical energy storage plant in the world.

However, some major issues remain. Vanadium is a scarce metal that is being mined only in a few countries across the globe. It is subject to high supply risk and has a high economic importance, therefore it is classified as a critical raw material by the EU (European Commission, 2020c). This leads to increasing and highly volatile raw material prices of vanadium pentoxide (V_2O_5), which is the basic substance for producing the electrolyte (Minke et al., 2017). Next to the criticality aspect, oxides of vanadium, which are used in VRFBs, are associated with toxicity and are detrimental to human health (Ghosh et al., 2015). Moreover, limited energy density values result in a bulkier system than lithium systems (Moore et al., 2016). Even though VRFBs are deployed all over the world and research is improving the performance of this technology, the energy density limitation, causing difficulty in competing with other batteries, and the vanadium criticality, limits its commercial success (Hollas et al., 2018; Reynard et al., 2018; Sánchez-Díez et al., 2021). This has promoted research for alternatives as more environmentally benign systems are required (Sánchez-Díez et al., 2021; Winsberg et al., 2017). Research on RFBs as flexible and scalable storage systems concluded that future RFB systems should employ noncorrosive, safe and low-cost storage materials, to reach sophisticated high-performing RFBs (Armand & Tarascon, 2008; Barnhart & Benson, 2013; Janoschka et al., 2015). This includes improving the electrolytes, developing electrolytes as a replacement for vanadium and avoiding expensive membranes used in current VRFBs (Sánchez-Díez et al., 2021).

In fact, given that most of the forementioned issues emanate from the chemistry behind the operating principle of the battery, replacing the electrolyte seems to be a straightforward solution. Using redox active organic molecules synthesised from earth-abundant elements such as carbon (C), hydrogen (H), oxygen (O), nitrogen (N) and sulphur (S) has emerged as a substitute for inorganic compounds (Sánchez-Díez et al., 2021; Singh et al., 2019; Wang & Sprenkle, 2016). Organic based redox active materials are expected to be manufactured at low cost and on large scale. Therefore, these materials have attracted intense research attention as alternative materials to achieve cost-effective RFBs with a high energy density (Wei et al., 2017).

The use of inorganic species (e.g., V, Fe, Ce) has been extended by the use of organic molecules back in 2010 with the introduction of tiron (disodium 4,5-dihydroxy-1,3-benzenedisulfonate) by Xu et al. (2010). Then, electrolytes were replaced by metal-ligand complexes with organic ligands (J. H. Kim et al., 2011) and organic additives were employed (J. H. Kim et al., 2011; Lai et al., 2013). Subsequently, RFBs with an organic and an inorganic electrolyte were developed (Wei et al., 2014; Winsberg et al., 2016). Finally, in recent years, new organic redox-active materials are discovered and all-organic RFBs are being developed, which refers to the use of organic redox-active material but not necessarily the solvent in which the material is dissolved (Winsberg et al., 2017). Among these, so called aqueous organic redox flow batteries (AORFBs), in which the material is dissolved in water, are of high interest (Gentil et al., 2020; Kwabi et al., 2020; Narayan et al., 2019; Singh et al., 2019).

Certain organic molecules are capable of multiple electron transfer events per molecule, meaning that the electrolyte can be very concentrated and an increased battery capacity is achieved (Sánchez-Díez et al., 2021). Besides potentially being non-toxic, organic based electrolytes are also potentially low-cost and offer the possibility to employ more economical membranes. Moreover, there is a high availability of raw materials and the electrolytes are potentially recyclable. Finally, since these organic molecules have high structure tunability they provide advantages for molecular engineering to adjust the redox potential, solubility, ionic charge and stability (Kowalski et al., 2016; Park et al., 2016; Wei et al., 2017). This is mainly achieved by modifying the redox moieties, or the surrounding molecular structure (Kowalski et al., 2016). This is a powerful advantage to enhance the energy and power density of organic redox flow batteries (Kowalski et al., 2016; Wei et al., 2017).

For these reasons it is widely recognised that organic based active redox compounds are able to solve many of the drawbacks of VRFBs for large-scale storage (Sánchez-Díez et al., 2021; Winsberg et al., 2017). For example, several new compounds have been researched: quinoids; quinones; viologen; quinoxalines; bipyridines; nitroxyl radicals; and ferrocenes (Chen et al., 2018; Luo et al., 2019), however, most of these are limited to the development of new anolytes (Er et al., 2015; Hu et al., 2018; Kwabi et al., 2020; Wedege et al., 2016). In practice, these anolytes are often combined with an organometallic or inorganic catholyte. Nevertheless, this should be considered a transition towards all-organic RFBs, since that is in the end the goal. Currently, there are several companies in Europe focused on developing AORFBs, among which Kemiwatt, Jena Batteries, Green Energy Storage and CMBlu. In 2019, Jena Batteries has even successfully completed a 30 kW/100 kWh pyridine-based anolyte system pilot, while they are aiming for MW scale (JenaBatteries GmbH, n.d.).

Future research on RFBs, among which AORFBs, will pave the road to the 2030 targets as stated in the SET Plan (10.000 cycles and 0,05 €/kWh/cycle). The European Commission is supporting this research through the HORIZON2020 calls LC-BAT-3 and 4, which are fully devoted to RFBs (National Agency for Research and Development, 2019).

BALIHT

BALIHT (www.baliht.eu) is one of the research consortia which are part of the European Union's Horizon 2020 research and innovation programme call LC-BAT-4-2019 *Advanced Redox Flow Batteries for stationary energy storage*. Some renewable RFB chemistries have already demonstrated promising performance in lab scale cells, however, they fall short of meeting technical requirements for large-scale application in commercial RFBs. Therefore, the aim of the BALIHT research project is to develop an organic redox flow battery with lignin-based electrolytes.

CMBlu Energy AG, one of the partners in the consortium, developed electrolytes synthesised from lignin. Lignin is a structural material in most plants to provide its rigidity. It offers a significantly lower price, vast abundance and high tunability of redox potential and solubility than vanadium based redox electrolytes. Besides being a renewable source, it is also considered a sustainable source, which can be extracted from the pulp and paper industry as it is regarded as waste without a profitable utilisation that is currently incinerated. This is the key difference compared to other RFBs and further development of the electrolyte is the main focus of the BALIHT project.

Most RFBs are designed to work at room temperature (<40 ºC) to prevent electrolyte degradation and battery malfunction. Sulphuric acid-based VRFBs only work between 10°C and 40°C. This generally requires a cooling system, especially in warm weather regions, since the battery heats up due to charging and discharging cycles. A cooling system utilises energy and therefore reduces the overall battery efficiency, while it increases operational cost. The BALIHT project partners aim to develop the AORFB to work at higher temperatures, which makes cooling obsolete and thus decreases operational energy use.