Technische Universität München
Fakultät für Elektrotechnik und Informationstechnik
Lehrstuhl für Energiewirtschaft und Anwendungstechnik

Development of Instruments for a Circular Energy Economy

Potential of the Circular Economy to Reduce the Critical Resource Demand and Climate Impact of Electric Vehicle Batteries

Anika Regett

Vollständiger Abdruck der von der Fakultät für Elektrotechnik und Informationstechnik der Technischen Universität München zur Erlangung des akademischen Grades eines

– *Doktor-Ingenieurs* –

genehmigten Dissertation.

Vorsitzender:		Prof. Dr.-Ing. Andreas Jossen
Prüfer der Dissertation:	1.	Prof. Dr.-Ing. Ulrich Wagner
	2.	Prof. Dr. rer. nat. Liselotte Schebek

Die Dissertation wurde am 13.11.2019 bei der Technischen Universität München eingereicht und durch die Fakultät für Elektrotechnik und Informationstechnik am 17.03.2020 angenommen.

Danksagung

Da hinter einer Promotion mehr als nur der Name auf dem Titelblatt steckt, möchte ich mich hiermit ganz herzlich bedanken: Bei meinem Doktorvater Prof. Ulrich Wagner für die Betreuung meiner Doktorarbeit und die Begleitung meines beruflichen Weges; bei Prof. Wolfgang Mauch für die Unterstützung bei der Themenfindung und den bedingungslosen Rückhalt in den letzten Jahren; bei der Stiftung Energieforschung Baden-Württemberg und der Hans und Klementia Langmatz Stiftung, die dieses Promotionsprojekt ermöglicht haben; bei meiner Zweitprüferin Prof. Liselotte Schebek und bei meinem Mentor Prof. Mario Schmidt für die inhaltlichen Impulse und kritischen Diskussionen; sowie bei meinen ehemaligen Kolleginnen und Kollegen der Uni Bremen, der Chalmers Universität, der Uni Leiden und der TU Delft, die mich für diese Themen und Methoden begeistert haben. Ein ganz besonderer Dank gilt zudem meinen Kolleginnen und Kollegen sowie den Studierenden an der FfE für die wunderbare Zusammenarbeit, die angeregten Diskussionen, die intensiven Workshops und Tagungen, die gegenseitige Unterstützung und natürlich die Vielzahl an Freizeitaktivitäten - ohne dieses unschlagbare Team wäre das alles nicht möglich gewesen! Schließlich möchte ich meiner Familie von ganzem Herzen dafür danken, dass sie rechtzeitig die Weichen für diese Doktorarbeit gestellt und mich an jeder Kreuzung dabei unterstützt hat, die für mich richtige Abzweigung zu wählen. Und dir, Ole, danke ich ganz besonders dafür, dass wir diesen langen Promotionsweg mit all den Tälern und Gipfeln stets zusammen gegangen sind.

Abstract

The circular economy (CE) is often proposed as a possible solution to counteract resource and environmental risks caused by the energy transition. In addition to recycling, it comprises approaches such as efficiency measures, renewable energy, sharing concepts and Second-Life (SL) applications. However, the actual potential of these CE approaches to reduce greenhouse gas (GHG) emissions and critical resource demand, depends on their technical feasibility, technological developments, interactions with the energy system as well as barriers to practical implementation. Therefore, the aim of this thesis is to develop a method to systematically assess the potential of CE approaches to reduce the critical resource demand and climate impact of future key technologies, and apply it to the case of electric vehicle (EV) batteries.

To this end, first, current climate and resource implications of EV batteries are identified based on recent literature to prove the need for a detailed assessment of CE approaches. Then, the technical feasibility of CE approaches for EV batteries is evaluated by matching the battery's characteristics with the requirements of CE approaches. Next, the selected, technically feasible CE approaches are assessed with regard to their critical resource and GHG emission savings. In this context, due to the integration of EV batteries in an increasingly complex energy system, assessment methods are developed which include future developments and energy system effects. Finally, the implementation potential is discussed by quantifying the economic feasibility of SL applications for EV batteries and identifying additional critical success factors for the implementation of CE approaches by the relevant stakeholders.

This procedure results in a set of instruments which include technological developments and interactions with the transforming energy system into emission and resource assessments. These instruments encompass procedures for dealing with uncertainties about future developments, methods for emission accounting and for the coupling of environmental assessment methods with battery and energy system models. The quantitative application for the selected CE approaches shows that the climate impact of battery production can be improved through energy efficiency and renewable energy, since scale and energy supply of the production plant are important determinants. It is further outlined that EVs must be accompanied by the expansion of renewable energy systems and optimised load management to fully exploit the advantages of electric mobility in the use phase. Since SL batteries do not automatically lead to critical metal and cost savings, ageing behaviour, time dependencies and substitution effects need to be considered in the implementation of CE concepts at the End-of-Life. Overall, the CE offers potentials to reduce the climate impact and critical metal demand for EV batteries, if current barriers are removed and a cooperation between the energy and mobility sectors is achieved. However, the actual effect depends on energy system interdependencies and future technological developments. Thus, a prospective approach over the entire life cycle is required when assessing GHG abatement measures, such as EVs, and the saving potential through the CE.

Kurzfassung

Die Kreislaufwirtschaft wird oft als mögliche Lösung vorgeschlagen, um dem Auftreten neuer Ressourcen- und Umweltrisiken durch die Energiewende entgegenzuwirken. Neben Recycling umfasst diese auch Ansätze wie Effizienzmaßnahmen, erneuerbare Energien, Sharing-Konzepte und Second-Life (SL)-Anwendungen. Das tatsächliche Potenzial von zirkulären Ansätzen Treibhausgas (THG)-Emissionen und den kritischen Rohstoffbedarf zu reduzieren, hängt jedoch von deren technischer Machbarkeit, technologischen Entwicklungen, Wechselwirkungen mit dem zukünftigen Energiesystem sowie Umsetzungshemmnissen ab. Ziel dieser Arbeit ist es daher eine Methodik zu entwickeln, die eine systematische Bewertung des Potenzials von zirkulären Ansätzen zur Reduktion des kritischen Rohstoffbedarfs und der Klimawirkung von Schlüsseltechnologien ermöglicht, und diese am Beispiel Elektrofahrzeugbatterien anzuwenden.

Hierfür werden zunächst der kritische Rohstoffbedarf und die Klimawirkung von Elektrofahrzeugbatterien auf Basis aktueller Literatur identifiziert, um die Relevanz einer detaillierten Bewertung von zirkulären Ansätzen für Batterien aufzuzeigen. Daraufhin wird die technische Machbarkeit von zirkulären Ansätzen analysiert, indem die Eigenschaften von Traktionsbatterien den Anforderungen der zirkulären Ansätze gegenübergestellt werden. Anschließend werden die ausgewählten, technisch realisierbaren Ansätze hinsichtlich der Einsparung an kritischen Rohstoffen und THG-Emissionen bewertet. Aufgrund der Integration von Elektrofahrzeugen in ein immer komplexer werdendes Energiesystem, werden hierfür Bewertungsmethoden entwickelt, die sowohl zukünftige Entwicklungen als auch Energiesystemeffekte berücksichtigen. Abschließend wird das Umsetzungspotenzial eingeordnet, indem die Wirtschaftlichkeit ausgewählter zirkulärer Ansätze für Elektrofahrzeugbatterien bestimmt und weitere kritische Faktoren für die umsetzenden Akteure identifiziert werden.

Aus diesem Vorgehen resultiert ein Satz an Instrumenten, die technologische Entwicklungen und Wechselwirkungen mit dem sich wandelnden Energiesystem in die Emissions- und Ressourcenbewertung einbeziehen. Die entwickelten Instrumente umfassen Verfahren zum Umgang mit Unsicherheiten bezüglich zukünftiger Entwicklungen, Methoden zur Emissionsbilanzierung und zur Kopplung von Umweltbewertungsmethoden mit Batterie- und Energiesystemmodellen. Die quantitative Anwendung auf die ausgewählten zirkulären Ansätze zeigt, dass die Klimawirkung der Batterieproduktion durch Energieeffizienz und den Einsatz erneuerbarer Energien verbessert werden kann, da die Größe und die Art der Energieversorgung der Produktionsanlage wichtige Einflussfaktoren darstellen. Es wird weiterhin aufgezeigt, dass Elektrofahrzeuge mit dem Ausbau von erneuerbaren Energien und einem optimierten Lademanagement einhergehen müssen, um die Vorteile der Elektromobilität in der Nutzungsphase voll auszuschöpfen. Da SL-Anwendungen nicht automatisch zu kritischen Rohstoff- und Kosteneinsparungen führen, müssen bei der Umsetzung von zirkulären Konzepten am Lebensende Alterungsverhalten, Zeitabhängigkeiten und Verdrängungseffekte Berücksichtigung finden. Insgesamt bietet die Kreislaufwirtschaft, im Falle eines Abbaus aktueller Hemmnisse und einer engeren Zusammenarbeit zwischen der

Energiewirtschaft und dem Verkehrssektor, Potenziale zur Reduktion der Klimawirkung und des kritischen Rohstoffbedarfs für Elektrofahrzeugbatterien. Die tatsächliche Auswirkung hängt jedoch stark von Wechselwirkungen mit dem Energiesystem und zukünftigen technologischen Entwicklungen ab. Daher ist bei der Bewertung von Klimaschutzmaßnahmen, wie beispielsweise Elektrofahrzeugen, sowie dem Einsparpotenzial durch zirkuläre Ansätze ein prospektiver Ansatz über den gesamten Lebenszyklus unbedingt erforderlich.

Contents

List of Figures

List of Tables

Abbreviations

AGEB Working Group on Energy Balances

BaaS battery as a service

BEV battery-electric vehicle

BMS battery management system

BMWi Federal Ministry for Economic Affairs and Energy

CAPEX capital expenditures

CE circular economy

CED Cumulative Energy Demand

CHP combined heat and power

Co cobalt

Cu copper

DERA German Mineral Resources Agency

EES Institute for Electrical Energy Storage Technology

EoL End-of-Life

EoSL End-of-Second-Life

eq. equivalents

EU European Union

EV electric vehicle

FCEV fuel cell electric vehicle

FfE Research Center for Energy Economics

GHG greenhouse gas

GWP global warming potential

HSS	home storage system
ICEV	internal combustion engine vehicle
ICT	information and communications technology
IEA	International Energy Agency
ISAaR	Integrated Simulation Model for Planning the Operation and Expansion of Power Plants with Regionalisation
IVL	Swedish Environmental Research Institute
LCA	Life Cycle Assessment
LFP	lithium-ion-phosphate
Li	lithium
Li-ion	lithium-ion
LMO	lithium-manganese-oxide
MES	multi-energy carrier system
MFA	Material Flow Analysis
MONA	Merit Order Netz-Ausbau
NCA	nickel-cobalt-aluminum
Ni	nickel
NMC	nickel-manganese-cobalt
NPV	net present value
OEM	original equipment manufacturer
OPEX	operational expenditures
P/E	Power-to-Energy
PCR	primary control reserve
PHEV	plug-in electric vehicle
PtX	Power-to-X
PV	photovoltaic
reman	remanufacturing

RES renewable energy system

SL Second-Life

SoH state of health

TCS trade, commerce and services

TraM FfE Transport Model

UBA German Environment Agency

V2G vehicle-to-grid

1 Introduction

Based on the motivation in Section 1.1, the research objective and specified research questions of the present thesis will be presented in Section 1.2.

1.1 Motivation

While reducing the demand for fossil fuels and contributing to climate protection, the energy transition requires new technologies, e.g. lithium-ion (Li-ion) batteries, photovoltaic (PV) systems and wind power plants, which themselves are not burden-free, but also have an environmental impact [1], [2] and resource footprint [3, p. 11], [4, pp. 158–160]. In this regard, especially the increasing demand for metals such as cobalt (Co), lithium (Li), platinum, indium and rare earth elements is often discussed [3, pp. 13–15], [5, pp. 9–10], [6, pp. 25–30], [7, pp. 11–14], since these metals can be classified as critical if their provision is associated with supply risks or environmental implications [8]. Thus, in order to counteract the occurrence of new resource risks and environmental side effects due to the energy transition, measures are needed to reduce the demand for so-called critical metals and the environmental impact of key technologies for future energy supply.

As outlined by the application-related emission balance in [9], one of the major contributors to climate change in Germany is the transport sector. In 2016, for example, 27 % of the energy-related CO_2 emissions in Germany could be attributed to mechanical energy for transportation. From the historical development of the emission balance in [9], it can further be seen that the emissions for mechanical energy have stagnated in the past decade. Against this background, the role of electric vehicles (EVs) as one option for greenhouse gas (GHG) abatement in the transport sector gains importance [10], [11].

Apart from preventing local emissions by eliminating the combustion process in the vehicle, one of the main advantages of EVs is the high efficiency of the drive train, which in most cases leads to lower operational GHG emissions compared to an internal combustion engine vehicle (ICEV) [12, p. 4–6], [13, pp. 685–686], [14], [15, pp. 28–31]. However, this advantage in the use phase is currently reduced by the demand for critical metals, especially Co and Li [16, pp. 34–35], as well as the carbon intensity of battery production [17, pp. 57–59], [12, p. 4–6].

In this context, the recent debate about the actual environmental impact of EV batteries is often unobjective and not fact-based. The results of the study of the Swedish Environmental Research Institute (IVL) [18], for example, raised controversies resulting in wide discussions and a lot of media attention. This was followed by a statement from the IVL to rectify misinterpretations of their study as well as a large number of other studies and articles about the carbon footprint of EVs such as [15, 17, 19, 20]. The partly opposing results of these assessments show that the exact carbon footprint of electric mobility is strongly dependent on the assumed boundary conditions.

However, in general, these studies indicate that the environmental advantage of an EV in the use phase is currently reduced by the climate and resource implications of battery production.

The circular economy (CE), as a counterpart to the current linear economic system, is often proposed as a means to reduce resource demand, decrease environmental impacts and create new opportunities for value creation [21, p. 4], [22, p. 2], [23, p. 12], [24, p. 4]. According to this understanding, the CE covers more than just recycling, since it targets all phases of the life cycle of a product or technology. This means that, apart from resource recovery, approaches from the CE also include the renewable and efficient supply of resources, the increased utilisation during the use phase as well as the extension of the technology's lifetime at its End-of-Life (EoL) [25, pp. 8–15], [23, p. 24], [24, p. 12]. Against this background, the question arises, to what extent CE approaches can lead to a reduction of critical metal demand and GHG emissions over the entire life cycle of Li-ion traction batteries, as a key component in EVs.

Existing publications explicitly dealing with the CE for EV batteries such as [26–31] cover different aspects in their evaluations. Hill et al. [26], for example, give a broad overview of technologies, environmental impacts, business models and policy implications across all life cycle phases of the EV battery. While the overview in [27] also builds on existing studies and comprises all phases of the vehicle's life cycle, here, the focus is on the environmental impact and the discussion of possible improvements through the CE. Other publications, on the contrary, focus on EoL approaches. Olsson et al. [28], for instance, identify barriers and opportunities for the implementation of so-called Second-Life (SL) applications and recycling based on interviews and workshops. Drabik and Rizos [29], on the contrary, use a quantitative scenario approach to estimate the impact of battery recycling on the economy and the climate. A more detailed quantification of the environmental impact of EoL approaches, such as reuse in mobile or stationary applications as well as recycling, is conducted by Richa et al. [30]. While the authors point out the time lag resulting from the lifetime extension of the EV battery in a secondary application, time dependencies are not included in the quantification of environmental impacts. The need to include time frames and system dynamics into the assessment of reuse, remanufacturing and recycling of EV batteries is also emphasised by Kurdve et al. [31]. However, so far, time dependencies, interactions with the energy system as well as interdependencies between different CE approaches have only been addressed to a limited extent in current assessments.

Importantly, to quantify the actual potential of the CE to reduce critical metal demand and GHG emissions of EV batteries, only a static assessment is not sufficient. This is, on the one hand, due to the fact that EV batteries and the underlying energy system are still undergoing a development process [32] and the battery's lifetime extension leads to temporal shifts [30], suggesting that time dependencies need to be accounted for. On the other hand, energy system effects need to be included in the assessment because CE approaches for EV batteries, such as reuse in stationary storage applications, lead to an increased coupling of the transport and the energy sectors [33, pp. 46-71]. This is especially relevant as the future energy system becomes increasingly complex due to a rising share of volatile renewable electricity as well as an increased coupling of energy carriers through Power-to-X (PtX) technologies [10, 34, 35].

1.2 Objective and Research Questions

As elaborated on in Section 1.1, the CE is often proposed as a means to reduce the climate and resource impact of technologies such as Li-ion traction batteries. However, the actual potential of these CE approaches to reduce GHG emissions and critical resource demand depends on the technology's current climate and resource implications, the technical feasibility of these approaches, technological developments, interactions with the future energy system as well as barriers to their practical implementation. Therefore, the aim of this thesis is to develop a method to systematically assess the potential of approaches from the CE (short: CE approaches) to reduce critical resource demand and GHG emissions, and apply it to Li-ion traction batteries used in battery-electric passenger cars (short: EV batteries).

To this end, this thesis is divided into five parts. First, a methodology is described which allows for a systematic assessment of CE approaches to reduce critical resource demand and GHG emissions. Second, the current climate and critical resource implications of EV batteries are identified to prove the technology's relevance for a further assessment of CE approaches. Then, in a third step, the technical feasibility of CE approaches for EV batteries is analysed. Fourth, the identified, feasible CE approaches are assessed with regard to their critical resource and GHG emission savings. In this context, due to the integration of EV batteries in a changing and increasingly complex energy system, there is a special need to move towards more dynamic assessment methods which include energy system effects as well as future developments. Finally, in the fifth step, the implementation potential is discussed by evaluating the economic feasibility of a selected CE approach for EV batteries and identifying other critical factors for practical implementation through the relevant stakeholders.

In concrete terms, this objective can be translated into the following research questions:

1. How can the potential of CE approaches to reduce critical resource demand and GHG emissions be systematically assessed?
2. What are the current climate and critical resource implications of EV batteries?
3. Which CE approaches are technically feasible for EV batteries?
4. To what extent can these CE approaches lead to savings of GHG emissions and critical resource demand for EV batteries, when considering future developments and energy system effects?
5. What are current barriers and success factors determining the practical implementation potential of CE approaches for EV batteries?

2 Methodology

To achieve the research objective described in Section 1.2, the method in Figure 2–1 was developed and applied to EV batteries. Analogous to the research questions 2 to 5, the methodology and the following chapters are structured around four topics. For each topic, the respective research question is answered by developing and applying different methods and instruments as depicted in Figure 2–1.

Climate and Resource Implications: To prove the relevance of EV batteries for further assessment, in Chapter 3, an overview of the current climate and resource implications of EV batteries is given. For this purpose, a resource criticality screening procedure is developed based on existing methods from literature which aim at classifying the criticality of different resources. This procedure is subsequently applied to EV batteries to identify the reasons for their resource criticality. Furthermore, based on an application-oriented emission balance, the relevance of electric mobility for GHG abatement is shown. In addition, the current climate impact of EV batteries is discussed based on a literature overview of the Life Cycle Assessment (LCA) of EV batteries. The generated insights with regard to the climate and resource implications of EV batteries emphasise the importance of a further assessment of the potential of CE approaches to reduce GHG emissions and critical metal demand.

Feasibility of Circular Economy Approaches: As EV batteries are classified as resource-critical and show improvement potential with regard to their climate impact, in a next step, the technically feasible CE approaches in each life cycle phase are identified in Chapter 4. For the implementation of CE approaches, certain requirements, such as modularity and accessibility of the technology, need to be met. Therefore, for each CE approach, first, these requirements are identified using the definition of CE approaches derived from literature. Then, for each life cycle phase, the characteristics of EV batteries are matched with the identified requirements of the respective CE approach, to determine and select technically feasible approaches for further analysis.

Greenhouse Gas Emission and Critical Resource Savings: In Chapter 5, for the identified CE approaches over the life cycle of an EV battery, an assessment of the potential reduction of GHG emissions and critical metal demand is conducted. For each of the selected CE approaches, in a first step, the main challenge for emission and resource assessment is identified based on current literature. Using this input, next, an instrument is developed which addresses the identified challenge. In a third step, the developed instrument is applied to an application example. This example serves, on the one hand, the improvement of the instrument in an iterative loop, and on the other hand, the quantification of the potential of the respective CE approach to reduce GHG emissions and critical resource demand. This procedure is then repeated for each of the chosen CE approaches, resulting in a set of instruments for emission and resource assessment of CE approaches for EV batteries. These developed instruments can be procedures for dealing with

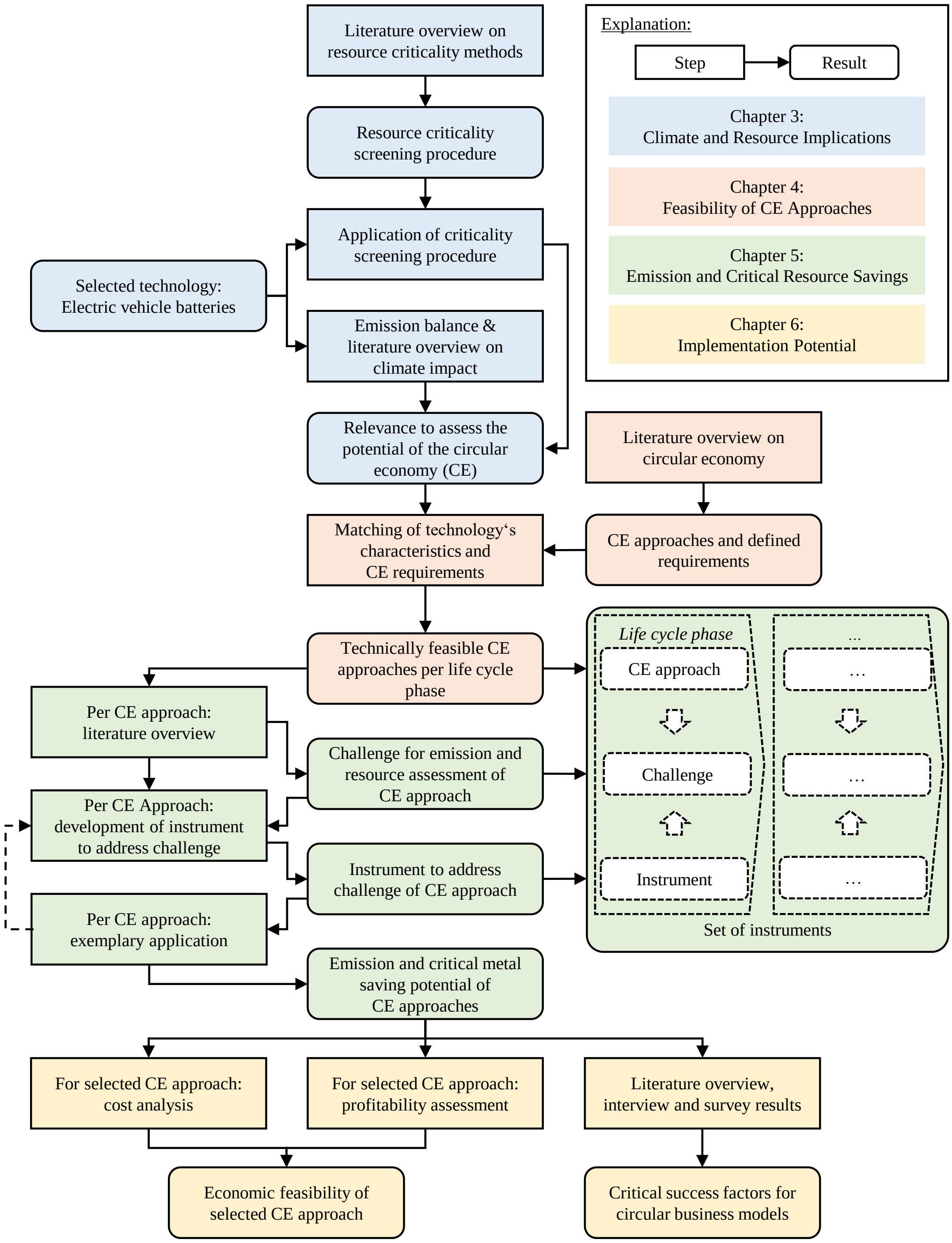

Figure 2–1: Method to assess the potential of approaches from the circular economy to reduce the critical resource demand and climate impact of electric vehicle batteries

uncertainties of future technological developments, methods for emission accounting as well as for the coupling of environmental assessment methods with battery and energy system models.

Implementation Potential: After analysing the potential for critical resource and GHG emission savings, in Chapter 6, the potential for a practical implementation of CE approaches for EV batteries is discussed. First, to demonstrate the opportunities and challenges for an economic implementation of CE approaches, the economic feasibility of a selected CE approach for EV batteries is determined. This is done by quantifying both cost savings from a system perspective and profitability from a stakeholder perspective. For this purpose, in addition to classical economic evaluation methods, selected instruments and results from Chapter 5 are also used. Second, based on current literature as well as results from interviews and a written survey, critical success factors for the implementation of circular business models for EV batteries are derived.

Based on the generated results, finally in Chapter 7, a conclusion is drawn with regard to the potential of CE approaches to reduce the critical resource and climate impact of EV batteries. Furthermore, an outlook of future research needed to establish a circular energy economy is provided.

3 Climate and Critical Resource Implications of Electric Vehicle Batteries

Starting point for assessing the potential of the CE is the identification of the current impact of EV batteries on climate change and critical metal demand. Therefore, in Section 3.1, first, an overview of the climate implications of battery-electric mobility is given. Then, in Section 3.2 the resource criticality of Li-ion batteries is discussed.

3.1 Climate Implications of Battery-Electric Mobility

After outlining the relevance of electric mobility for reaching climate targets in Subsection 3.1.1, in Subsection 3.1.2 an overview of the current status quo with regard to the climate impact of battery-electric vehicles (BEVs) in general, and traction batteries in particular, is given.

3.1.1 Relevance of Electric Mobility for Greenhouse Gas Abatement

In the course of the energy transition ("Energiewende"), the German energy system is being transformed with the aim of phasing out nuclear and coal electricity, and reducing GHG emissions. The German government has set itself the target of reducing GHG emissions by 80 % to 95 % by 2050 compared to 1990 [36, p. 91]. With the adoption of the Paris Climate Agreement [37], the international community added weight to Germany's efforts by committing itself to a significant reduction in GHG emissions.

A recent progress report [38] shows that emission reductions in Germany are currently mainly achieved in the energy supply sector, which is largely covered by the European Union Emissions Trading System. The share of renewable energy sources in gross electricity consumption, for example, was increased to 36 % in 2017, with a further upward trend [38, p. 6]. However, on the application side, i.e. in the consumption sectors transport, private households, industry as well as trade, commerce and services (TCS), the implementation of GHG abatement measures progresses slowly.

Emission balances are usually determined according to the so-called "source principle", meaning emissions are accounted for in the sector where they physically occur. However, the basis for achieving a significant emission reduction is the identification of those applications which are responsible for a large share of the energy demand, and thus also the associated emissions ("cause principle"). Therefore, the approach of the application-oriented emission balance described in [9, 38, 39] was developed in the course of the project Dynamis [10], by means of which the biggest levers for GHG abatement in the consumption sectors can be identified. By showing the historical development of the emission intensity of the analysed applications (mechanical energy, process heat, space heating, lighting, hot water, information and communications technology (ICT), process cold and space cooling), furthermore, areas with currently low reduction achievements can be pointed out. As depicted in Figure 3–1, following this method the emissions associated

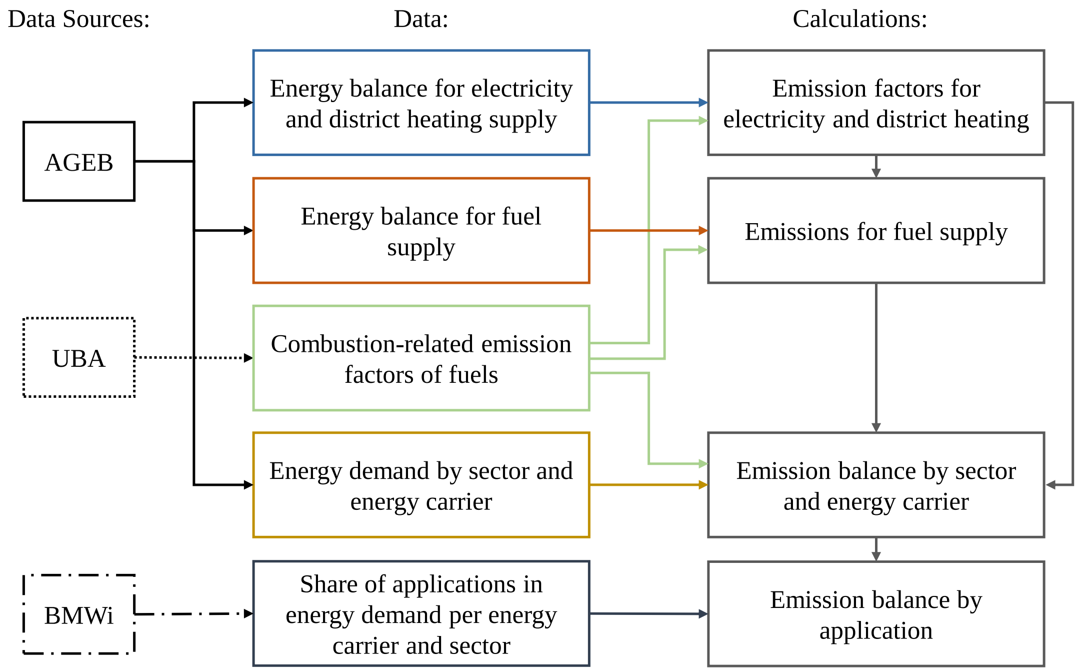

Figure 3–1: Data basis and calculation procedure for the application-oriented emission balance based on [9, p. 2] (AGEB: Working Group on Energy Balances, UBA: German Environment Agency, BMWi: Federal Ministry for Economic Affairs and Energy)

with the supply of electricity, district heat and fuels are first quantified following the source principle, and are then assigned to the different sectors according to their final energy demand.

As described by Pichlmaier, Regett and Guminski [9, pp. 2–3], first, emission factors of district heating and electricity are determined using the German energy balances from 2006 to 2016 from the Working Group on Energy Balances (AGEB) [40] and the combustion-related emission factors from the German Environment Agency (UBA) [41, pp. 822–825]. These emission factors then serve as an input for calculating the emissions for the supply of other fuels. In a next step, the computed emissions for fuel supply are allocated to the consumption sectors in proportion to the sector's demand for gas-, coal- and oil-based fuels from [40]. Equally, the emissions originating from the generation of electricity and district heating are assigned to the different sectors in proportion to their final demand for electricity and district heat. In a next step, these emissions occurring in the supply sector are combined with the emissions occurring in the consumption sectors due to fossil fuel combustion so as to quantify the emission balance by sector. For this purpose, the energy demand by sector and energy carrier from [40] is combined with the combustion-related emission factors from [41]. Finally, the share of applications in energy demand per energy carrier and sector from the Federal Ministry for Economic Affairs and Energy (BMWi) [42, Energy Data, Tables 7a, 7b] is made use of to assign the sectoral emissions to the different applications. Due to the strong dependency on outside temperatures the emissions for space heating are temperature adjusted according to the method described in [43].

In Figure 3–2 the resulting application-oriented emission balance for 2016 is shown, which only

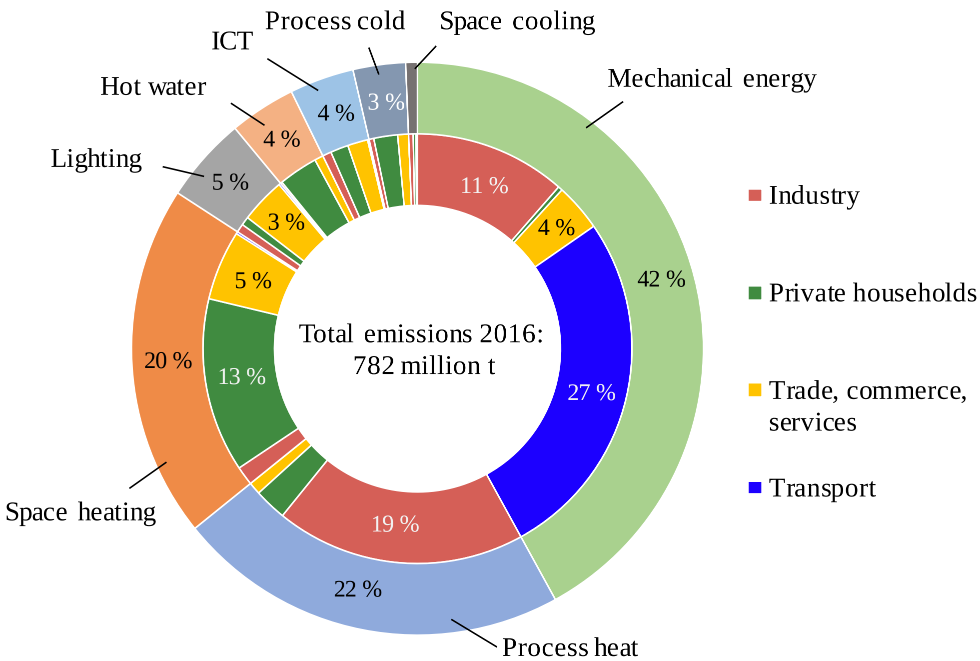

Figure 3–2: Energy-related CO_2 emissions by sector and application for Germany in 2016 [9]

accounts for energy-related CO_2 emissions. However, as energy-related CO_2 emissions made up 83 % of total GHG emissions in Germany in 2016 [44], a large share of total emissions is covered. As Germany was a net exporter of electricity in 2016, those emissions allocated to the export surplus are not included in the depicted emission balance. From the results in Figure 3–2 it can be seen that with a share of 27 % mechanical energy in the transport sector strongly contributes to energy-related CO_2 emissions in Germany. This is mainly due to the combustion of oil-based fossil fuels for road transport.

The historical development of energy-related CO_2 emissions for the four most emission-intensive applications is depicted in Figure 3–3. It can be seen that the emissions for space heating and lighting have been reduced by over 20 % between 2006 and 2016. This is due to increasing insulation and a switch from oil- to gas-based heating systems in the case of space heating, and a decreasing emission factor of electricity in the case of lighting. However, for process heat and mechanical energy, which are the largest contributors according to Figure 3–2, the emissions have stagnated in the considered decade. Thus, to reach future climate targets stronger efforts are required especially in these applications.

To decrease emissions for mechanical energy in the transport sector there are several options available. In addition to a decrease in transport service, a modal shift and the use of renewable fuels, this also includes the switch to fuel cell or battery electric vehicles. As shown in [10], BEVs are an important measure for reducing energy-related CO_2 emissions for road transport. However, for an holistic assessment the climate impact over the whole life cycle needs to be considered. Therefore, in the following, an overview of the climate impact of BEVs, and especially the contained Li-ion traction batteries, is given.

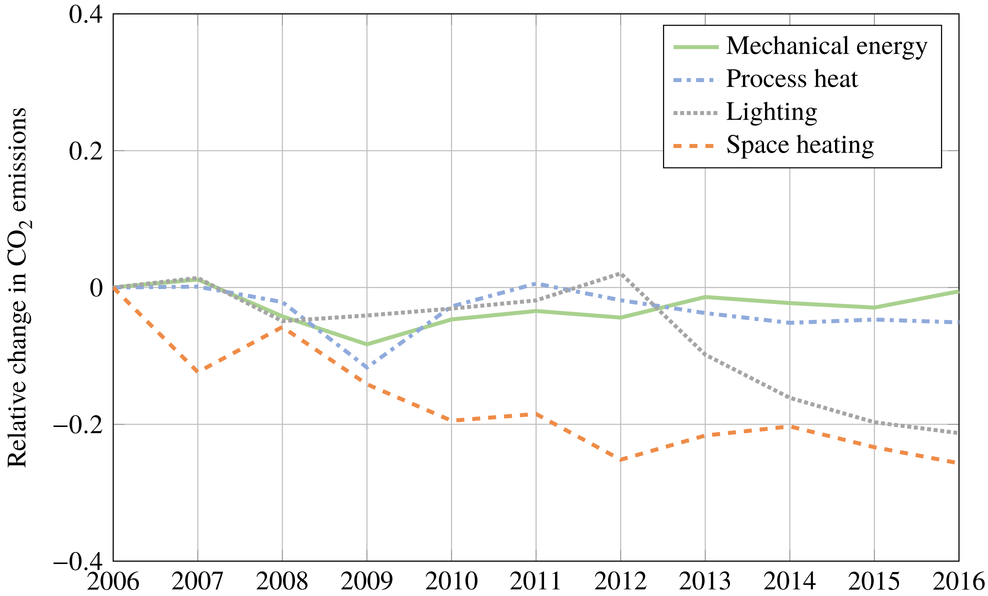

Figure 3–3: Change in energy-related CO_2 emissions in comparison to the base year 2006 for selected applications in Germany based on [9]

3.1.2 Status Quo: Climate Impact of Battery Electric Vehicles

Recent overviews and analyses of the climate impact of BEVs, such as [13] and [17], show that the actual carbon footprint of a BEV, and thus also its advantage over an ICEV, are strongly dependent on a variety of parameters. This strong sensitivity of a vehicle's carbon footprint is confirmed by the example depicted in Figure 3–4, for which both for BEVs and ICEVs a minimum and a maximum scenario are defined.

While the minimum scenario represents compact class vehicles (Golf and e-Golf), in the maximum scenario upper medium class vehicles (Tesla Model X, Mercedes E-Class) are considered. These vehicle classes differ, on the one hand, with regard to the consumption values per 100 km which are taken from ADAC EcoTest [45]. And, on the other hand, different battery sizes are considered, amounting to 35.8 kWh for the e-Golf and 100 kWh for the Model X. Furthermore, the uncertainties with regard to the emissions for battery production, as outlined by Helms et al. [17, pp. 24–27], are taken into account by assuming 50 kg CO_2 equivalents (eq.) per kWh battery capacity for the minimum scenario (range of [46] and [47]) and 200 kg CO_2 eq. per kWh for the maximum scenario (upper value from [18, p. 42]). The carbon footprint for the production of other vehicle components from Hawkins et al. [48], on the contrary, is not varied for the two scenarios. For a better comparability, also the conversion of vehicle kilometres into years of operation is kept constant, with an annual mileage of German passenger cars in 2017 of 13 257 km [49, p. 1].

To show the strong dependency of the vehicles' climate impact on the operation phase, for the ICEV a diesel is chosen in the minimum scenario and a gasoline vehicle in the maximum scenario. For BEVs the impact in the operation phase is dependent on the charging electricity which in the

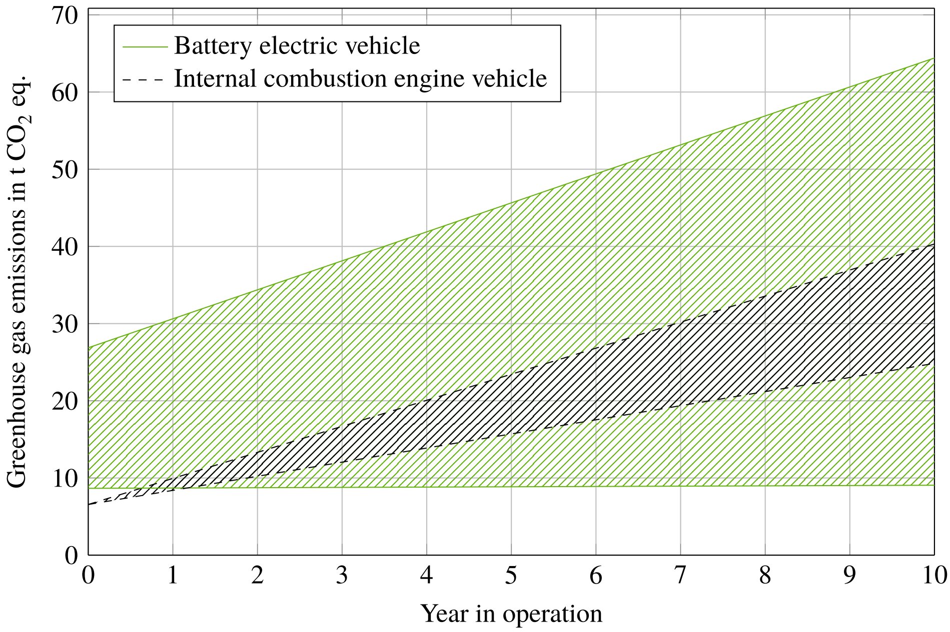

Figure 3–4: Range of the climate impact of an internal combustion engine vehicle and a battery-electric vehicle for the defined minimum and maximum scenarios

minimum scenario is assumed to be from onshore wind power and in the maximum scenario from a lignite power plant. While for the upstream emissions in the operation phase, for both electricity and fuels, GHG emission factors from the ecoinvent database [50, GWP100, CML 2001, cut-off system model] are used, the combustion-related CO_2 emission factors for gasoline and diesel originate from the GHG inventory report [51, p. 812].

The results in Figure 3–4 show that especially for BEVs the range of the climate impact is large. In the operation phase, next to the electricity consumption, the source of electricity strongly influences the slope of the graphs and therefore the climate impact over the vehicle's operation time. This is underlined by the analysis by Marmiroli et al. [52] who point out that the variability of the climate impact of BEVs in literature can to a large extent be explained by the assumed carbon intensity of electricity. Due to the larger efficiency of the electric drive train the operational emissions of a BEV would equal the operational emissions of a diesel and gasoline vehicle if the emission factor of electricity amounts to as much as $0.8\,\mathrm{kg\,kWh^{-1}}$ and $1.5\,\mathrm{kg\,kWh^{-1}}$, respectively. These values lie in the area of coal power plants, which means that even for recent electricity mixes with significant shares of conventional power plants BEVs already outperform ICEVs in the use phase.

For the production phase, apart from the battery size, also the carbon footprint of battery production plays a decisive role. While Romare and Dahllöf [18, p. 42] disclose a range of $150\,\mathrm{kg\,CO_2}$ eq. to $200\,\mathrm{kg\,CO_2}$ eq. per kWh battery capacity as a likely range, the range in literature is with $38\,\mathrm{kg\,kWh^{-1}}$ to $356\,\mathrm{kg\,kWh^{-1}}$ [53] even wider. According to the review by Ellingsen et al. [53], next to differences in the mass balances, this variability can be mainly explained by the assumed energy demand for cell manufacturing and battery pack assembly. This is confirmed by the results of Peters et al. [54] who disclose an average of 100 kg CO_2 eq. per kWh battery capacity, with a large range of under 50 kg kWh^{-1} to about 350 kg kWh^{-1}. According to [54], this can be attributed to the different modelling approaches of energy demand during battery manufacturing, leading to large differences in assumed energy demand. With the report from Dai et al. [55] a new dataset for industrial plants in China is made available, which has not been part of the previously mentioned reviews. Dai et al. [55, pp. 9–11] point out that the energy demand strongly depends on the state of the art of the production plant considered, since economies of scale and an efficient process design lead to a decrease in specific energy demand per battery capacity produced. While the energy demand in older studies such as Ellingsen et al. [56] are valid for smaller-scale plants, the disclosed dataset for the Chinese plant in [55, pp. 9–10] holds true for current industrial plants with an annual production in the GWh range.

As with production, also the climate impact of battery recycling is subject to large uncertainties [53]. However, the overview by Romare and Dahllöf [18, p. 36] indicates that most studies comparing the effort for the recovery of secondary materials with the credit resulting from the avoided production of primary materials disclose a potential for GHG emission savings. The detailed analyses of the LiBRi, LithoRec and LithoRec II processes by Buchert et al. [57–59] illustrate that these savings strongly depend on the exact recycling process. The LiBRi process, consisting of a combination of pyro- and hydrometallurgical processes (see Subsection 3.2.2), for example, leads to an increase in emissions of 15 kg CO_2 eq. per kWh battery capacity if an additional hydrometallurgical Li recovery takes place. However, the same process without the additional process step leads to a reduction in GHG emissions of 9 kg kWh^{-1} [57, pp. 23, 41, 49]. This is mainly due to the low technical maturity of the process for Li recovery. The LithoRec process, which consists of mechanical separation and hydrometallurgical processes (see Subsection 3.2.2), on the contrary, leads to GHG emission savings of 12 kg kWh^{-1} and 24 kg kWh^{-1} for nickel-manganese-cobalt (NMC) and lithium-ion-phosphate (LFP) batteries, respectively [58, pp. 20, 66, 70]. Assuming the same energy density as in [58, pp. 20], the LithoRec II process even leads to savings of 32 kg kWh^{-1} for NMC batteries [59, p. 29]. As outlined by Cerdas et al. [60, p. 285], the GHG emission savings through recycling are largely determined by the materials recovered from the dismantling process, such as aluminium, steel and copper. Furthermore, the climate impact of the recycling process depends on the quality of the recovered materials due to the trade-off between energy demand and material quality [60, p. 285].

Overall, it can be summarised that the bigger carbon footprint of BEVs in the production phase can in principle be offset in the use phase due to the larger efficiency of the electric drive train. However, the current status quo shows that there is still a large potential to improve the climate impact of EV batteries in all phases of the life cycle to further strengthen this advantage. As, apart from the climate impact, also the demand for critical metals is an argument often brought forward against electric mobility, in the following Section 3.2 the resource criticality of EV batteries is further examined.

3.2 Resource Criticality of Electric Vehicle Batteries

The criticality of a material can not simply be explained by its physical scarcity, but is determined by its supply risks, the vulnerability of the economic system to supply restrictions and its environmental implications [8]. As the classification as a critical material strongly depends on the chosen criticality method, in Subsection 3.2.1, first, existing concepts for the assessment of resource criticality are briefly summarised, and are then aggregated into a simplified and practical criticality screening procedure. In Subsection 3.2.2 this procedure is then applied to outline the criticality of Li-ion traction batteries. The following summary of criticality methods and the derived criticality screening procedure is based on the description by Regett and Fischhaber [61].

3.2.1 Methods for Resource Criticality Assessment

The comparison of different criticality studies by Glöser and Faulstich [62] shows that the criticality of a material is often classified by the probability for supply shortages (supply risks) and the vulnerability of the system in case of supply shortages (economic importance). This follows the understanding of risk in ISO 31000, where a risk is determined by the likelihood of occurrence of a potential event and its consequences. Thus, a large number of criticality assessments, for example by the European Commission [63, 64] and by Erdmann et al. [65], determine the criticality by means of a criticality matrix, according to which a raw material is classified as critical if it is characterised both by a high supply risk and an economic importance.

As these two dimensions solely represent economic risks, an environmental dimension is added by Graedel et al. [8] who set up a criticality space by adding an environmental axis to the criticality matrix. The criticality can then be derived from the length of the vector. According to the European Commission [64, p. 32], however, a raw material is defined as critical if the raw material is of economic importance and the access is either characterised by a supply or an environmental risk. Also Glöser und Faulstich [62] argue that there is no additive relation between these risks and therefore other parameters such as environmental, price and social risks should be considered separately from the supply risk.

Since, next to cost effectiveness and security of supply, environmental protection is another important goal of German energy policy [66], hereafter the economic importance as well as supply and environmental risks are taken into consideration. To make the abstract criticality concepts more tangible, in the following, specific criteria are defined which must be fulfilled by an energy technology in order to be classified as critical:

- The technology plays an important role for the future energy system
- and leads to a strong increase in demand of metals
- which come along with either supply or environmental risks
- and are currently characterised by a limited substitutability and recyclability.

Based on these criteria the procedure for a simplified criticality assessment of key technologies for the decarbonisation of the energy system depicted in Figure 3–5 has been derived. It should be noted that the purpose of the developed criticality screening procedure is not the quantification and comparison of the absolute criticality of different metals. It should rather be understood as a practical guideline to identify critical technologies and to understand the reasons for the criticality of contained metals based on existing literature. The procedure consists of three main steps which are briefly described in the following.

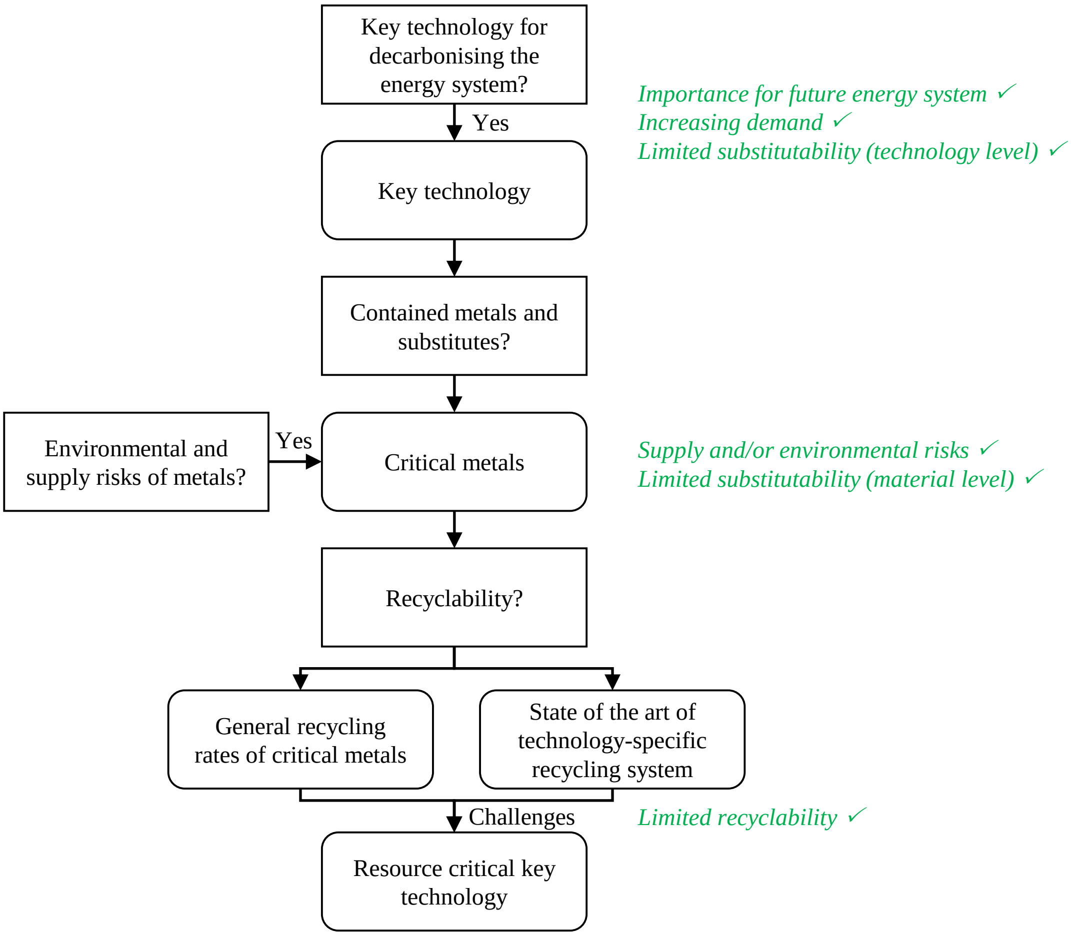

Figure 3–5: Procedure for a criticality screening of key technologies for the decarbonisation of the energy system

Key Technology: First, it needs to be determined whether the technology to be assessed constitutes a key technology for the decarbonisation of the energy system as the overarching aim. For this purpose, the following definition needs to be fulfilled: "Key technologies are technologies which until 2050 play an increasingly important role for the provision of electricity, heat and mobility, while considering the political goal of the German government of reducing GHG emissions in 2050 by 80 % to 95 % compared to 1990." If a technology meets this definition the three criticality aspects "importance for future energy system", "increasing demand" and implicitly a "limited substitutability on a technology level" are fulfilled.

To identify whether a technology meets the definition, first, the application-oriented emission balance in Figure 3–2 is used to assess whether the technology addresses a significant share of energy-related CO_2 emissions, and can therefore directly contribute to decarbonising the energy system. In a second step, existing scenario studies on future energy systems are used to identify the extent to which an increase in demand for the analysed technology is expected until 2050. Lastly, the scenario studies also indicate whether there are technological alternatives available and, thus, provide information on the substitutability on a technology level.

Criticality of Metals: If the analysed technology meets all criteria for a key technology, in a next step, the criticality of the contained metals are assessed. Based on a mass balance, first, the relevant metals contained in the technology are determined. Building on recent overviews on the criticality of metals, then, the supply and/or environmental risks of these metals are identified, based on which the most important critical metals for the technology under assessment are derived. In this context, also possible options for a substitution on the material level are discussed.

Recyclability of Critical Metals: The final step of the criticality screening procedure consists of an analysis of the recyclability of the identified critical metals. For this purpose, first, the current recycling rates of the metals on a global scale are analysed. To identify technology-specific challenges for the recovery of the contained critical metals, furthermore, the current state of the art of the collection and recycling system of the technology is examined in more detail.

3.2.2 Resource Criticality of Electric Vehicle Batteries

To determine the resource criticality of Li-ion batteries for EVs, hereafter, a step-wise application of the previously described screening procedure is carried out.

Key Technology: As shown by the application-oriented emission balance in Subsection 3.1.1, electric mobility plays an important role for the abatement of GHG emissions in Germany. This is emphasised by the target corridor for the year 2030 of 7 million to 10.5 million BEVs and plug-in electric vehicles (PHEVs) defined in [67]. Also in future energy system scenarios, such as [10] or [11], BEVs make up a significant share of the passenger car fleet. But, as illustrated by the two scenarios in Figure 3–6, the number of EVs strongly depends on the degree of GHG abatement. However, even for the conservative "start" scenario, with a reduction of GHG emissions of only 65 % in 2050 compared to 1990, a significant increase in BEVs and PHEVs up to almost 9 million vehicles in 2050 can be expected. For the ambitious "fuEL" scenario, in which the 95 % reduction target is reached, this number increases by more than factor 3 to almost 31 million vehicles, corresponding to 75 % of the car fleet.

Apart from BEVs, other technological alternatives for GHG emission abatement in the transport sector are fuel cell electric vehicles (FCEVs), gas vehicles and renewable liquid fuels from biomass or electricity. However, the potential for sustainable biomass in Germany is limited [68, pp. 165–168] and the production of gases or fuels from electricity is characterised by additional conversion losses during the electrolysis, methanation and synthesis processes. Furthermore, apart from being the most efficient way for integrating renewable electricity into the transport sector, BEVs are also characterised by low CO_2 abatement costs especially in car segments with low ranges [10].

Due to the requirements with regard to energy density currently Li-ion batteries are used in BEVs. According to the battery roadmap by Thielmann et al. [32, pp. 3, 86, 87], Li-ion batteries will continue to play an important role in the coming decades with the potential to move towards solid state batteries or other battery technologies in the long-term, if the required breakthroughs in material design and production technologies are achieved.

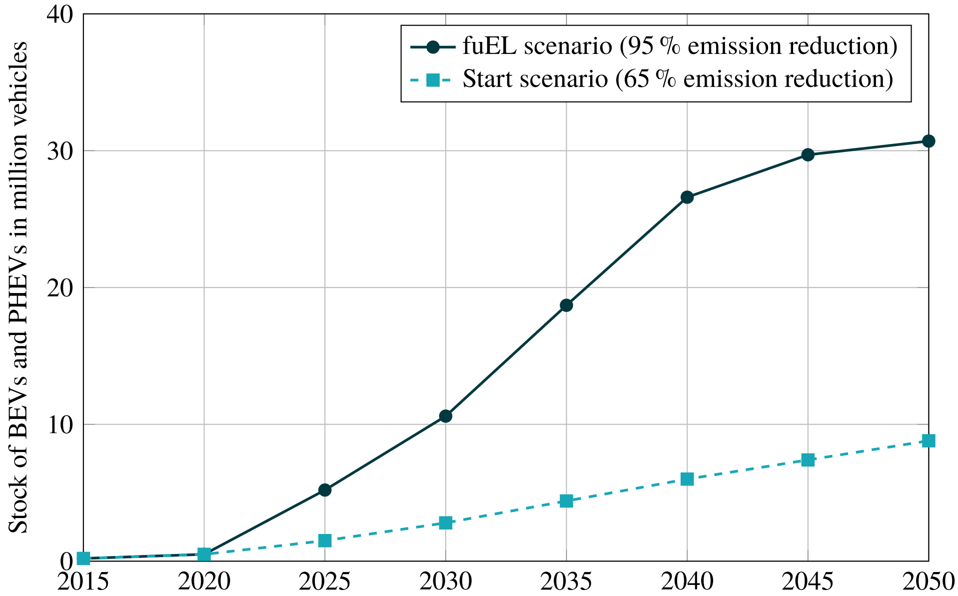

Figure 3–6: Stock of battery-electric and plug-in hybrid electric vehicles according to the Dynamis scenarios [10]

Overall, it can be stated that Li-ion batteries for BEVs can be classified as a key technology as they are expected to play an increasingly important role for the decarbonisation of the future transport system. Furthermore, due to the advantages with regard to efficiency a limited substitutability on the technology level is given, and a substitution of Li-ion batteries by new battery technologies is only expected in the long-term.

Criticality of Metal Demand: As described in [69, pp. 2–8], a battery pack essentially consists of modules, a battery management system (BMS) and a housing. While the housing comprises the isolation, the cooling system as well as mounting systems, the BMS is an electronic component which monitors and controls the state of charge, the remaining capacity and the thermal management. The modules, as the core of the battery system, consist of interconnected cells and a cell control system. The cells can be further broken down into the negative anode and the positive cathode which each consist of an active material and a current collector. These two electrodes are separated by an ion-conducting electrolyte and a separator which ensures the electronic separation of the anode and cathode.

The mass balance of a Li-ion battery system with a capacity of 30 kWh consisting of an NMC cathode and a graphite anode according to BatPac [70] is shown in Table 3–1. It can be seen that, with a share of about 25 %, the active material for the cathode makes up the largest share.

But as illustrated in Table 3–2, the exact composition of the cathode material depends on the cell chemistry used. It can be seen that Co and nickel (Ni) are only contained in NMC and nickel-cobalt-aluminum (NCA) cells which are especially suitable for traction batteries due to high energy densities [69, p. 25]. In this context, to decrease Co content and increase energy density a recent trend to move towards NMC622, and in the future potentially to Ni-rich cell

Table 3–1: Composition of an NMC622 traction battery with a capacity of 30 kWh according to [70]

Material	Mass in kg	Share in %
Cathode material	45	25
Aluminium	36	20
Graphite	32	18
Copper	21	12
Electrolyte	20	11
Plastic	6	4
Others	17	10

types, such as NMC811 and NCA with a Ni share of more than 80 %, is observed [32, pp. 16, 22, 30]. For LFP and lithium-manganese-oxide (LMO) cells which are characterised by lower energy densities, on the contrary, a smaller demand for the listed metals is required.

Table 3–2: Content of selected metals based on the mass balance of a 30 kWh battery from [70] and the stoichiometry of the cathode material

Metal:	Content in kg per kWh dependent on cell technology:				
	LFP	NMC111	NMC622	NCA	LMO
Lithium	0.090	0.137	0.115	0.099	0.109
Nickel	-	0.349	0.528	0.667	-
Manganese	-	0.327	0.165	-	0.224
Cobalt	-	0.351	0.177	0.126	-

The European Commission [71, p. 2] identifies Co, Li, Ni and graphite as four important raw materials for batteries. In the following, the focus lies on the criticality of Co and Li, since the markets for these two metals are dominated by battery demand [16, pp. 42, 44]. Reuter et al. [16, p. 34] identify Li and Co as especially critical for BEVs, while for graphite more flexible production routes are available and Ni is characterised by a lower supply risk. This is confirmed by Weil et al. [72, p. 69], who identify Co and Li as the most critical metals for EV batteries if the future increase in demand is compared with existing reserves, as well as by Helbig et al. [73].

Contrary to common understanding, the geological availability is not the only reason for the criticality of a metal. On the contrary, according to existing criticality analyses such as [8, 62, 63, 65] there are several other reasons leading to supply risks. Bottlenecks on the supply side resulting from a fast increase in demand, for example, can lead to supply shortages. If the metal is produced as a by-product, furthermore, there is a dependency of metal availability on the development of other metal markets. In addition, the concentration of mining and refining activities in a small number of countries and companies can pose a risk, especially if the countries of origin are politically unstable. Finally, these limitations on the supply side can potentially lead to volatile price developments with price peaks posing a risk for secure metal supply.

With a static depletion time (ratio of reserves and annual production) of 58 years in 2017, the geological availability of Co is according to [74, p. 73] not classified as alarming. However, the German Mineral Resources Agency (DERA) [74, pp. 11–12] identifies several other reasons for supply risks of Co. For instance, the high annual growth rates of Co demand can potentially lead to supply risks if the planned expansion of production capacities are delayed. This is especially relevant as Co is mainly mined in the Democratic Republic of the Congo (share of 70 % in 2017), a country with a high geopolitical risk. And also the refinery production of Co is dominated by a limited number of countries, with China making up a share of 60 %. Furthermore, there is a risk resulting from the volatile Co market which has recently shown a strong increase in Co prices by factor 3 between the end of 2016 and the beginning of 2018. In this context, Reuter et al. [16, pp. 43, 78–79] point out the dependency of Co supply and Co prices on the development of copper (Cu) and Ni markets, since Co is predominantly mined as a by-product. With regard to environmental risks, the electricity-related GHG emissions for refined Co as well as the local environmental impacts need to be considered [16, pp. 98, 123]. These local effects in connection with the poor working conditions, especially in artisanal and small-scale mining, show the need for establishing standards for a responsible sourcing of Co [74, p. 12].

For Li the geological availability is, with a static depletion time of more than 200 years according to [75, p. 82], even less critical than for Co. However, also for Li several reason for supply risks are identified by the DERA [75, pp. 9–11, 37, 50]. The Li production, for example, shows oligopolistic structures with 80 % of global production being concentrated to only three companies. Furthermore, with a share of 80 % Li mining is currently mainly conducted in Chile and Australia, with a future shift towards Australia, Argentina, Canada and potentially Bolivia. And also the processing of Li mineral concentrates to Li carbonate or hydroxide is dominated by one region, namely Asia. To what extent the sharply increasing demand of Li for Li-ion batteries can be counteracted by an expansion of production capacities depends on future growth rates. In recent years, also for Li, price fluctuations could be observed. The prices of Li carbonate, for example, doubled from 2016 to 2017 [16, p. 59]. As far as environmental risks are concerned, Li supply is characterised by a lower energy demand and therefore also lower GHG emissions as compared to other metals [16, p. 98]. However, in the desert region in Chile, where Li is extracted from brine, the large water demand does not only effect the environment, but also the drinking water supply of the local population [16, p. 121].

Recyclability of Critical Metals: The overview of global recycling rates for different metals by Graedel et al. [76, 77] shows that the status of recycling largely differs between metals. For example the EoL recycling rate, which is defined as the share of metals reaching their EoL being functionally recycled, amounts to less than 1 % for Li and to above 50 % for Co [77, pp. 16, 19]. However, these values are valid for the global scale and do not differentiate between different products and technologies. Therefore, below, an overview of the current status of the collection and recycling of EV batteries with the focus on Germany and Europe is given.

The European directive 2000/53/EC on end-of-life vehicles, which is transferred into German law by the "AltfahrzeugG", requires reuse and recycling rates of 80 % of the average weight of an EoL vehicle. In addition, the batteries directive 2006/66/EC, which was transposed into the German "BattG", sets battery-specific collection and recycling targets. With regard to battery collection, the EoL batteries collected must amount to at least 45 % of the mass of batteries sold in the respective year. Concerning the recycling targets, a minimum of 50 % of the EoL batteries reaching the recycling processes have to be recycled on a weight basis.

Currently, the overall share of EoL vehicles in Germany reaching the domestic recycling system is low, amounting to only around 17 % in 2015 due to vehicle exports [78, p. 39]. For EV batteries, on the contrary, analogous to recent collection rates for starter batteries, a much larger collection rate of about 95 % of EoL batteries is assumed to be feasible [79, p. 21].

After collection, the EoL batteries are fed into recycling processes. Already today there are several industrial recycling plants available for Li-ion battery recycling which make use of different combinations of processes such as deactivation, mechanical treatment, hydrometallurgy and pyrometallurgy [80, pp. 14–19]. One of the most advanced commercial process is the Umicore process which can deal with a mix of cell chemistries and consists of a pyrometallurgical process followed by a hydrometallurgical refining of Co and Ni, while Li used to get lost in the slag [81, p. 23–28]. As outlined by Hanisch et al. [80, p. 1], in the past the focus of commercial recycling processes was on the recovery of Co and Ni which is due to lower Li prices and higher material costs. Ziemann et al. [82], for example, outline that the costs of recovering secondary Li are in the same range as the costs of producing primary Li.

However, due to a strong increase in Li demand resulting from BEVs [82], leading to rising prices as well other supply and environmental risks, the recycling of Li gains in importance. Therefore, in the LiBRi project a subsequent hydrometallurgical process for the recovery of Li from the slag of the Umicore process has been developed [81, p. 25–27]. When looking a the recycling efficiencies of the Umicore/LiBRi process, which are defined as the share of functionally recycled materials compared to the amount of metals reaching the recycling process [77, p. 16], efficiencies of more than 90 % can be achieved for the materials being extracted from the dismantling process, such as stainless steel, aluminium and copper [57, p. 33]. While the recycling efficiency of Co from the pyrometallurgical and refining processes amounts to 94 %, the efficiency for hydrometallurgical Li recycling in form of battery-grade Li carbonate is 56 %. These efficiencies are derived from the inputs and credits disclosed by Buchert et al. [57, pp. 34, 36] as well as the stochiometric Li content of the resulting Li carbonate.

With the LithoRec projects an alternative recycling process, focussing on the energy-efficient recovery of battery-grade Li, was developed [83, pp. 33-34]. Instead of making use of high temperatures, the process mainly consists of mechanical processes for cell and cathode separation as well as a hydrometallurgical treatment of the separated active materials to finally recover metal compounds in battery quality [59, pp. 19-20]. While for the materials from the dismantling process also recycling efficiencies of over 90 % are expected, the dedicated LithoRec process, in which LFP and NMC cells have to be treated separately [83, p. 37], leads to higher efficiencies for Li and Co recovery. Using the mass flows from Buchert et al. [58, pp. 20, 34] and the stoichiometric Li content in the resulting Li hydroxide, for NMC batteries the Li and Co recycling efficiencies amount to 93 % and almost 100 %, respectively. For Li from LFP batteries, on the contrary, a slightly lower recycling efficiency of 80 % can be reached [58, pp. 20, 40].

According to Hagelücken [84, p. 11], Umicore by now already recovers Li on an industrial scale. However, Stahl et al. [85, p. 67] point out that the industrial-scale recovery of Li is currently still an exception. It can be summarised that the recycling of the critical metals Li and Co from Li-ion traction batteries is in principle technical feasible and in some cases already economically viable. But due to the early stage of industrial maturity there are still improvement potentials especially with regard to the energy and material efficiency of Li recovery (see also Subsection 3.1.2).

Classification of Resource Criticality: Overall, EV batteries are classified as a resource critical technology because Li-ion batteries are the main driver for a strong increase in future demand for Co and Li. For these two metals price increases have been observed in recent years and the mining activities, especially in countries like Congo and Chile, are characterised by local social and environmental issues. Furthermore, the substitutability on the technology level is limited because alternatives such as FCEVs and synthetic fuels or gases lead to other challenges. These include for example the increase in demand for renewable electricity due to lower efficiencies or the increase in demand for other critical metals (e.g. platinum). On the material level, even when moving towards innovative battery technologies, such as Li-sulphur batteries, Li will still play an important role in the future. Despite the trend to reduce Co content in the cathode material, a complete substitution of Co for high energy batteries is not expected in the short- to medium-term. Finally, due to currently still low numbers of EoL traction batteries, the industrial maturity of dedicated collection and recycling processes for Li-ion batteries from EVs is still low, with an improvement potential especially with regard to the recycling of Li.

4 Feasibility of Approaches from the Circular Economy

Starting with a general description of the CE, in Section 4.1 CE approaches are identified for each phase of a technology's life cycle and described with regard to their requirements. Based on a brief description of the life cycle phases of EV batteries, in Section 4.2 the battery's characteristics are matched with the requirements of the defined CE concepts to identify technically feasible CE approaches for EV batteries.

4.1 Background and Definition of Circular Economy Approaches

With the so-called action plan for the circular economy [22], in 2015, the European Union (EU) laid the basis for the implementation of a CE in Europe. As disclosed in the recent monitoring report [86, p. 1], by now the EU's circular economy package is finalised, since all defined actions have been completed or are being implemented. In parallel, several countries have adopted national roadmaps and strategies, while Germany is currently still lacking a strategic plan for the implementation of a CE [21, p. 5]. However, with the German resource efficiency program ProgRess and the launch of a circular economy initiative the basis has already been laid.

As outlined in [87], there are currently different understandings about the CE. In their review of CE definitions Kirchherr et al. [87] summarise that the CE is an economic system building on business models, which reduce, reuse, recycle or recover materials, with the overarching aim of achieving sustainable development. According to the Ellen MacArthur Foundation [23, pp. 23–25], the CE is, in general, based on three principles, namely the preservation and enhancement of natural capital, the optimisation of yields from resources in use and the fostering of system effectiveness. While the first principle encompasses the preservation of finite and the use of renewable resources, the second principle addresses the sharing, repairing, reusing, remanufacturing and recycling of materials. Finally, the third principle aims at minimising negative externalities resulting from emissions and resource use.

These principles show that the CE is not limited to recycling, but targets the whole life cycle of a product, or in this case technology. Therefore, based on the approach by Lacy et al. [24], in Figure 4–1 for each life cycle phase potential CE approaches are depicted which can be classified into four categories. The first category covers approaches addressing the supply of resources (energy and materials) by either decreasing the demand for resources through efficiency measures or by increasing the supply of renewable resources. Furthermore, CE approaches aiming at an increased utilisation such as sharing concepts can be applied. Apart from the extension of the product's lifetime through repair, remanufacturing and reuse, the fourth category of CE approaches aims at the recovery of resources through recycling. In the following, for each of the four categories the depicted CE approaches are explained in more detail.

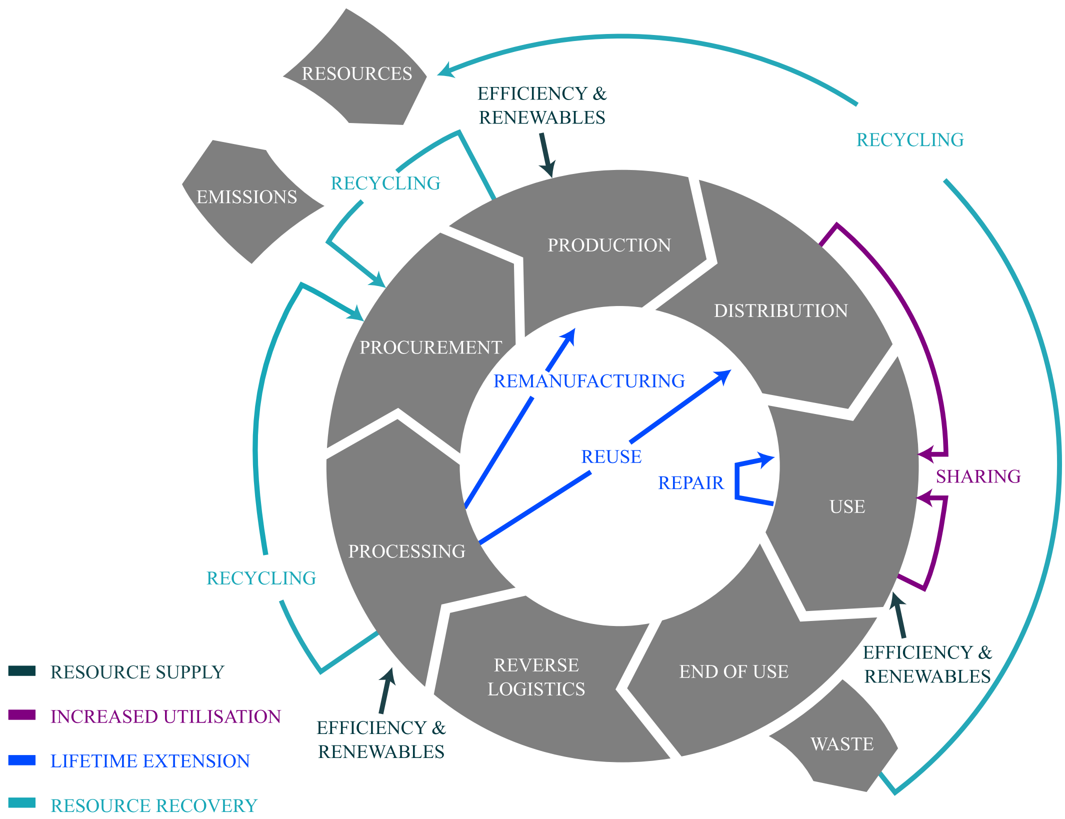

Figure 4–1: Overview and classification of approaches from the circular economy in different life cycle phases (own illustration based on [24, p. 12])

Resource Supply: According to [24, p. 12], the resources supplied in a CE should be renewable, bio-based or fully recyclable. In this context, especially the use of renewable energy sources is pointed out by [88, p. 22] and [89, p. 6] as a key requirement for a CE. The prerequisite for a renewable resource supply is the availability of renewable alternatives. While for energy there are several renewable options available, also products such as chemicals can in principle be produced from biomass [90]. The renewable supply of other resources such as metals, however, is not feasible. Thus, also resource efficiency plays an important role which according to [89, p. 6] can be supported by ecodesign and encompasses both a careful use of energy and materials as well as the replacement of materials. In principle, the CE approaches *efficiency and renewables* can be applied to any life cycle phase, but are especially relevant for the resource-intensive production, use and processing phases.

Increased Utilisation: As outlined in [24, p. 14] and [23, p. 25], the utilisation of a product can be maximised by means of *sharing* concepts. The general idea behind sharing is that the provided function in the product's use phase is increased. Here, two cases are distinguished because the utilisation of the product can either be maximised by an increased use through multiple user, or by an increased use through multiple purposes. The most important prerequisite is the accessibility of the product for multiple users or multiple use cases. This can, for instance, be achieved through sharing platforms [24, p. 14]. Furthermore, in this context so-called product as a service concepts gain of importance which replace the traditional selling approach by leasing, renting, pay-per-use or performance-based business models [89, p. 7].

Lifetime Extension: As shown in [23, p. 24], the first option to extent the product's lifetime is to *repair* the product during the use phase. As a prerequisite, the accessibility of the product and the interchangeability of components need to be ensured. Apart from a lifetime extension in the use phase, [23, p. 24] also point out approaches after the product's EoL, namely reuse and remanufacturing. *Reuse* aims at further utilising the entire product in the same or a different application. In the case of *remanufacturing*, on the contrary, single components are fed into the production process of a new product. While for reuse a suitable application must be available, for remanufacturing the possibility of disassembling the product is a crucial requirement. As outlined in [89, pp. 6, 15], this prerequisite can already be considered in the design process, for example through modular design. Since the exact delimitation of the two EoL approaches is often unclear, in the following, the term Second-Life (SL) is used to refer to both reuse and remanufacturing.

Resource Recovery: Finally, *recycling* as the most traditional CE approach targets the use of less primary resources through resource recovery [89, p. 5]. Here, a distinction can be made between the recycling of scrap in the production phase, the energetic recycling at EoL and the recovery of materials in processing plants (see Figure 4–1). According to [91, p. 49], the separated collection and, if necessary, sorting of waste streams constitute prerequisites for the recovery of materials in dedicated recycling processes. Furthermore, apart from hazardous substances, recycling can be limited by the environmental impact of the recycling process once it exceeds the advantage resulting from resource recovery [91, p. 49].

4.2 Feasibility of Circular Economy Approaches for Electric Vehicle Batteries

Based on the previous description, the feasible CE approaches for EV batteries are identified. For this purpose, the three main life cycle phases (production, use and EoL) are each briefly described with regard to the battery's characteristics, which are then matched with the requirements of the CE approaches described above.

Production: As outlined in Chapter 3, the main hot spots for battery production are the use of critical metals such as Co and Li as well as the energy demand in the manufacturing process. Apart from other components such as the housing and the BMS, in this context especially the manufacturing of battery cells and the battery back assembly are of interest. Therefore, below, the process steps are briefly explained based on [55, 92, 93]. First, in a mixing process, slurries are produced by mixing each the anode and the cathode material with additives, solvents and binders. The produced anode and cathode slurries are used for the coating of the copper and aluminium carrier foils. By means of a drying process the solvent is then recovered and, subsequently, the coated foils are compressed by a rolling process, referred to as calendaring. After slitting of the electrodes, the electrode strips are fed into a vacuum dryer to remove the moisture, and are then being transferred to a dry room. In the dry room, first, the stacking or winding of the anode, cathode and separator takes place. Second, the current collectors are welded and the cells are enclosed in a container. This is followed by the process of electrolyte filling and the final sealing of the cell. After a pre-charging of the produced cells which aims at the formation of the boundary layer between electrolyte and electrode, finally, the different components are assembled into the battery pack.

In view of the need for energy-intensive drying processes, it is evident that especially the CE approaches of energy efficiency and renewable energy supply can play an important role in decreasing the climate impact of the battery's production phase. Furthermore, the material efficiency can be increased for example by shifting to cell technologies containing less Co (see Subsection 3.2.2) or by the recycling of production waste.

Use: In a next step, the produced batteries are integrated into the EV. It has become established that the battery is installed between the axes in the vehicle's underbody [94]. In combination with the inverter and the electric motor the battery serves the propulsion of the EV [95]. According to [96], in principle, there are several possibilities to charge the battery in the vehicle. Currently, the charging process is conducted with alternating or direct current (so-called AC or DC charging). While inductive charging is still under development, the option of a battery swap does so far not play a role for passenger cars due to a lack of standardisation. In [96] it is further pointed out that load management can be used to decrease the stress on the grid and provide energy system services. In this context, also vehicle-to-grid (V2G) gains increasingly of importance, with demonstration projects already in place [26, p. 139]. In the course of a V2G concept, load is not only shifted, but electricity from the traction battery is fed back into the grid. Overall, as pointed out in Chapter 3, the electricity demand during the use phase is a major contributor to the EV's climate impact.

Thus, not only in the production, but also in the use phase the supply of renewable energy is of importance, while energy efficiency is less relevant due to already high efficiencies of both Li-ion batteries and the electric motor. When it comes to sharing approaches, there are in principle several options available. Next to the typical car sharing, which is already widely spread, the swapping of batteries as a replacement for the charging process is tested in pilot projects. However, as described above, a large-scale roll-out of this approach is currently not technically feasible for passenger vehicles due to missing standardisation. With regard to increasing the battery's utilisation through multiple purposes, the prerequisites for multi-use cases are fulfilled as the EV can be equipped for load management and potentially V2G. In that case, the traction battery provides, apart from its original purpose, also other functions to the energy system.

End-of-Life: As described in Subsection 3.2.2, the collection rate of EoL vehicles in Germany is low, but with the right incentives for EVs a larger collection rate than for conventional vehicles can be expected. In Subsection 3.2.2, it is further outlined that there are already industrial plants for the recycling of Li-ion batteries available. In this context, the recovery of Li is the current challenge because an additional hydrometallurgical process step is required. According to [80, p. 4], the battery recycling process starts with a deactivation step, followed by either mechanical, pyrometallurgical and/or hydrometallurgical treatment processes. While mechanical treatment includes the crushing of the battery as well as the exposure and sorting of valuable materials, in pyrometallurgical processes either the whole cell or cell components are melted. In that case, transition metals such as Ni, Co and Cu can be recovered, whereas Li is lost in the slag. Therefore hydrometallurgical processes can be used to recover Li either directly from the separated materials of the mechanical process step or from the slag of the pyrometallurgical process. In view of these energy-intensive processes, the approaches of energy efficiency and renewables can also be applied to reduce the environmental impact of battery recycling, since the recycling process does not necessarily lead to GHG emission savings (see Subsection 3.1.2).

Prior to the actual recycling process, already today there are several demonstration projects for an SL of EV batteries in stationary battery applications in place [97]. To prepare the batteries for SL applications a processing step is required. This processing mainly comprises the disassembly, a visual inspection, the measurement of voltage and resistance to identify failed modules, a testing process to determine module capacity and power capability, the sorting as well as the assembly into new battery packs [98, p. 29]. However, as different battery applications come along with different requirements [33, pp. 46–71], one of the main challenges for SL concepts is the identification of suitable applications, for which the requirements of the storage application fit the characteristics of the SL battery. In this context, one of the advantages of batteries are there inherently modular design which makes a modification of battery characteristics possible.

From the described EoL process steps, it can be seen that the possible CE approaches in the EoL phase depicted in Figure 4–1 are all feasible for EV batteries. For the lifetime extension approaches at EoL especially the modular design of batteries is of advantage. However, both SL applications as well as Li-ion battery recycling are currently still undergoing a development process.

Overview and Selection: In Figure 4–2 the feasible CE approaches for EV batteries are finally summarised. The CE approaches which are selected for further analysis in the exemplary applications in Chapter 5 are highlighted in black. As the energy demand in the manufacturing process was identified as a major driver for the environmental impact of batteries in Chapter 3, for the production phase the approaches of renewable energy and energy efficiency are chosen for a detailed assessment. In the use phase, apart from the impact of renewable electricity, also a sharing concept is analysed. Here, the application of the traction battery for multi-use cases through load management and V2G is chosen because this approach is characterised by strong interactions with the electricity system. This holds also true for the EoL approach of deploying used traction batteries in stationary SL applications. Furthermore, the recycling of materials is chosen for a detailed analysis, since this approach can potentially lead to a significant reduction in demand for primary metals as large amounts of critical metals are available in EoL batteries.

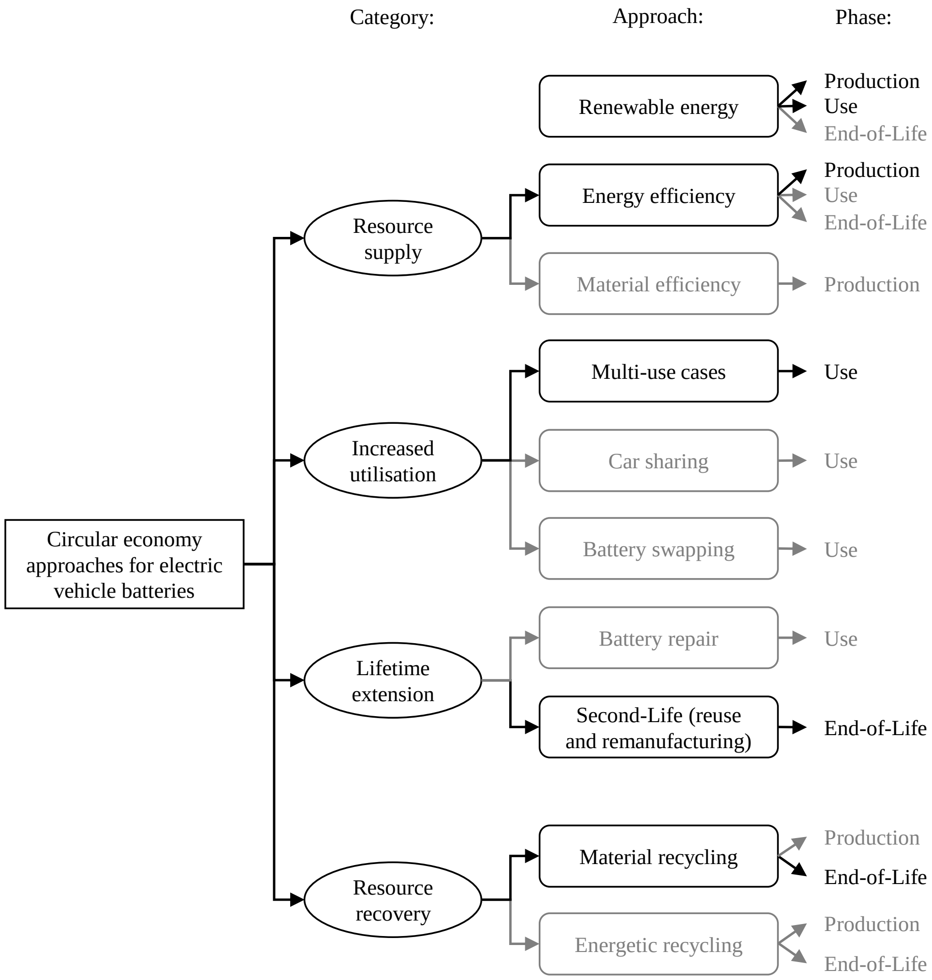

Figure 4–2: Overview and selection of circular economy approaches for electric vehicle batteries

5 Emission and Critical Resource Savings through the Circular Economy

In the following, first, the selected indicators and environmental assessment methods suitable to determine GHG emission and critical resource savings are described in Section 5.1. The following Section 5.2 to Section 5.6 are structured along the life cycle phases of the battery. As described in Chapter 2, in each section, first, the main challenge for resource and emission assessment of CE approaches in the respective life cycle phase is discussed based on current literature. Then, an instrument addressing the identified challenge is developed, which is finally applied to the selected CE approach for EV batteries. In Section 5.7 the resulting set of instruments over all life cycle phases is summarised.

5.1 Environmental Assessment Methods

In Chapter 3 it is outlined that for EV batteries especially the provision of Co and Li is associated with supply and environmental risks. Therefore, the demand for primary Co and Li are chosen as indicators for the quantification of critical resource savings through CE approaches. Furthermore, the overview in Chapter 3 shows that energy demand is the main driver for the climate impact in the different life cycle phases of a battery. Thus, the impact of CE approaches on energy-related GHG emissions is chosen as a further assessment indicator. To quantify these indicators LCA and Material Flow Analysis (MFA) constitute suitable assessment methods, for which the basics are described below.

5.1.1 Life Cycle Assessment

As defined in ISO 14040 and 14044, LCA is a methodology aiming at the assessment of the environmental impact of a product or service over its entire life cycle, meaning from cradle-to-grave. The ISO standards define four iterative phases for conducting an LCA. Starting with the *goal and scope definition*, first, the aim of the study is specified. Furthermore, the reference or so-called functional unit is chosen, the system boundaries are defined and methodological choices are described. Then, in the *life cycle inventory* phase, data on inputs and outputs of the considered processes are collected, prepared, validated and finally referred to the functional unit. In this context, the Cumulative Energy Demand (CED), as defined in the guideline VDI 4600, can serve as a basis for quantifying energy flows. In the inventory phase, one of the major challenges is the allocation of input and output flows in case of multi-product systems. Here, the ISO standards only provide a rough guideline. The proposed approaches include both a system expansion to avoid allocation as well as a partitioning of flows based on physical properties or economic metrics. Subsequently, in the course of the *life cycle impact assessment* the resulting flow data per functional unit is translated into potential environmental impacts. For this purpose, for the chosen impact categories (e.g. climate change) an impact indicator (e.g global warming potential (GWP)) is calculated making use of a certain impact assessment method (e.g. CML 2001). The results of the previous phases are further analysed and discussed in the *life cycle interpretation* phase so as to finally derive conclusions and recommendations with regard to the defined goal of the study.

The computational structure, on which LCA is based, is described in detail by Heijungs and Suh [99]. As outlined in [99, pp. 16–20], the emission inventory $\boldsymbol{g}$ is in principle determined from

$$\boldsymbol{g} = \mathbf{B}\boldsymbol{s} \tag{5–1}$$

with

$$\boldsymbol{s} = \mathbf{A}^{-1}\boldsymbol{f}. \tag{5–2}$$

In this context, the final demand vector $\boldsymbol{f}$ represents the functional unit and therefore the demand for the provided products, technologies or services. Considering the technology matrix $\mathbf{A}$, which contains the exchanges between different processes, the scaling vector $\boldsymbol{s}$ can be determined. The scaling vector $\boldsymbol{s}$ corresponds to the total demand for the output of each process to deliver the final demand $\boldsymbol{f}$. The emission inventory $\boldsymbol{g}$ associated with the provision of the functional unit is then calculated by multiplying the environmental intervention matrix $\mathbf{B}$, which contains the emissions per process, and $\boldsymbol{s}$.

It is common practice not to set up a complete environmental intervention matrix. Rather the environmental impact of the background processes, which are not part of the modelled foreground system, are directly extracted from LCA reports and databases. In the following case, this holds true for the emissions associated with the supply and combustion of energy carriers. The resulting emission factor vector $\boldsymbol{emf}$ is then directly multiplied with the scaling vector $\boldsymbol{s}$ to determine energy-related GHG emissions.

5.1.2 Material Flow Analysis

As outlined by Brunner and Rechberger [100, p. 3], MFA is a method used for decision support in resource, waste and environmental management by systematically assessing the stocks and flows of materials in a system. The general idea behind MFA is that the inputs and outputs of a certain material in a system are balanced so as to gain a better understanding of material demand, waste flows as well as the depletion or accumulation of material reservoirs [100, p. 3].

According to [100, p. 4], a system is defined in time and space and consists of several processes transporting, transforming or storing materials. These processes are connected via material inputs and outputs and comprise, in the case of storage processes, also material stocks. MFA methodology consists of several steps, namely the system definition, the quantification of mass flows, the balancing of goods, the determination of concentrations, the balancing of substances and finally the illustration and interpretation [100, pp. 53–54].

While the classical, static MFA only provides a snapshot at a certain point of time, the dynamic MFA approach has evolved aiming at tracking the system's development by modelling the material stocks and flows as a function of time [101]. The overview by Müller et al. [101] points out that dynamic MFA analyses mainly differ with regard to the time frame (retrospective vs. prospective), the modelling of the material stock (top-down vs. bottom-up) as well as the parameter driving the model (input-driven vs. stock-driven). While in case of a top-down model the material stock is determined from the net material flows (difference between inputs and outputs), in a bottom-up model the stock is directly derived from the stock's material content. Depending on the availability of data, the model is either input- or stock-driven. While in input-driven models the output and stock is quantified from the input and a lifetime distribution function, in stock-driven models the inflows and outflows are derived from the stock development and a lifetime distribution.

5.2 Production: Future Improvement Potential

As outlined in Subsection 3.1.2, the energy demand in the manufacturing process has a strong impact on the carbon footprint of battery production. Therefore, in Section 4.2 energy efficiency and renewable energy supply have been identified as relevant CE approaches for the production phase. But Li-ion batteries as well as the corresponding production processes are currently still undergoing a development process, which makes an environmental assessment challenging. Thus, in Subsection 5.2.1, first, a brief overview of existing approaches for LCA of emerging technologies is given. These approaches are then translated into a step-wise procedure for dealing with uncertainties of emerging technologies in Subsection 5.2.2. With the aim of quantifying the potential of energy efficiency and renewable energy supply, in Subsection 5.2.3 the method is finally applied to battery production.

5.2.1 Overview: Assessment of Emerging Technologies

When assessing the potential of CE approaches for battery production, one of the main challenges is to deal with the uncertainty about the future improvement potential of the emerging production process. The topic of dealing with uncertainties in LCA is already addressed in ISO 14044. In the ISO standard it is proposed that in the interpretation phase, first, significant parameters are identified which are then further evaluated with methods such as sensitivity analyses. As the dealing with uncertainties is especially relevant for emerging technologies, the field of prospective LCA, which according to [102] aims at assessing the environmental impact of future technological systems, came up.

Both Cucurachi et al. [102] and Arvidsson et al. [103] propose scenarios as a means to assess emerging technologies, while the reliability of predictions based on learning curves is still an area of future research [103]. Therefore, Arvidsson et al. [103] recommend the use of ranges and extreme scenarios if predictions about future developments are difficult. Also Cucurachi et al. [102] propose the use of extreme scenarios, next to other types of scenario including expert opinions.

However, the use of scenarios is not only relevant when assessing the technology's foreground system, but also the development of the background system needs to be considered in a prospective LCA [103]. This is also emphasised by Mendoza et al. [104] who use future energy system scenarios to account for the impact of a changing background system in the assessment of emerging technologies.

5.2.2 Step-Wise Procedure for Dealing with Uncertainties of Emerging Technologies

Considering the general procedure in ISO 14044 and the scenario ranges proposed in [103] and [102], a step-wise procedure for dealing with uncertainties of emerging technologies is defined in Figure 5–1. First, a contribution analysis is conducted to point out the processes with the largest contribution to the environmental impact. Then, critical parameters are identified by examining the input parameters of these processes with regard to uncertainties, which can result from data quality or unknown future developments. In a third step, a possible scenario range for the identified critical parameters is determined based on the status quo and the potential for future development. Finally, in the course of a sensitivity analysis, the critical parameters are varied according to the defined range so as to determine the sensitivity of the technology's environmental impact. By following the described step-wise procedure, the possible improvement potential of an emerging technology can be systematically pointed out.

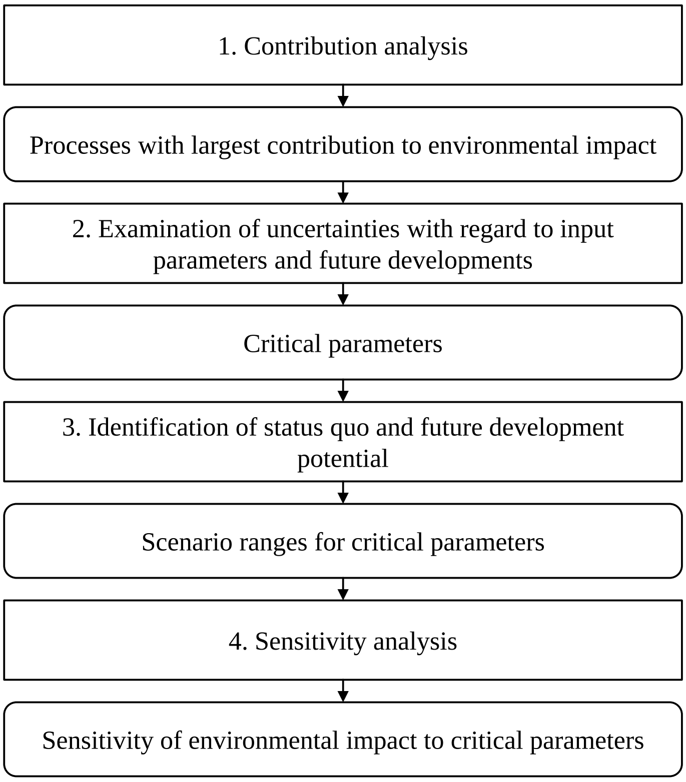

Figure 5–1: Step-wise procedure for dealing with uncertainties when assessing emerging technologies

5.2.3 Exemplary Application: Energy Efficiency and Renewable Energy in Battery Production

The described procedure is now applied to battery production with a special focus on the potential of energy efficiency and renewable energy supply to reduce GHG emissions. The following description and illustrations contain extracts from the analysis by Regett et al. [105, 106].

Goal and Scope

The potential of energy efficiency and renewable energy supply to reduce the climate and critical resource impact of battery production is assessed on the basis of energy-related GHG emissions as well as Co and Li demand. The object of investigation is a Li-ion traction battery system consisting of an NMC622 cathode and a graphite anode, with the functional unit of 1 kWh battery capacity.

As shown in Figure 5–2, in addition to the energy input in battery manufacturing, the energy demand for raw material extraction and material production is taken into account. In the following, the term "battery manufacturing" refers to the processes of cell manufacturing and battery assembly, and the term "battery production" to the sum of all processes, including material production and raw material extraction.

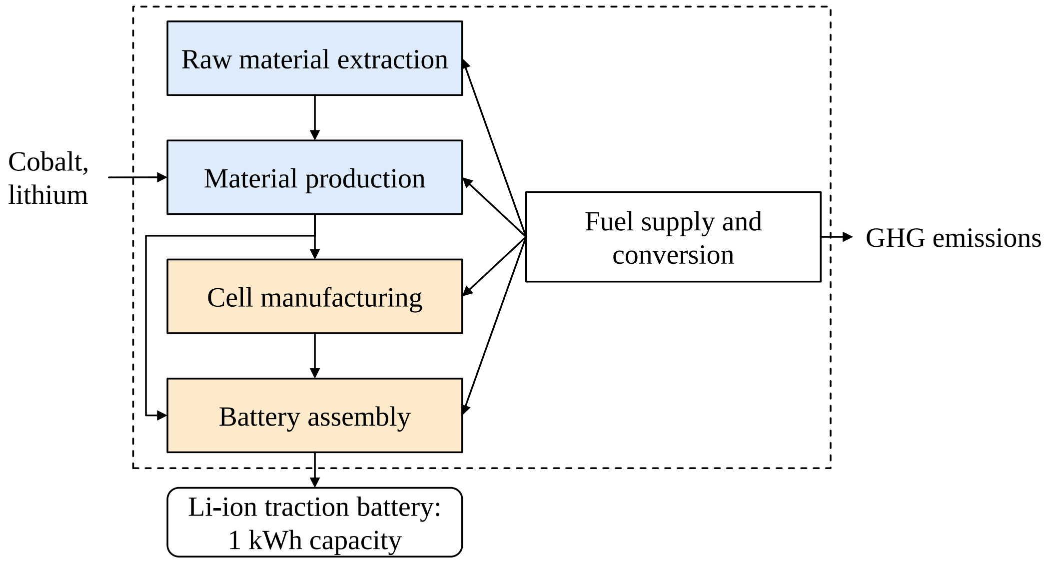

Figure 5–2: System boundaries for the assessment of battery production

The transport of intermediate and final products as well as the construction of the battery production plant are not accounted for. Furthermore, no process-related emissions are taken into account. Thus, only the energy-related GHG emissions resulting from the supply and conversion of fuels are in the scope of this analysis. These also include the emissions resulting from the construction of the energy infrastructure.

Because the GHG emissions for electricity vary between regions, for the following analysis, it is assumed that the battery manufacturing takes place in the battery-producing regions according to the short-term trend scenario from [32, p. 11]. In this scenario the battery production mix is dominated by China with 49 %, followed by the USA with 20 %, Europe with 12 % and South Korea and Japan with 5 % and 3 %, respectively. For the electricity used in the processes of raw material extraction and material production the global mix is assumed.

To calculate the climate and resource impact, first, for each battery production process an energy and material balance is generated and related to 1 kWh of battery capacity produced. The energy demand per process is then multiplied by a specific GHG emission factor in order to calculate the energy-related GHG emissions. The critical metal demand is derived from the stoichiometry of the materials.

Input Data

The work from the Argonne National Laboratory serves as a starting point for the following analysis. The mass balance of the traction battery is calculated with BatPac [70], and the energy input for processes is extracted from GREET [107] as well as the accompanying background reports. The global shares of primary and secondary materials are taken from [108, p. 17], [109, p. 8] and [110, p. 9] for aluminium, copper and steel, respectively.

According to BatPac [70], the analysed Li-ion battery system with a capacity of 30 kWh, consisting of an NMC cathode and a graphite anode, has a total mass of 177 kg. For the cathode material NMC622, a less cobalt-containing alternative to NMC424 and NMC111, is chosen because it is already the state of the art [32, p. 30]. The material composition of the battery system is broken down in detail in Subsection 3.2.2.

The energy demand for the production of NMC active material, cell manufacturing and battery assembly is derived from Dai et al. [55]. The reported energy demand is based on data from industrial plants in China. This energy demand is validated using the values measured at a pilot plant from [92]. While the specified final energy demand of the Chinese plants amounts to 47 kWh per kWh battery capacity produced [92, pp. 9–10], the electricity demand for cell manufacturing of the pilot plant in [92] is 13 kWh per cell, corresponding to about 108 kWh per kWh. In Table 5–1 the electricity demand for battery manufacturing is broken down by the process steps described in Section 4.2. For an industrial process, Yuan et al. [92] indicate possible savings of up to 72 % compared to the pilot plant, which implies that the electricity demand for cell manufacturing can potentially be reduced to 30 kWh per kWh.

The energy demand of the Chinese battery factories in [55] is therefore classified as plausible and used as a reference for further analysis. In the Chinese plants under consideration, part of the final energy demand is covered by district heating. Since this is an individual case, in the following, it is assumed that in consistency with other studies the final energy is provided exclusively by electricity. With an efficiency of 99 % of an electrode heating boiler [111], this results in an electricity demand for battery manufacturing of 48 kWh per kWh battery capacity produced. This coincides with the 50 kWh per kWh battery capacity for a highly utilised production plant according to Volkswagen, as stated in [17, pp. 60–61].

The Li and Co demand of the battery system are derived from the mass balance and the stoichiometry of cathode materials (see Subsection 3.2.2). To translate the energy demand for battery production into GHG emissions, the emission factors from the National GHG Inventory Report [51, pp. 811–813] are used for direct CO_2 emissions from fuel combustion. The global warming potential (GWP)100 according to the CML 2001 impact assessment method and the cut-off system model from the ecoinvent database [112] is deployed for the emission factors of electricity and the upstream chain of fuel supply. The GHG emission factor for electricity

Table 5–1: Share of total electricity demand for each process step in battery manufacturing for the pilot plant in [92]

Process step	Share of electricity demand in pilot plant in %
Mixing	0.2
Coating	0.4
Drying	38.4[a]
Calendaring	2.3
Slitting	4.3
Vacuum drying and drying room	43.4[a]
Stacking or winding	4.7
Welding and enclosing	1.4
Electrolyte filling	0.4
Final sealing	3.7
Pre-charging	0.6
Assembly	0.1

[a] In industrial process significant reduction of energy demand possible.

in battery manufacturing is determined by weighting the country-specific emission factors of electricity with the country's share in battery production.

Results and Discussion

The cathode of an NMC622 traction battery system contains 0.115 kg of Li and 0.177 kg of Co per kWh capacity (see also Table 3–2). Also the electrolyte contains Li, however, the amounts are negligible compared to the Li content of the cathode. Thus, the Li and Co demand for a battery system with a nominal capacity of 30 kWh adds up to a total demand of about 3.5 kg of Li and 5.3 kg of Co.

Taking into account the assumptions and data described above, the energy-related GHG emissions for the production of a traction battery amount to 106 kg CO_2 eq. per kWh battery capacity. The contribution analysis depicted in Figure 5–3 shows that about 40 % of the emissions are attributable to the electricity demand in battery manufacturing (including cells) and almost a quarter to the production of NMC active material. However, as outlined in Subsection 3.1.2, the energy demand in battery manufacturing is subject to large uncertainties. Furthermore, the emissions associated with this energy demand are strongly dependent on the electricity mix prevailing at the battery production site. Therefore, in the following, the effect of energy efficiency and renewable energy supply on GHG emissions for battery production is illustrated.

In Figure 5–4 the energy-related GHG emissions of the battery production in kg CO_2 eq. per kWh battery capacity are shown as a function of the electricity demand for battery manufacturing and

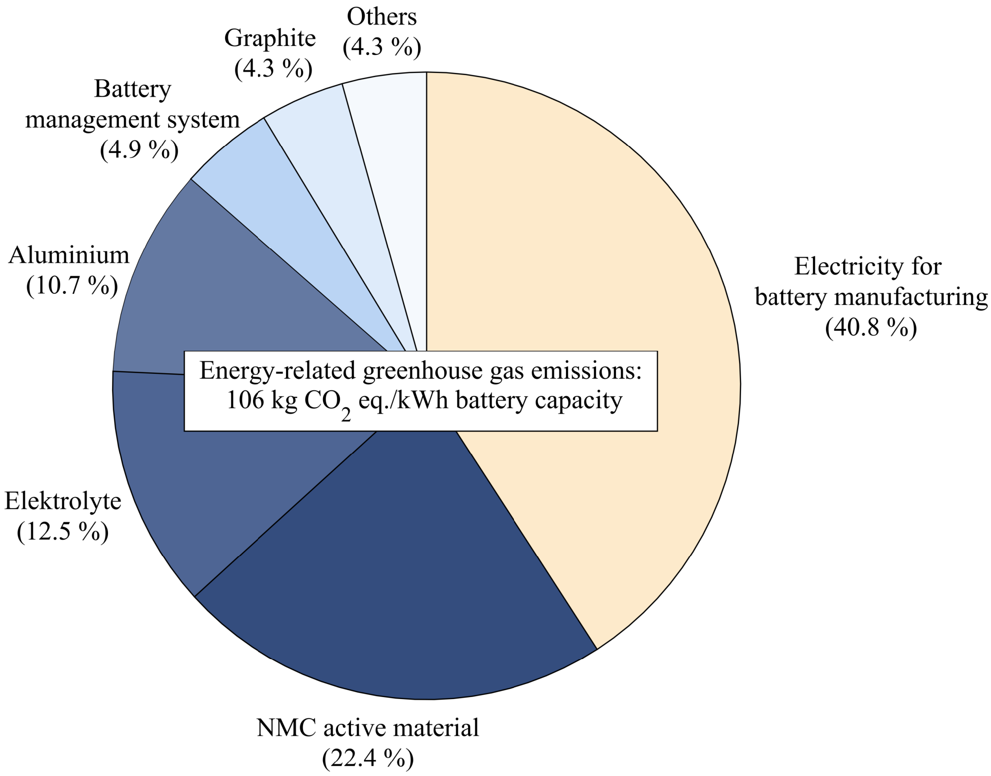

Figure 5–3: Energy-related greenhouse gas emissions of battery production and share of processes

the emission factor of the electricity used in the manufacturing process. The range for electricity demand is derived from the overview by Ellingsen et al. [53], according to which previous LCA studies disclose an energy demand in the range of less than 10 kWh to more than 170 kWh per kWh of battery capacity produced. For the emission factor of electricity the range from a hypothetical electricity factor of zero (entirely renewable) to an emission factor of electricity of 1 kg kWh^{-1}, corresponding to coal power, is selected.

Starting from the reference point (energy demand for manufacturing of about 50 kWh per kWh battery capacity and a GHG emission factor of electricity for the battery production mix of around 0.9 kg kWh^{-1}), it can be seen that the carbon footprint of the traction battery improves considerably if the production process is supplied with electricity in countries with a lower emission factor. For instance, the emissions from battery production are reduced by 18 % to 87 kg CO_2 eq. per kWh battery capacity, in case an emission factor of 0.5 kg kWh^{-1}, corresponding to the German electricity mix in recent years, is applied. If the electricity for battery production is increasingly supplied from renewable energy systems (RESs), the energy-related GHG emissions from battery production approach the emissions for material extraction and production of 62 kg CO_2 eq. per kWh battery capacity.

In addition, the carbon footprint of battery production is strongly dependent on the electricity demand in battery manufacturing. While the present analysis builds on data from the industrial

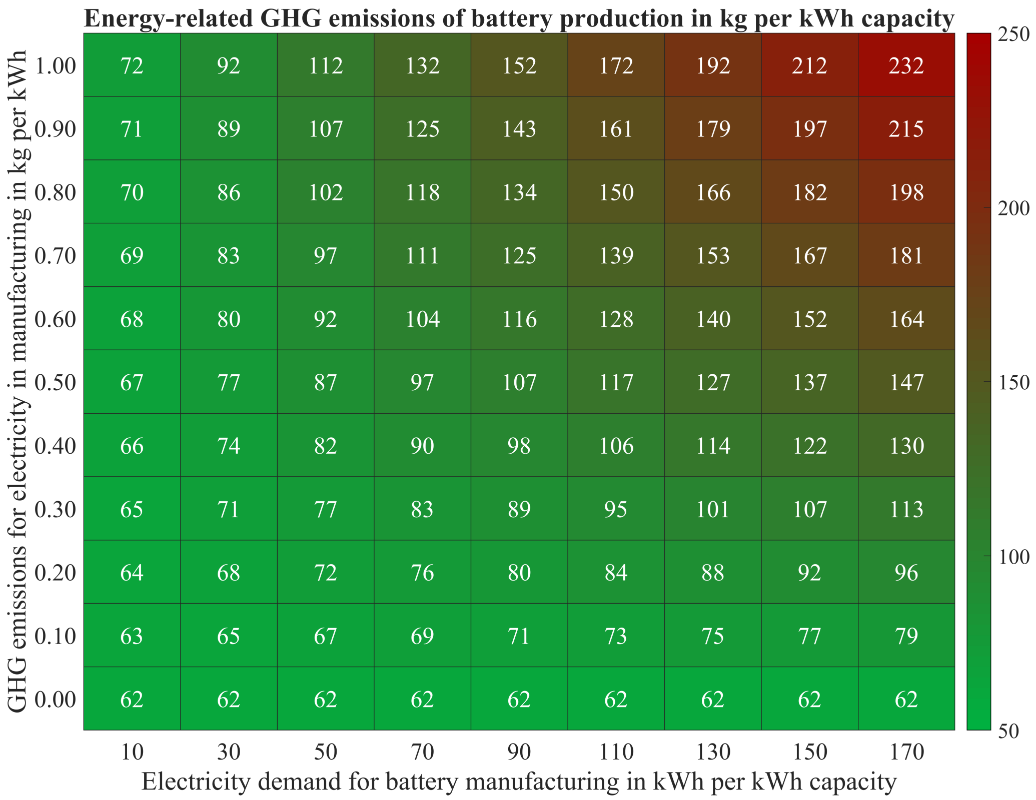

Figure 5–4: Impact of electricity demand and the emission factor of electricity in battery manufacturing on energy-related greenhouse gases for battery production

plants in [55], the carbon footprint worsens for the electricity demand of smaller-scale plants, corresponding to the upper limit shown in Figure 5–4. In that case, the carbon footprint is within the range indicated by Romare and Dahllöf [18, p. 42] (see Subsection 3.1.2). The lower specific energy demand of industrial plants can be explained by economies of scale and optimised process design.

Another option described in [55] is to provide the heat from natural gas instead of electricity. In that case, the carbon footprint of battery production is reduced from 106 kg CO_2 eq. to 81 kg CO_2 eq. per kWh battery capacity. Furthermore, the results depend on the material composition and energy density which both differ depending on the battery system. Therefore, the calculations described above are again carried out for the battery system from [113]. The material composition differs from the reference system in Table 3–1 primarily with regard to lower proportions of graphite (13 %) and aluminium (5 %) and a considerably higher proportion of steel (28 %) in the total weight. Also, instead of NMC622, the more Co-containing cathode material NMC111 is used. The resulting increase in energy-related GHG emissions for battery production to 113 kg CO_2 eq. per kWh battery capacity, however, is not due to the material composition, but largely results from the lower energy density of the battery system. For this sensitivity analysis, simply the same specific energy demand for manufacturing per kg battery as in the previous case is assumed, which was derived based on the energy density of the considered NMC622 battery.

However, in view of sharply increasing energy densities and new battery technologies, there is a need for further research on the correlation of energy demand in the manufacturing process and battery capacity.

Another parameter affecting the energy-related GHG emissions of the battery system is the use of secondary materials. If for example, instead of the aluminium mix from [108], only primary aluminium is used, GHG emissions increase to 113 kg CO_2 eq. per kWh, while the sole use of secondary aluminium results in a decrease to 97 kg CO_2 eq. per kWh battery capacity. The consideration of process-related CO_2 emissions in NMC production [55, p. 16], on the contrary, has a minor impact and leads only to a slight increase in emissions of less than 0.5 kg CO_2 eq. per kWh battery capacity.

Overall, it can be stated that the energy-related GHG emissions for battery production, depending on the exact composition and energy density of the battery system, are currently in the range of 100 kg CO_2 eq. per kWh battery capacity. Approximately half of the emissions are attributable to material production and the other half to battery manufacturing. This value applies to an electricity demand in battery manufacturing of about 50 kWh per kWh battery capacity and an emission factor for electricity of around 0.9 kg kWh^{-1}, which is dominated by the Asian market. In the case of an increase in the efficiency of the manufacturing process and an increase in renewable electricity supply for battery manufacturing, the carbon footprint of the battery can be reduced by almost half. Further potential for improvement can be expected from increasing energy densities.

Summary

When assessing CE approaches for emerging technologies, such as the production of Li-ion batteries, uncertainties with regard to the technology's improvement potential need to be considered. Here, a systematic, step-wise procedure to deal with uncertainties is defined which consists of a contribution and sensitivity analysis, as proposed in ISO 14044, combined with the scenario approach from prospective LCA. The application of the procedure to battery production outlines the strong dependency of the battery's carbon footprint on the scale of the production process and the energy supply of the production plant. Due to an increased energy efficiency for the production on an industrial scale, an improvement of the climate impact of batteries can be expected in the future. Furthermore, the electricity supply should be taken into account when choosing a location for new production plants, since the origin of electricity has a strong effect on the carbon footprint of the produced batteries.

5.3 Use: Development of Energy System

As shown in Subsection 3.1.2, the carbon footprint of a BEV is also strongly dependent on the GHG emissions of the charged electricity during the vehicle's operation time. For this reason, in Section 4.2, renewable energy supply has been identified as an important CE approach for the battery's use phase. As the increase in renewable energy has an impact on the electricity's carbon intensity, the emission factor of electricity can serve as an indicator for renewable energy supply. While in the production phase the emission factor at the time of battery production is essential, in the use phase also the temporal course of the emission factor of electricity over the battery's lifetime in the vehicle is important, as outlined by Mendoza et al. [104].

In this context, the emission accounting of future electricity systems becomes relevant. For this purpose, often energy system models are used in order to account for complex system interdependencies. In the following, an overview of the different approaches for emission assessment of electricity systems is given.

5.3.1 Overview: Emission Assessment of Electricity Systems

As outlined in [114], methods for the emission assessment of electricity can strongly differ with regard to their complexity and field of application. Based on the overviews by Marmiroli et al. [52] and Ryan et al. [115], following dimensions can be distinguished for emission accounting in electricity systems:

- Time horizon: historical, present and future
- Temporal resolution: e.g. hourly, seasonal, yearly
- Geographical boundaries: e.g. regions, states, countries
- Consideration of cross-border flows: production vs. consumption (including imports and exports)
- Accounting method: specific technologies, average/mix, marginal
- Extent of marginal effects: short-term/operational margin vs. long-term/build margin
- Used data and models: top-down approach (empirical data and statistical relationship models) vs. bottom-up approach (power system optimisation models)

According to Sandén et al. [116], in LCA a distinction can be made between attributional and consequential approaches. Attributional approaches focus on assigning occurring emissions equally to different services, products, or in this case technologies. Consequential approaches, on the contrary, aim at quantifying system effects which occur due to changes in demand for a certain technology. When transferring this to electricity, in attributional studies often the electricity mix is used, and in consequential analyses marginal approaches are applied to quantify the emission intensity of electricity demand. In this regard, Marmiroli et al. [52] emphasise the distinction between so-called "short-term" marginal effects, resulting from the change in operation of power plants (both in present and future scenarios), and "long-term" marginal effects, which also include the building of new capacities due to load changes. In the course of the decarbonisation of the energy system a trend towards electrification and an increasingly important role of load management strategies can be observed. Facing the advancing roll-out of electricity-consuming or -shifting technologies, such as EVs and batteries, the assessment of emissions associated with load changes is gaining in importance. In this context, the question arises how to include the interactions with the energy system into the assessment of load-changing measures.

Furthermore, as outlined in [116], the chosen time horizon plays an important role for the assessment of technologies. Future energy systems are characterised by an increased volatility of electricity generation due to fluctuating RESs as well as stronger linkages between energy carriers.

These new interdependencies result from the coupling of previously separate energy carriers in multi-energy carrier systems (MESs), as defined in [35], by technologies such as Power-to-Heat and Power-to-Gas. Therefore, when assessing future technologies with regard to GHG emissions, not only the time of electricity consumption and generation need to be considered, but also the linkages between energy carriers need to be accounted for.

In recent studies dealing with the decarbonisation of the German energy system, such as [11, 117, 118], the focus lies on describing changes in absolute emissions. There are some studies available, e.g. [119] and [120], which display the resulting specific emission factor of the annual electricity mix. However, there are very few analyses on the future German energy system reporting the specific emission factor of electricity with a high time resolution, much less for other energy carriers. Existing approaches, such as by Ripp and Steinke [121] and by Jochem et al. [122], can be used to determine hourly average and marginal emission factors of electricity based on power system optimisation models. Considering the increasing coupling of energy carriers in future MESs, these methods need to be expanded from electricity and district heating to other energy carriers such as gas and hydrogen. In this context, the allocation of emissions to multiple strongly interconnected energy carriers is the main challenge to be solved.

From the overview above two challenges for emission assessment are identified which are addressed in the following. This is, on the one hand, the incorporation of future developments of the energy system while dealing with increasing linkages between energy carriers. And, on the other hand, the interaction of load-changing measures with the energy system. To address the first challenge, in Subsection 5.3.2, a method for the quantification of emission factors of integrated energy carriers in hourly resolution is provided and applied to a future German MES scenario until 2050. These emission factors can be used to determine the GHG emissions of future electricity-consuming technologies while considering the dependency of emissions on the load profile and on linked energy carriers. In Subsection 5.3.3 the resulting year-dependent emission factors are then applied to assess the impact of renewable electricity supply on the carbon footprint of BEVs by considering the time of purchase and the reduction in operational emissions over the vehicle's lifetime.

Then, in the next Section 5.4, the second challenge is addressed by comparing the electricity mix method and the marginal power plant method with regard to different indicators describing the underlying energy system. This comparison points out the suitability of different emission accounting methods and indicators for the assessment of load-changing technologies. As an example, the two emission accounting methods are then applied to the selected battery sharing concept of load management with V2G for industrial peak shaving.

5.3.2 Method for Emission Assessment of Future Multi-Energy Carrier Systems

In the following, first, the MES model and the future energy system scenario are described. Subsequently, the developed approach of emission accounting is explained in general and then specifically for the used MES model and scenario. Finally, the resulting year-dependent emission factors of electricity, which serve as an input for the application example in Subsection 5.3.3, are shown and discussed. The following description and illustrations contain parts from the analysis by Böing and Regett [123].

Multi-Energy System Model and Scenario

The MES model used for the following analysis is the "Integrated Simulation Model for Planning the Operation and Expansion of Power Plants with Regionalisation (ISAaR)". As outlined in [123], ISAaR is a linear programming optimisation model with the objective of minimising the overall system costs c of the energy system as described by

$$c = \min \boldsymbol{f}^T \boldsymbol{x} \tag{5–3}$$

subject to

$$d_{\mathrm{lb}} \leq \boldsymbol{x} \leq d_{\mathrm{ub}} \tag{5–4}$$

and

$$b_{\mathrm{l}} \leq \mathbf{A}\boldsymbol{x} \leq b_{\mathrm{r}}. \tag{5–5}$$

While $\boldsymbol{f}$ contains the specific costs of each process, the variable vector $\boldsymbol{x}$ is optimised so as to minimise c. These variables (e.g. electrical generation, fuel consumption) are limited to the lower and upper bounds d_{lb} and d_{ub}. The system is described by the constraint matrix $\mathbf{A}$ as well as the left and right boundaries of the constraints d_{l} and d_{r}. The mathematical principles of the ISAaR model are explained in detail in [123–126].

As outlined in [123], the model's main feature is the capability to conduct an energy market optimisation for Europe until the year 2050. In this context, the German market is modelled in detail, while the European neighbours are represented in a simplified way. Next to electricity and district heating, also hydrogen, methane, biomass and synthetic fuels are covered by the MES model.

Below, the main principles of the model are explained by briefly summarising the modelling and optimisation of the "Dynamis start" scenario, which is used for the further emission assessment and is described in detail in [123]. The focus of the project Dynamis is the dynamic assessment of CO_2 abatement measures in the energy system with regard to emission savings and cost efficiency [10]. For this purpose, the so-called start scenario forms the reference point, starting from which the assessment of different measures takes place. The scenario therefore constitutes a conservative path in which climate targets are not met.

On the demand side, the final energy demand from 2020 to 2050 is determined by the four consumption sector models for transport [127], industry [128], households [129] as well as the TCS sector. Due to the need for a detailed breakdown of data for the bottom-up modelling approach, the input data for the sector models is mainly based on [130]. On the generation side, the installed conventional capacities for the simulated years are primarily derived from [131] for Germany and from [132] for the neighbouring countries. For Germany, these values are updated based on the decisions on the coal phase-out outlined in [133]. With respect to RESs, the installed capacities from [131] are first distributed regionally so as to then deduct electricity generation profiles based on regional weather data and plant characteristics. The exact RES modelling approach is summarised in [123] and described in detail in [10] and [134].

The installed capacities of energy conversion units (e.g power plants, heating plants, PtX) as well as the modelled renewable generation and load profiles serve as inputs for the optimisation of the dispatch and expansion of conversion units. As the unit's dispatch in principle follows the merit order, as described in Subsection 5.4.1, the dispatch is further determined by the costs for operation, fuels and CO_2 emission certificates. Table 5–2 contains an extract of relevant input parameters which are described in detail in [123]. The fuel prices are derived from [135, scenario B] and [130]. While in the "Dynamis start" scenario a stagnating oil price is used for 2050, in [130] a slight increase and in the scenario by the International Energy Agency (IEA) used in [11, part B, p. 74] a slight decrease is assumed.

Table 5–2: Costs for selected fuels and CO_2 certificates for the "Dynamis start" scenario

Year:	Fuel and CO_2 prices (real) in € per MWh:				
	Hard coal	Lignite	Methane	Oil	CO_2 certificates
2020	8.4	4.3	22.7	40.0	20.1
2030	8.4	5.6	26.4	48.3	41.8
2040	8.9	5.6	28.0	53.0	63.5
2050	9.8	5.6	28.1	53.0	85.2

The optimisation run of the scenario delivers a cost-optimal dispatch and expansion of the modelled conversion units in hourly resolution. This finally results in a time-resolved fuel consumption and energy output per conversion unit as well as marginal costs of the modelled energy carriers. In Figure 5–5 the aggregated optimisation results for electricity consumption and generation are summarised by means of the electricity balance which is described in detail in [123]. In particular, it becomes apparent that the share of RESs in electricity generation is increasing from 42 % in 2020 to 82 % in 2050. With regard to conventional electricity, in 2020 hard coal and lignite power plants still play an important role, but are gradually substituted by gas-fired power plants.

Methodological Approach of Emission Accounting

Transferring the LCA approach described in Subsection 5.1.1 to MES modelling, the final demand $\boldsymbol{f}$ is an input for the model ISAaR and corresponds to the load from the consumption sectors for all modelled energy carriers. The technology matrix $\mathbf{A}$ is an output of the model and includes all incoming and outgoing loads per simulated energy carrier. The intervention matrix $\mathbf{B}$ can also be derived from ISAaR results by multiplying the fuel inputs per simulated energy carrier with the corresponding combustion-related emission factors. As in this case the matrix $\mathbf{A}$ resulting from the optimisation is exactly valid for $\boldsymbol{f}$, all values in the scaling vector $\boldsymbol{s}$ are equal to one. The ISAaR optimisation results, thus, provide all data required to set up the total emissions balance for the MES energy system. However, to derive specific emission factors for the n simulated energy carriers while considering their linkages, in the following, an emissions balance for each energy carrier ec is set up.

For each ec it must be fulfilled that the emissions allocated to the outgoing energy carrier E_{out}

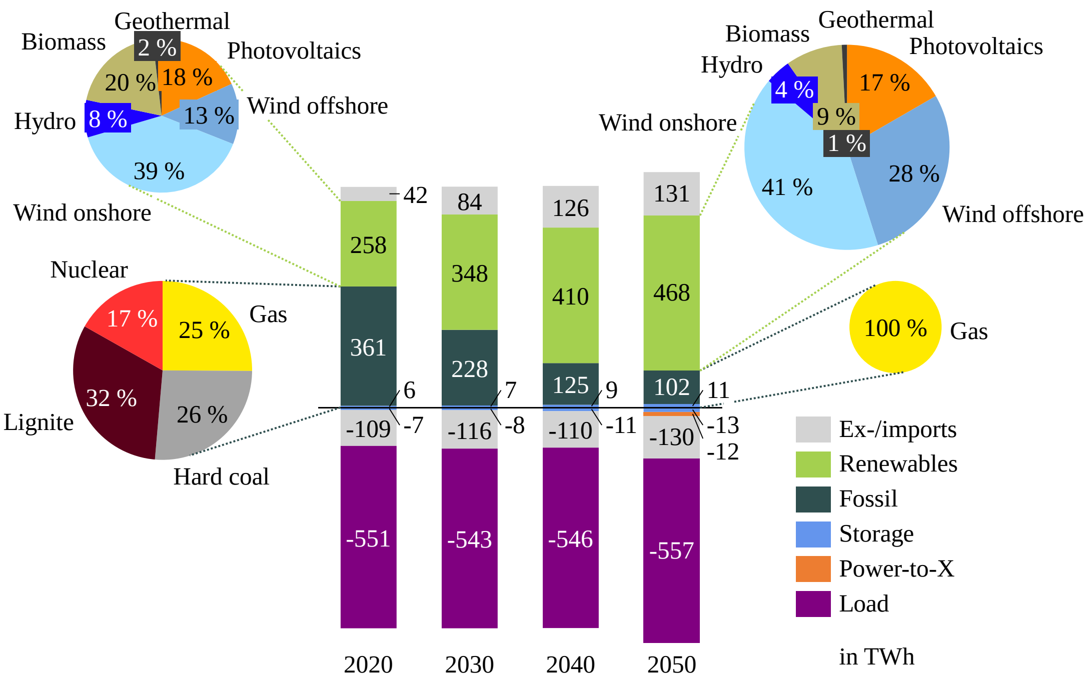

Figure 5–5: Electricity balance for the "Dynamis start" scenario for selected years [123]

are equal to the emissions occuring due to the generation of the energy carrier E_{in}. E_{out} can be described by

$$E_{\text{out}}(ec) = emf(ec) \cdot (P_{\text{dem}}(ec) + P_{\text{in}}(ec, ec')), \tag{5–6}$$

where emf is the emission factor of the energy carrier, P_{dem} the final demand for the energy carrier and P_{in} the input of the energy carrier for the generation of linked energy carriers ec'. The occurring emissions during energy carrier supply E_{in} are determined from

$$E_{\text{in}}(ec) = emf_{\text{f}} \cdot P_{\text{f}}(ec) + emf(ec') \cdot P_{\text{in}}(ec', ec), \tag{5–7}$$

using the fuel input P_{f} and the respective conversion-related emission factor emf_{f}, as well as the input of linked energy carriers ec' to generate ec and the respective emission factor for the supply of ec'.

This results in a system of n equations of type

$$emf(ec) \cdot (P_{\text{dem}}(ec) + P_{\text{in}}(ec, ec')) = emf_{\text{f}} \cdot P_{\text{f}}(ec) + emf(ec') \cdot P_{\text{in}}(ec', ec), \tag{5–8}$$

for which the solution results in n emission factors emf. For the total emissions E_{tot} it then holds true that

$$E_{\text{tot}} = \sum_{ec} P_{\text{f}}(ec) \cdot emf_{\text{f}} = \sum_{ec} P_{\text{dem}}(ec) \cdot emf(ec). \tag{5–9}$$

The determined emission factors emf comprise the CO_2 emissions associated with the supply of the simulated energy carriers and can become negative in case more CO_2 is bound than emitted during the generation of the energy carrier. In contrast, the combustion-related emission factors emf_{f} are external parameters. They reflect the emissions occurring due to the combustion of both external and simulated energy carriers as well as the CO_2 bound during the conversion process, and can also become positive or negative. Their quantification is based on the stoichiometry of the respective energy carrier input. For fuel combustion these values are extracted from [51, pp. 811–813]. However, it needs to be considered that in this case the emissions occurring during the provision of fuels, due to for example mining and transport processes, are not included.

Application of Emission Accounting Method to Multi-Energy System Model

The defined emission accounting approach is now applied to the previously described MES model ISAaR. For this purpose, for each simulated year of the "Dynamis start" scenario the total emissions are assigned to different energy carriers by setting up an emission balance based on Equation 5–8 for each region reg, time step t and simulated energy carrier ec. While each energy carrier is connected to its linked energy carriers ec' via devices dev, in the case of electricity each region is also connected to the neighbouring regions reg' via trading capacities. The emission factors for the supply of the simulated energy carriers emf are the unknown variables of the linear equation system, which can be specified by

$$
\begin{aligned}
& emf(t, ec, reg) \cdot \\
& \left(\sum_{sec} P_{\mathrm{dem}}(t, ec, sec, reg) + \sum_{dev} \sum_{ec'} P_{\mathrm{in}}(t, ec, ec', dev, reg) + \sum_{reg'} P_{\mathrm{ex}}(t, ec, reg, reg') \right) \\
& = \sum_{dev} \left(emf_{\mathrm{f}} \cdot P_{\mathrm{f}}(t, ec, dev, reg) + emf(t, ec', reg) \cdot P_{\mathrm{in}}(t, ec', ec, dev, reg) \right) \cdot a(t, ec, dev) \\
& + \sum_{reg'} P_{\mathrm{im}}(t, ec, reg', reg) \cdot emf_{\mathrm{im}}(t, ec, reg'). \qquad (5\text{–}10)
\end{aligned}
$$

All other variables are direct or indirect results from the optimisation or external input data, as in the case of combustion-related emission factors emf_{f}. It can be seen that the demand is differentiated by consumption sectors sec, and that energy carrier imports P_{im} and exports P_{ex} are considered. In the case of electricity, a simplified approach is used to determine the emission factors of imports emf_{im}. For the respective neighbouring country, these factors are determined by means of the ratio of CO_2 emissions to electricity generation in each hour of the year, which result from the optimisation. The charging power of storage systems is not explicitly included in Equation 5–10, meaning that all emissions occurring at a certain point of time are directly allocated to the final demand in the respective hour. The discharging process is implicitly included in the optimisation results, since in the event of discharging a storage system the power of generation plants and therefore emissions are reduced.

To divide emissions between different energy carriers, for multi-output processes an allocation factor a is introduced in Equation 5–10. Since the allocation method can strongly impact the results [136], two different methods are presented. For one thing, the method used by the IEA [137, p. 48] is chosen, being also referred to as "energy method". In this case, for each simulated year the allocation factor is determined from the load balance in each time step t. The allocation factor for each generated energy carrier ec and device dev can be calculated using the time-resolved output P_{out} of the respective energy carrier and the device's total output of energy carriers as described by

$$a(t, ec, dev) = \frac{P_{\mathrm{out}}(t, ec, dev)}{\sum_{ec} P_{\mathrm{out}}(t, ec, dev)}. \tag{5–11}$$

Secondly, the Carnot method described in [136] is applied, which reflects the exergy of the outgoing energy carriers and is therefore also referred to as "exergy method". In this case, for each type of combined heat and power (CHP) conversion process *pr* the share of emissions allocated to electricity is derived from the electric and thermal fuel efficiencies η_{el} and η_{th} as well as the theoretical Carnot efficiency η_{c} according to

$$a_{\mathrm{el}}(pr) = \frac{\eta_{\mathrm{el}}(pr)}{\eta_{\mathrm{el}}(pr) + \eta_{\mathrm{c}}(pr) \cdot \eta_{\mathrm{th}}(pr)}. \tag{5–12}$$

While the fuel efficiencies are expressed by the ratio of the output of the respective energy carrier to the total fuel input, for η_{c} it holds true that

$$\eta_{\mathrm{c}}(pr) = 1 - \frac{T_{\mathrm{u}}(pr)}{T_{\mathrm{o}}(pr)}, \tag{5–13}$$

with T_{u} and T_{o} being the upper and lower temperature level of the process which are taken from [138, pp. 141, 376]. Here, an average Carnot allocation factor is quantified for each simulated year by weighting the different types of CHP processes by their annual share in total district heating generation in the "Dynamis start" scenario.

Finally, the solution of the system of equations delivers emission factors for the supply of each simulated energy carrier in each time step of the considered year and region, in this case Germany. The quantified emission factors do not only consider the exchanges between different energy carriers in MESs, but also the exchange of energy carriers between regions in the context of an increasingly integrated European energy system. However, instead of using the described simplified approach, imports and exports could be considered in more detail by setting up separate equations for each neighbouring country. A similar approach has for example been chosen by Tranberg et al. [139] who determine real-time emission factors of electricity for coupled regions using flow tracing methods.

Resulting Emission Factors for Electricity

In the following, the main results of the emission assessment, which are described in more detail in [123], are summarised. In Figure 5–6 the resulting average direct CO_2 emission factors of electricity in Germany for the simulated years are depicted. Furthermore, the corresponding GHG emission factor is shown which includes also other GHG as well as upstream emissions for fuel supply.

To translate the computed direct, combustion-related CO_2 into GHG emissions including fuel supply, a factor is determined based on the CO_2 and GHG emissions factors per power plant type from the ecoinvent database [50, GWP100 indicator, CML 2001 method, cut-off] and the

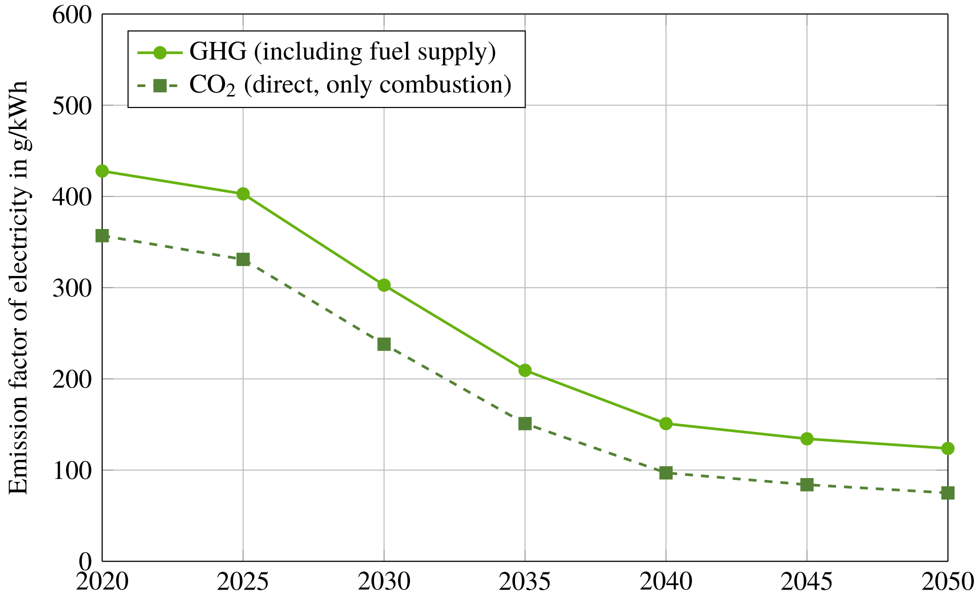

Figure 5–6: Load-weighted average CO_2 and greenhouse gas emission factors of the German electricity mix for the "Dynamis start" scenario (allocation method: carnot)

electricity balance for the "Dynamis start" scenario (see Figure 5–5). Using this data, both for CO_2 and GHG emissions a weighted emission factor for the electricity generation mix in the respective year is determined. The ratio of these two emissions factors is then used as a scaling factor to translate the CO_2 emission factor, resulting from the integrated emission balancing described above, into GHG emissions including upstream emissions. Since the optimisation is carried out in five-year steps, a linear interpolation is conducted for the interim years.

From the results in Figure 5–6 it can be seen that the CO_2 emission factor for electricity decreases by 79 % from 2020 to 2050. This is due to the expansion of RESs as well as the reduction of coal power capacities. The decrease from 2020 to 2025 is less steep, which can be attributed to the phase-out of low-emission nuclear power plants. As discussed in [123], the choice of the IEA allocation method would lead to a further decrease of the emission factor by 11 % in 2050 as the higher exergy of electricity is not accounted for. Compared to the estimated CO_2 emission factor in 2018 of 474 $g\,kWh^{-1}$ reported in [140, p. 9], the calculated CO_2 emission factor in 2020 is relatively low. Apart from the rapidly increasing share of RESs as well as the decreasing share of coal power, this can be explained by the different methods for allocation and accounting of cross-border electricity flows.

When looking at the annual duration line of the hourly emission factors in Figure 5–7, it becomes obvious that in 2020 there are no hours with an emission factor of zero. Thus, this analysis of the European market shows that there is no emission-free electricity available in 2020 when using the mix method and the considered scenario. This contradicts the concept of so-called renewable surpluses. However, if grid constraints within the market area were considered, local surpluses would occur. Furthermore, the number of hours with emission factors close to zero increases in the future to about 750 h in 2035 and to around 2 150 h in 2050. Also a more ambitious scenario

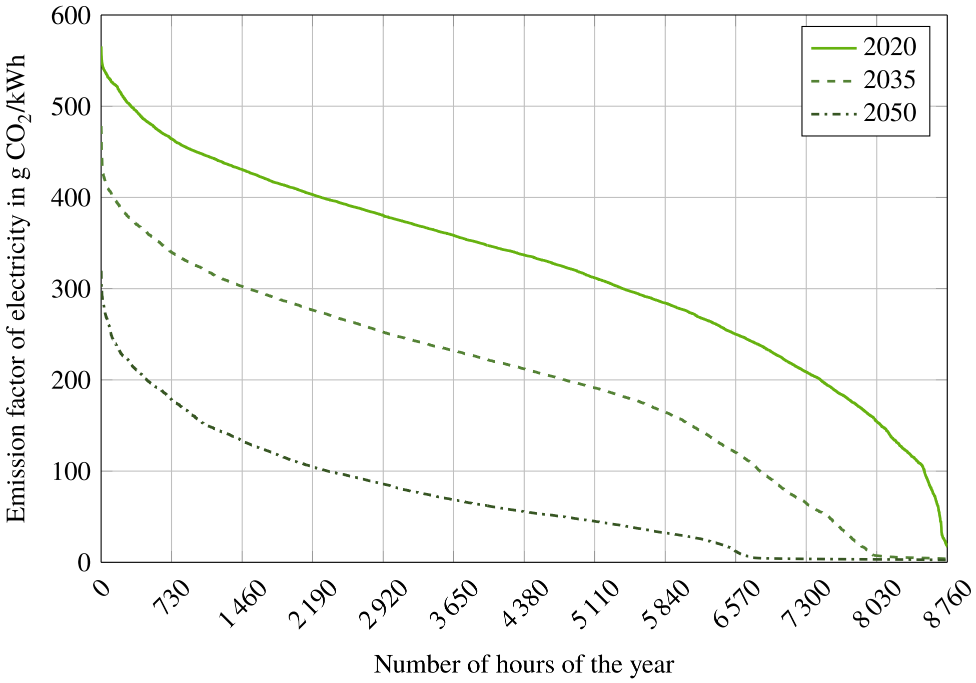

Figure 5–7: Annual duration line of hourly direct CO_2 emission factors of the German electricity mix for the "Dynamis start" scenario (allocation method: carnot)

with a larger RES penetration would lead to an increase in renewable surpluses. The variation in hourly emission factors further indicates that the actual CO_2 abatement of future sector-coupling measures, such as EVs, strongly depends on the time of operation.

5.3.3 Exemplary Application: Renewable Energy in the Battery Use Phase

As shown in Subsection 5.3.2, the increasing share of renewable electricity generation leads to a decrease in the emission factor of electricity in the coming years. This fact needs to be accounted for when determining the so-called "payback period" of a BEV compared to an ICEV. Therefore, in the following, the calculated carbon footprint of battery production (see Figure 5–3) and the future development of the emission factor of electricity (see Figure 5–6) are put into context by means of a simplified vehicle comparison for compact class vehicles. The following description and illustration are based on Regett et al. [105, 106] as well as Fattler and Regett [141].

Input Data

For battery production the climate impact of 106 kg CO_2 eq. per kWh of battery capacity derived in Subsection 5.2.3 is used. The climate impact of the other vehicle components, on the contrary, is taken from [48] who quantify the GWP of the different components of a BEV and an ICEV. According to the values from [48] the production of a vehicle in Germany leads to approximately 6.6 t CO_2 eq. for an ICEV and 6.9 t CO_2 eq. for an EV without battery system. The fact that these two values lie in a similar order of magnitude, corresponds with the results of the comparison of the CED of conventional and electric drive trains in [142]. Assuming a battery system with a capacity of 35.8 kWh, as for the recent e-Golf, the total emissions for the production of an EV total 11.6 t CO_2 eq., which is line with recently published values from the manufacturer [143, p. 14].

For the operation phase, the underlying consumption values per 100 km are 5.8 l for the gasoline, 5.0 l for the diesel and 17.3 kWh for the battery-electric vehicle. These values are not taken from manufacturer specifications, but are based on consumption data for Golf class vehicles from the ADAC Ecotest [45]. The operational emissions for ICEVs comprise both the combustion-related CO_2 emissions from [51, p. 812] and the upstream GHG emissions for gasoline and diesel supply from [50, GWP100, CML2001, cut-off system model]. For the operational emissions of BEVs three cases are distinguished. The "DE 2020 constant" case, for which the electricity mix in Germany for the year 2020 is assumed and kept constant for the coming years of operation, serves as a baseline. For the "DE 2020+" case, also the year 2020 is assumed as a starting point, but the annual decrease in the emission factor of electricity over the time of operation is considered. With the "DE2030+" case, the sensitivity of the results with regard to the year of purchase is analysed. In this case, the development of the electricity system from 2030 over the years in operation is considered. Furthermore, analogous to the analysis in Subsection 5.2.3, a decrease in electricity factor for battery manufacturing is assumed, while the emission factors for the production of battery materials are kept constant.

For all of the described cases the previously calculated year-dependent GHG emission factors of the German electricity mix from Figure 5–6 are applied for the BEV's use phase. For the emission factor of electricity in battery manufacturing the same relative decrease from 2020 to 2030 is assumed, leading to a reduction of the carbon footprint of battery production from 106 kg CO_2 eq. to 91 kg CO_2 eq. per kWh of battery capacity.

Results and Discussion

Figure 5–8 shows the GHG emissions of the considered vehicles over the minimum required lifetime of about 10 years stated in [32, pp. 14, 70]. For the conversion of vehicle kilometres into years, the average annual mileage of German passenger cars in 2017 of 13 257 km according to [49, p. 1] is assumed. It must be taken into account that this type of vehicle comparison presumes a similar annual mileage, lifetime and utilisation of both vehicle types, while potential advantages due to a larger range of ICEVs are not covered.

The results show that for all considered cases the larger carbon footprint in the production of the BEV is offset in less than five years of operation due to lower operational emissions resulting from the higher efficiency of the electric drive train. While for gasoline and diesel vehicles the operational emissions amount to 168 and 138 g CO_2 eq. km^{-1}, respectively, the higher efficiency leads to lower operational emissions for BEVs of 74 g km^{-1} for the year 2020. If the future decarbonisation of the electricity system is considered, this value further decreases to an average of 68 g km^{-1} for the "DE 2020+" and of 39 g km^{-1} for the "DE 2030+" case. This means that once the break-even between the emissions of the two vehicle types is reached, the relative carbon footprint of the BEV compared to the ICEV is increasingly improving.

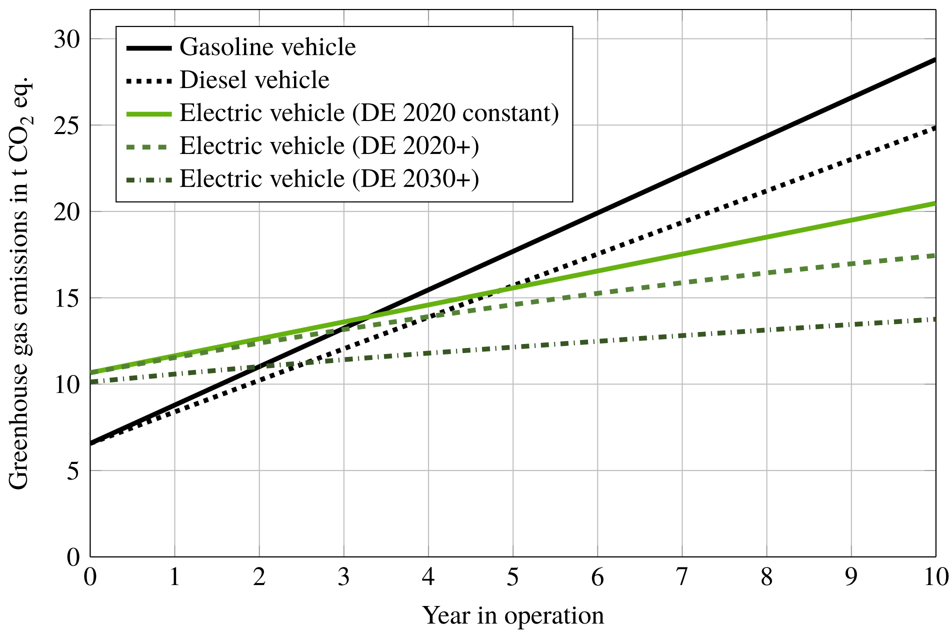

Figure 5–8: Climate impact of a gasoline and diesel combustion engine vehicle and a battery-electric compact-class vehicle as a function of operation year and charging electricity

When comparing the BEV to the gasoline vehicle, the consideration of the future development of the electricity system leads to a decrease of the break-even point from 3.3 years for the “DE 2020 constant” to 2.9 years for the “DE 2020+” case. For the diesel vehicle, which is characterised by lower operational GHG emissions than the gasoline vehicle, this amortisation period is reduced from 4.8 to 4.0 years when considering the decreasing emission factor of electricity. Furthermore, the comparison of the “DE 2020+” and “DE 2030+” cases illustrates that the climate impact of a BEV is considerably improving in the future. While the emissions of a BEV purchased in 2020 are equal to those of a gasoline and diesel vehicle after 2.9 and 4.0 years, respectively, a purchase in 2030 reduces this amortisation period to 2.0 and 2.6 years. It should be noted that these values do not consider future improvements in the production of battery materials, vehicle production and the supply chain of conventional fuels. However, as shown in [104] the future improvement potential for ICEVs is significantly lower compared to BEVs.

These results are valid for a compact-class BEV with a 35.8 kWh battery system. If instead a BEV with a 50 kWh battery is compared to a gasoline vehicle, the payback period increases from 2.9 to 4.0 years for “DE 2020+”. This applies only for a simplified scaling of the results, however, current trends indicate an increase in energy density in the future which can potentially lead to a decrease in specific GHG emissions per kWh battery capacity. In addition, the carbon footprint of the battery can be reduced to around 62 kg CO_2 eq. per kWh battery capacity (see Figure 5–4), if renewable electricity is deployed in battery production. In this case, the payback period for “DE 2020+” decreases to 1.8 years for the comparison with a gasoline vehicle.

For the present analysis the load-independent average emission factors from Figure 5–6 are used.

Instead, the emission factors in hourly resolution can be used to include the load characteristics of BEVs into the assessment. In that case, as outlined by Fattler and Regett [141], also different load management strategies can be evaluated, which can lead to a further emission reduction.

Summary

This assessment shows that when comparing the carbon footprint of a BEV with an ICEV, it needs to be considered that for the BEV a significant improvement in operational emissions is to be expected due to the transformation of the electricity system. This leads to a relative improvement of the climate impact of BEVs compared to ICEVs over the vehicle's lifetime and to an improved carbon footprint for BEVs purchased in the future. This development potential in the medium- to long-term needs to be considered when developing strategies for reaching future climate targets in the transport sector. With the developed emission accounting method, which considers increasing linkages between different energy carriers and the variability of renewable electricity supply, an instrument for the assessment of future energy systems is provided. However, the developed method does not cover repercussions of load changes on the energy system. Therefore, the interaction of load-changing measures with the energy system is subject of the following analysis.

5.4 Use: Interaction with the Energy System

Apart from renewable energy, another CE approach identified for the use phase is the sharing of the battery for multi-use cases (see Section 4.2). This means that during the charging process the traction battery is deployed for other energy system services by means of load management or V2G, which leads to a change in the load profile. But, as outlined in Subsection 5.3.1, a major challenge for emission assessment of electricity is to include the interaction with the energy system. Therefore, in Subsection 5.4.1, the attributional mix method is compared to a consequential marginal method to identify suitable indicators for the assessment of load-changing measures interacting with the energy system. In this context, load-changing measures include storage processes, load management strategies as well as electrification and efficiency measures. Then, in Subsection 5.4.2, the two methods are applied to a CE approach for EV batteries by assessing the emission savings of a battery sharing concept. In this case, the climate impact of a change in load profile due to load management for peak shaving is compared for the electricity mix and the marginal power plant method.

5.4.1 Marginal Power Plant Method and Comparison with Mix Method

The following description and comparison of the mix and marginal power plant method, which are elaborated on by Kranner [144], Plege [145] and Taylor [146], originates from Regett, Böing, Conrad, Fattler and Kranner [147, © 2018 IEEE].

Methodology and Input Data

To identify the suitability of the two emission assessment methods for the evaluation of load-changing measures, first, the *emission factor of electricity* for the electricity mix is compared to the emission factor of the marginal power plant in each hour of the year 2030. The marginal power plant is the one with the highest marginal costs which is in operation in the respective hour, and increases or decreases generation if a marginal change of load occurs. The differences between the two assessment methods for the considered *energy system scenario* are then explained by comparing the *merit order curve* of conventional power plants and their corresponding emission factors. Then, for each method a *correlation analysis* of the hourly emission factors with the share of renewable electricity and the "residual load 2.0" is conducted, which in [148] is defined as the residual load (loss less renewable generation) including cross-border trade flows. Finally, the strength and weaknesses of the derived indicators are discussed with regard to their suitability for assessing load-changing measures. Below, the four main steps of the described procedure are explained in more detail.

Emission factor of electricity: First, the specific emission factors of electricity according to the electricity mix and the marginal power plant method are compared by plotting the emission factor of the electricity mix against the emission factor of the marginal power plant in each hour of the year. The emission factor of electricity for the mix method $emf_{\mathrm{el,mix}}$ in each hour h is determined by

$$emf_{\mathrm{el,mix}}(h) = \frac{\sum_{pp} E_{\mathrm{pp}}(h)}{\sum_{pp} P_{\mathrm{el,pp}}(h)} \tag{5–14}$$

with E_{pp} being the CO_2 emissions from fuel combustion in the power plant pp and $P_{\mathrm{el,pp}}$ being the power plant's electricity output. The CO_2 emissions of each power plant amount to

$$E_{\mathrm{pp}}(h) = emf_{\mathrm{f}} \cdot P_{\mathrm{f,pp}}(h) \cdot \frac{P_{\mathrm{el,pp}}(h)}{(P_{\mathrm{el,pp}}(h) + P_{\mathrm{th,pp}}(h))} \tag{5–15}$$

where $P_{\mathrm{f,pp}}$ is the energy content of the fuel f burnt in the power plant pp and emf_{f} is the combustion-related CO_2 emission factor. To allocate the total emissions of a CHP plant to its electricity and heat output the energy method of the IEA is used. For this purpose, the determined emissions are multiplied with the share of electricity $P_{\mathrm{el,pp}}$ in the plant's total energy output, including the heat output $P_{\mathrm{th,pp}}$ (see also Subsection 5.3.2).

For the marginal method, the specific CO_2 emission factor of electricity is equal to the emission factor of the marginal power plant $emf_{\mathrm{el,m}}$ in the respective hour h and is determined by

$$emf_{\mathrm{el,m}}(h) = emf_{\mathrm{f}} \cdot \frac{P_{\mathrm{f,mpp}}(h)}{P_{\mathrm{el,mpp}}(h)}, \tag{5–16}$$

with $P_{\mathrm{f,mpp}}$ being the fuel consumption of the marginal power plant mpp and $P_{\mathrm{el,mpp}}$ being the plant's electricity output. In the day-ahead electricity market the marginal power plant sets the price. Therefore the marginal power plant in each hour is determined by matching the time series of electricity prices with the marginal costs of each power plant. As described in [144, pp. 33-34], in case there is no exact match, the power plant with the closest marginal costs is selected. Moreover, due to the additional district heating demand, it is assumed that CHP plants don't constitute marginal power plants [144, p. 31].

The fuel-related emission factors come from the German national GHG inventory [51, pp. 811–813] and entail only direct CO_2 emissions from fuel combustion. The marginal costs of all German and Austrian power plants are taken from the power plant database of the Research Center for Energy Economics (FfE). The database consists of three parts, namely the lists of existing plants and planned additions or deconstructions from [149–151], manually researched data on plant-specific parameters, such as efficiencies, as well as techno-economic parameters of different plant types, e.g. start-up or operational costs from [126, 152, 153]. The time series of electricity generation and prices are simulation results from the energy system model ISAaR which is described in Subsection 5.3.2.

Energy system scenario: The simulated time series represent a scenario which has been developed in the context of the project Merit Order Netz-Ausbau (MONA) 2030 and is described in [154] and [155]. Table 5–3 summarises the key parameters of the "MONA 2030 standard" scenario applied here. This scenario is supplemented by parameters for the European neighbouring countries following "Vision 2" of the ten-year network development plan 2016 [156]. As described in Subsection 5.3.2, the installed RES capacities are translated into generation profiles using regionalisation algorithms and weather data. Combined with the other input data from Table 5–3, this forms the basis for the subsequent dispatch planning of the ISAaR model which delivers the electricity generation and fuel consumption per power plant unit as well as the electricity price for a whole year in hourly resolution. Strictly speaking, the electricity prices resulting from the optimisation constitute hourly marginal costs of electricity generation which in a perfect market correspond to electricity prices.

Table 5–3: Key scenario parameters for Germany in the "MONA 2030 standard" scenario © 2018 IEEE

Parameter	Value
CO_2 certificate price in € t^{-1}	30
Fuel prices of oil/gas/hard coal/lignite in € MWh^{-1}	52/29/9.5/1.5
Installed fossil electrical capacity without reserves in GW	59
Installed electrical capacity of wind offshore/onshore/PV in GW	15/59/77
Electricity demand incl. grid losses in TWh a^{-1}	499
Renewable share without curtailment in %	61

Merit order curve: The differences between the two emission assessment methods can be explained by the merit order effect. Therefore, first, the merit order of conventional power plants is generated by plotting the marginal costs for electricity of each power plant, comprising fuel, operation and CO_2 costs, against its installed capacity based on data from the FfE power plant database. The power plants are sorted by ascending order according to their marginal costs so as to reflect the order of bids in the day-ahead electricity market. While there is a feed-in priority for RESs, conventional power plants are dispatched according to their marginal costs. Depending on the residual load, the electricity price is determined by the marginal costs of the last power plant needed to meet the demand. The merit order curve is then complemented by an additional figure showing the corresponding emission factor of electricity for each power plant. The emission factor is derived from the fuel-specific emission factor from [51, pp. 811–813] divided by the power plant's efficiency.

Correlation analysis: For further analysis, for both methods the share of RESs in total electricity generation and the residual load 2.0 are plotted against the emission factor of electricity in each hour. The time series for renewable and total electricity generation as well as the residual load 2.0 are derived from the optimisation results for the "MONA 2030 standard" scenario.

It should be noted that due to the scope of the analysed scenario only direct combustion-related CO_2 emissions are determined. As this analysis aims at a relative comparison of the two methods, in this case, no up-scaling to GHG emissions as in Section 5.3 is carried out.

Results

In Figure 5–9 the emission factor of the marginal power plant (abscissa) is compared to the emission factor of the electricity mix (ordinate) for each hour (dots) of the year 2030. The colours of the dots indicate the type of marginal power plant in the respective hour. The comparison shows that the marginal power plant and the electricity mix method can lead to opposing hourly emission factors. This applies especially for those hours in which the marginal power plant is a lignite power plant with a high emission factor or a gas-fired power plant with a low emission factor. This can be explained by the so-called merit order dilemma of emissions as illustrated in Figure 5–10.

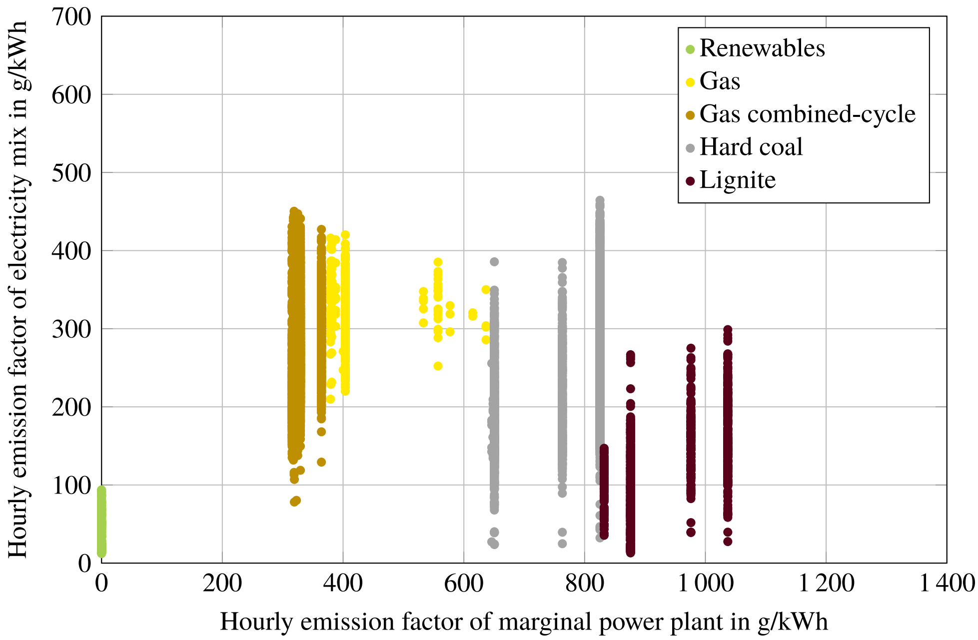

Figure 5–9: Comparison of the hourly, direct CO_2 emission factors according to the electricity mix and the marginal power plant method for the "MONA 2030 standard" scenario © 2018 IEEE

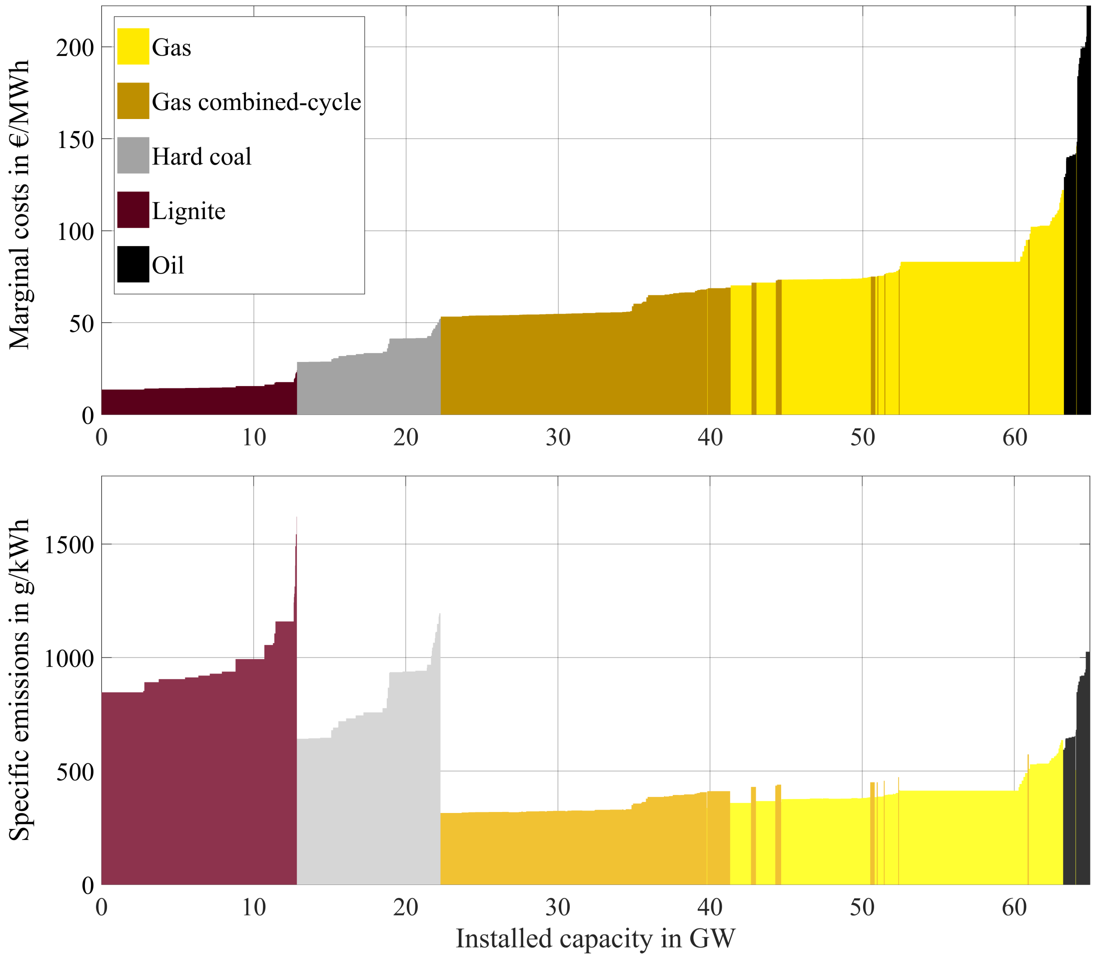

Figure 5–10: Merit order of conventional power plants in Germany and Austria in 2030 and corresponding direct CO_2 emission factors (for combined heat and power: full allocation to electricity) © 2018 IEEE

While power plants with a high emission factor such as lignite have relatively low marginal costs, less emission-intensive power plants running on gas are characterised by high marginal costs. Therefore in times of a low residual load, mostly corresponding to a large share of renewable electricity generation and therefore a low emission factor of the electricity mix, the marginal power plant is usually coal-fired. In contrast, less emission-intensive gas-fired power plants mostly run in times of high residual load, coinciding with smaller shares of RESs as well as larger shares of electricity generation from coal, and therefore larger emission factors of the electricity mix. As discussed in Böing, Regett et al. [157], this dilemma is reduced if an increase in CO_2 certificate costs results in a switch of gas- and coal-fired power plants in the merit order.

Figure 5–11 and Figure 5–12 show the correlation of the hourly emission factors according to the electricity mix and the marginal power plant method with the share of RESs in electricity generation and the residual load 2.0. For the electricity mix method a strong negative correlation of the emission factor with the share of renewable generation (R^2 = 0.95) and a medium positive correlation with the residual load 2.0 (R^2 = 0.46) can be observed. This means that, in case of using the electricity mix method for load assessment, the share of RESs in the system is reflected well. Furthermore, the results indicate that, when using the mix method, a load shift to hours with a low emission factor would not immediately lead to a further increase of peak residual loads.

For the marginal power plant method, on the contrary, no correlation can be observed, but depending on the type of marginal power plant certain patterns are identified. The hours in which the marginal power plant is renewable, for example, can be used to identify whether there is a surplus of renewable electricity available. These hours go along with high shares of renewable electricity and low residual loads. Despite the marginal power plant being renewable, the share of renewable electricity is lower than 1 and the residual load is not always smaller than 0 because of inflexible, must-run and CHP power plants. In general, it can be said that these are the hours which should be targeted in order to integrate renewable surplus electricity from a market perspective. While for these hours the marginal power plant method constitutes a good indicator for load management, it needs to be considered that the load shift is limited by the extent of negative residual load in the corresponding hour. Furthermore, Figure 5–12 (b) shows that due to the merit order effect the residual load 2.0 is higher in hours in which gas-fired plants determine the price than in hours in which emission-intensive coal-fired power plants constitute the marginal power plant. Therefore, an optimised load management based on hourly marginal emission factors would lead to an increase in peak residual load. With regard to the share of renewable electricity, there are large variations for all types of conventional power plants. The hours in which lignite power plants are marginal are mostly characterised by large shares of RESs, which can be explained by the front position of lignite power plants in the merit order. Thus, the marginal emission factor is not a good indicator for reflecting the share of RESs in the system.

Discussion

In Table 5–4 the strength and weaknesses of using the two types of emission factors as indicators for the assessment of load-changing measures are summarised. As both emission assessment methods do not fully reflect excess renewable electricity, the residual load 2.0 is added as a separate indicator. It can be seen that all indicators are valid for a certain field of application. The emission factor of the electricity mix, for instance, is a good indicator for the share of RESs and the carbon intensity of electricity. The emission factor of the marginal power plant, on the contrary, provides insights into the short-term emission effect of a marginal change of load resulting from load management, efficiency and electrification measures or storage processes. The residual load 2.0 can serve as an additional indicator for the marginal power plant method to provide information on the amount of surplus renewable electricity.

However, it needs to be considered that the described marginal power plant method is not valid for energy systems with large shares of RESs. This is illustrated by the future scenario for 2050 from [10] in which the GHG emission reduction target for Germany of 95 % compared to 1990 is reached. In that case, the optimisation results show that the electricity price is not only determined by domestic power plants, but is largely determined by foreign power plants and other conversion units such as PtX. Therefore in Böing and Regett [123] another marginal assessment approach is proposed, according to which the hourly marginal emission factors are determined by comparing two optimisation runs with a marginal increase in load. While system effects

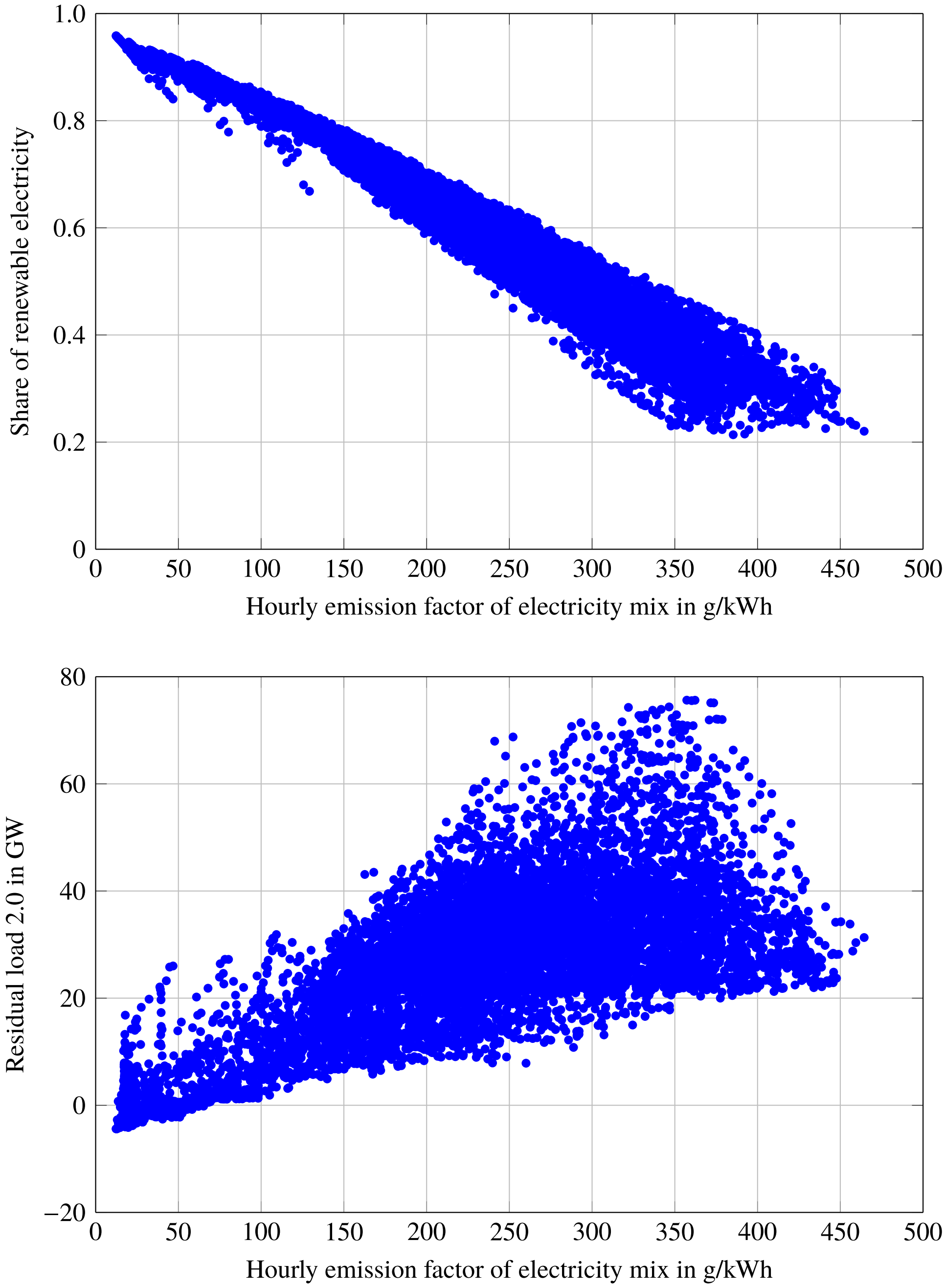

Figure 5–11: Correlation of direct CO_2 emission factors of the electricity mix with the share of renewable electricity (a) and the residual load 2.0 (b) for the “MONA 2030 standard” scenario © 2018 IEEE

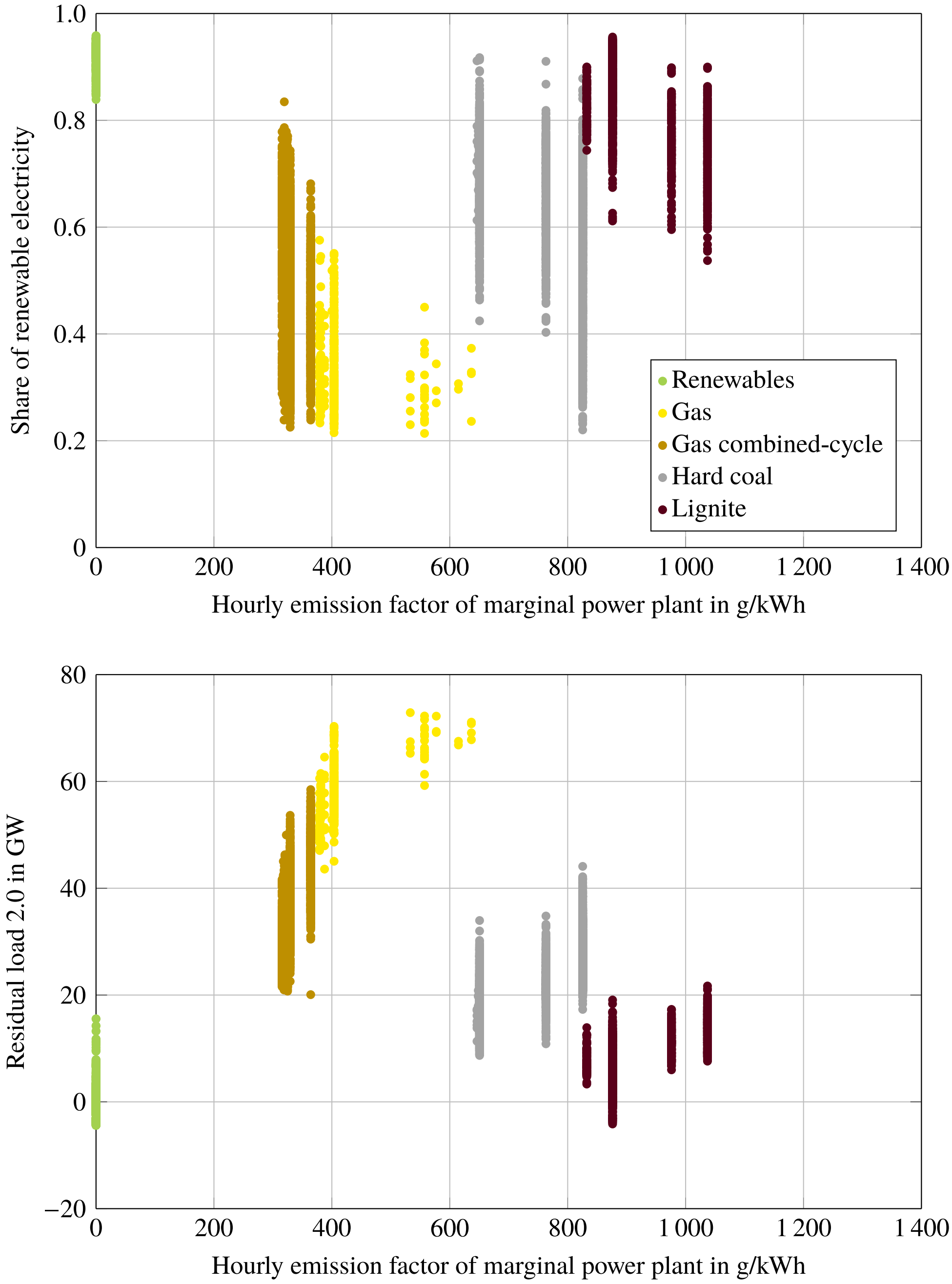

Figure 5–12: Correlation of direct CO_2 emission factors of the marginal power plant with the share of renewable electricity (a) and the residual load 2.0 (b) for the “MONA 2030 standard” scenario © 2018 IEEE

are better accounted for, this approach has the disadvantage that the hourly emission factors for two separate optimisation runs can only be compared to a limited extent, due to the temporal dependencies of the energy system model.

But the use of static indicators, derived from existing scenarios, and marginal approaches, with their discussed shortcomings, are insufficient when large load changes and a long-term perspective are to be considered. Hence, in [10, 158] a step-by-step approach is described, which increasingly incorporates energy system effects into the assessment of CO_2 abatement measures. For this purpose, changes in final energy demand resulting from the implementation of load-changing measures in the consumption sectors are handed over to an energy system model. By comparing two optimisation runs, before and after the implementation of the measure, large-scale changes as well as long-term effects on the energy supply sector are incorporated into the assessment.

Table 5–4: Strength and weaknesses of the analysed indicators for the "MONA 2030 standard" scenario © 2018 IEEE

Representation of:	Indicator:		
	Emission factor of electricity mix	Emission factor of marginal power plant	Residual load 2.0
Share of renewable electricity	High correlation (R^2 = 0.95)	Low correlation due to merit order dilemma	Medium correlation with renewable share (R^2 = 0.6)
Excess renewable electricity	No information about surplus electricity	Times with surpluses are shown, but not amount of surplus	Times and amount of renewable surpluses are represented
Carbon intensity of electricity sector	Quantification of average emissions of total electricity generation	Only emissions on the margin are quantified	Emissions are not considered
System effects of load-changing measures	Average values of existing system do not reflect effects of load changes	Quantification of marginal effects on emissions due to load changes	Quantification of marginal effects on residual load, but not on emissions

Summary

With the electricity mix and the marginal power plant method two different approaches for calculating hourly emission factors of electricity are presented. Due to the merit order dilemma of emissions, for the analysed scenario, discrepancies between hourly emission factors occur for the two methods, with some hours even showing significantly opposing results. Therefore, when using the calculated emission time series for the assessment of load-changing measures, such as storage processes, load management strategies as well as efficiency and electrification measures, the two methods lead to different results with regard to emission reduction and integration of renewable surplus electricity. While the electricity mix method is suitable for describing the existing energy system and the share of renewable electricity, the marginal power plant method indicates times of renewable surplus electricity and reflects short-term marginal effects resulting from small load changes.

These differences between the two methods bear the risks of a misuse to promote or discredit a certain technology. Therefore a thorough choice of method depending on the application and the question to be answered is required. As summarised in [10], the electricity mix method is a good choice for an assessment of existing technologies, since emissions are allocated to the different electricity consumers. Marginal methods, on the contrary, are to be used for the assessment of energy system effects. The marginal power plant method, for example, is suitable to determine the impact of a load change on the dispatch of power plants and is, in the case of EVs, therefore especially useful for load management strategies. While the analysed indicators can be calculated from existing simulation results, the incorporation of large-scale and long-term system effects requires a more extensive assessment approach, for which complex energy system optimisation runs are needed. These kinds of analysis are relevant for long-sighted policy making, as for example the demand for RESs and storage capacities resulting from a large-scale penetration of EVs can be determined.

5.4.2 Exemplary Application: Battery Sharing through Load Management for Peak Shaving

The two previously described emission accounting methods, electricity mix and marginal power plant method, are now applied to the case of sharing the battery's functionality for industrial peak shaving. The description and illustration of the case study stem from Regett, Kranner, Fischhaber and Böing [159], building on [144] and [160].

Case Definition

As an exemplary sharing concept, a bidirectional charging management for industrial peak shaving in an office building is analysed. In this multi-use case, the power and storage capacity of the EV batteries is shared between the car owners and the company. The analysed load profile originally comes from a real office building of a software company with around 100 employees, which is complemented by the load for directly charging the BEV fleet. The load profile is characterised by a maximum annual peak load of 141.3 kW. The charging process of the BEVs is responsible for the load peaks in the morning. The load peaks in summer are induced by air conditioning, for which the load shifting potential is limited.

Therefore, in order to decrease the peak load and thereby reduce the demand charge for electricity, a load management strategy with V2G is examined. In the load management scenario, the EV fleet consists of three vehicles being available between 7 am and 6 pm. Each EV battery system is characterised by a 20 kWh storage capacity, 22 kW charging and discharging power as well as a system efficiency of 85 %. Under these circumstances, the maximum peak load can be reduced to 80.4 kW. This is done by shifting the charging process and by deliberately charging and discharging the EV batteries, whilst ensuring that the state of charge at the end of the day is equal to the case without peak shaving. Next to the comparison with the unsmoothed load profile, the load management scenario is further compared to the use of a diesel generator which generates electricity every time the load boundary of 80.4 kW is exceeded. It is assumed that the diesel generator with an efficiency of 34 % is purchased specifically for the peak load management application.

To assess the emission effect of load management for industrial peak shaving, the changes in direct, energy-related CO_2 emissions for electricity generation due to the change in load profile are quantified. For the comparison with the diesel scenario, the emission changes resulting from the change in load profile and the saved CO_2 emissions from diesel combustion are accounted for. Thus, in both cases only the effects on combustion-related CO_2 emissions for electricity generation in the operation phase are considered. For diesel the emission factor from [51, p. 812] is used. The direct CO_2 emissions associated with the increase or decrease of electricity generation are quantified using the time-resolved emission factors of the electricity mix and the marginal power plant for the "MONA 2030 standard" scenario described in Subsection 5.4.1.

The load profiles needed for the assessment of the load management scenario are calculated using the simple peak shaving model described in [144]. Based on the company's load profile, including an uncontrolled charging process of the selected BEV fleet, a smoothed load profile due to load shifting and V2G is calculated. For this purpose, the BEV fleet is considered as a storage system. The model derives the charging and discharging power of the storage system in order to keep the total load below a preset limit, while considering the battery parameters described above. The load limit and the number of BEVs are chosen in a way that an almost optimal configuration for peak shaving of the analysed load profile can be achieved.

For further calculations, a differential load profile is derived by subtracting the load profile for the scenarios "no peak shaving" and "diesel generator" from the modelled load profile of the "load management" scenario. The differential load profile is then multiplied with the time series of emission factors from Subsection 5.4.1 so as to determine the emissions of the change in electricity demand due to load management for peak shaving. This is done both for the case without peak shaving as well as for the peak shaving scenario with a diesel generator. Additionally, for the diesel generator scenario the emissions from diesel combustion are subtracted.

Results and Discussion

When comparing load management for peak shaving to the load profile without peak shaving in 2030, a slight increase of CO_2 emissions for electricity of 33 kg a^{-1} for the marginal method and a slight annual reduction of 38 kg a^{-1} for the mix method are observed. When attributing these emission savings of the load management concept to the traction battery, the emissions for battery production can be reduced by around 5 % for the mix method, if GHG emissions for battery production of around 106 kg CO_2 eq. per kWh battery capacity (see Section 5.2) and a life time of electric vehicles of around ten years (see Subsection 5.3.3) are assumed. However, it needs to be considered that these savings only include direct, combustion-related CO_2 emissions.

The comparison of load management for peak shaving with the diesel generator scenario emphasises that the emission effect is strongly dependent on the substituted technology. The large emission savings of 2 118 kg a^{-1} for the marginal method are mainly due to the saved emissions from diesel combustion for smoothening the morning peaks induced by the BEV fleet. If instead a load management concept substitutes stationary batteries with the same parameters as the BEV fleet, the emission savings would amount to 326 kg a^{-1} for the marginal and 161 kg a^{-1} for the

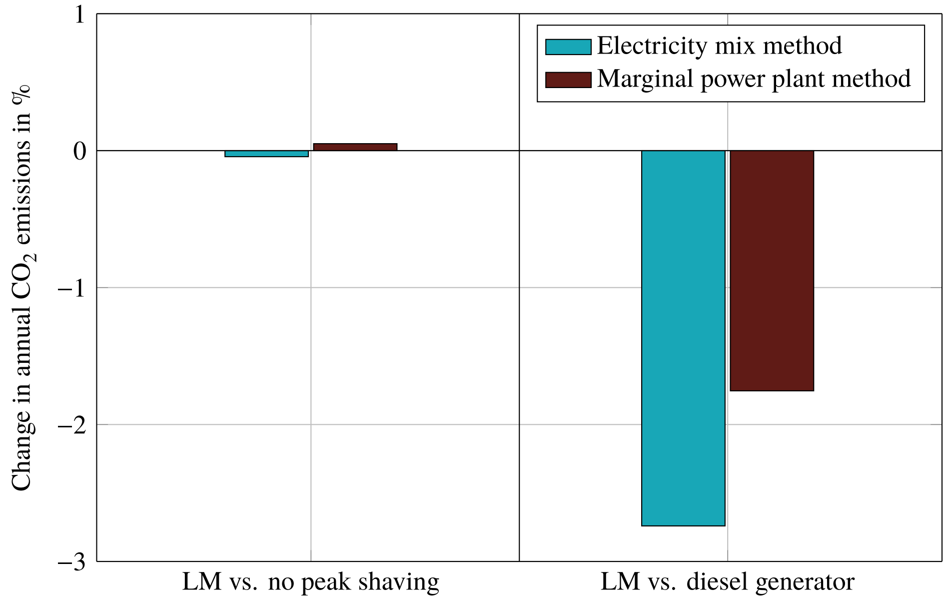

Figure 5–13: Percentage change in annual CO_2 emissions for electricity demand due to load management (LM) for peak shaving compared to no peak shaving (left) and peak shaving by a diesel generator (right)

mix method. These savings can be attributed to the additional losses of the stationary battery when shaving load peaks. If a charging management is already implemented in the reference case, so as to prevent additional load peaks from BEVs, the emission savings would decrease. On the contrary, in case not only the operation phase, but also the prevented production of the substituted technology (e.g. diesel generator or stationary battery system) is accounted for, the CO_2 emission savings would increase.

As can be seen from Figure 5–13, the impact of peak load management on the total annual emissions for electricity demand of the analysed company are for both reference cases and methods negligible, with values lying in the range of model and data uncertainties. Considering that in case of a peak load management application the amounts of electricity shaved or shifted are low (around 2.5 % of the total annual electricity demand), a larger change in annual emissions can be expected for applications characterised by a greater number of charging and discharging cycles. Furthermore, Figure 5–13 points out that the comparison of the load management with the diesel scenario leads to a larger change in annual emissions than the comparison with the unsmoothed load profile. This can be explained by a larger difference in emission factors of electricity from the diesel generator (782 g kWh^{-1}) and electricity from the grid, as compared to the difference in hourly emission factors of electricity from the grid due to load shifting in the load management concept.

For a better understanding of the difference between the marginal and the mix methods, the differential load profiles (load management less reference case), as well as the specific emission factors of electricity for both methods, are shown in Figure 5–14. The depicted time period is

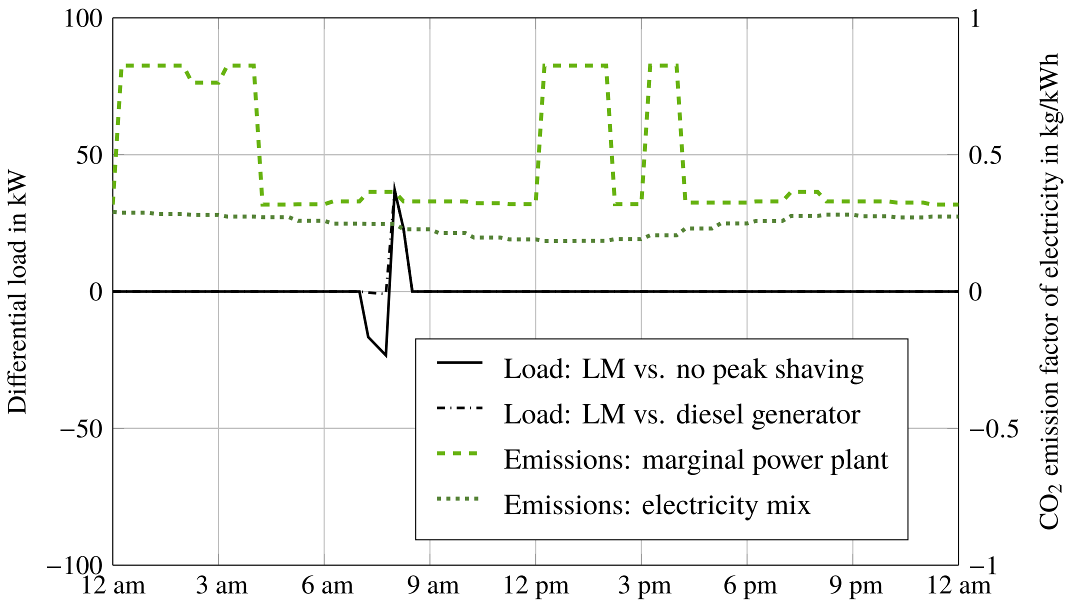

Figure 5–14: Differential load (left axis) and direct CO_2 emission factor of electricity for the marginal and the mix method (right axis) for an exemplary day

an exemplary day close to the average day of the year. In general, the hourly emission factor of the electricity mix is in about 85 % of the year lower than the hourly emission factor of the marginal power plant which is mostly gas- or coal-fired. However, the differences between the two methods vary over the day, meaning that the impact of the chosen method depends on the analysed load profile.

Looking at the differential load profile for the load management scenario compared to the unsmoothed load profile, it can be seen that the charging process is partially postponed from 7 am to 8 am. As the emission factors for these two hours are similar for both the mix and the marginal methods, neither a large change in annual emissions nor a large difference between the two methods can be observed. This can be explained by the fact that in case of a load shift, the hourly emission factors at times of negative and positive differential load determine whether the emissions are levelled out. Thus, for the mix method, the change in annual emissions would for example increase if the load is shifted between day and night, since the differences in hourly emission factors are larger.

The differential load profile for the load management concept compared to the diesel scenario, on the contrary, shows an increased electricity demand from the grid at 8 am. This results from the postponed charging process which does not occur in the diesel scenario, since the peak load is provided by the generator. For the diesel scenario the difference between the two methods is larger because the emissions for electricity from the diesel generator stay the same, while in the respective hour the increased emissions from the grid are larger for the marginal than for the mix method.

Overall, the results indicate that from the company's perspective the percentage changes in

CO_2 emissions for electricity demand due to load management with V2G for peak shaving are low. In contrast, for an annual demand charge of 80 € kW^{-1} the peak load application leads to significant cost savings of almost 5 000 € a^{-1}. It needs to considered, however, that the quantitative results for this specific application are not directly transferable to all load management applications. This is attributable to the fact that the emission changes from bidirectional charging management strongly depend on the used energy system modelling results, the analysed application, the load characteristics, the parameters of the BEV fleet as well as the precise charging management strategy. In the investigated load management application for peak shaving, the sensitivities with regard to emission savings and load reduction are large, and depend essentially on factors which are specific to the use case under investigation. This includes the number of BEVs, the attendance time, the available battery capacity as well as the level, time and duration of the load peaks. The chosen parameters and load profile constitute a load management-friendly scenario. Thus, in a real case a thorough analysis of the described factors is needed before implementation. Also the load shifting algorithm has an impact on the load shaving potential and the emission savings, and can for example be improved by considering monthly instead of yearly peak loads.

Summary

The exact impact of bidirectional charging management applications on CO_2 emission for electricity is determined by various factors. However, it can be noted that the change in emissions depends on the temporal shift of the load, leading to different emission factors for electricity demand, as well as the additional energy demand due to battery losses in case of a feed-in to the grid. While peak load management leads to a decrease of electricity costs due to a reduced demand charge, in the analysed scenario a small relative change in CO_2 emissions compared to the total emissions for the company's electricity demand was observed. This can be attributed to the small share of electricity demand affected by peak load management and the small difference between the hourly emission factors due to load shifting. When attributing the emission savings from the load management application to the production of traction batteries, it can be seen that the savings strongly depend on the substituted technology. While the savings are small or even negative for the comparison with the unsmoothed load profile, the emission savings due to load management can exceed the emissions for battery production in case a diesel generator is substituted.

It is demonstrated that existing energy system modelling results can be used for assessing the environmental effects of a small-scale change of load resulting for example from battery sharing concepts, such as load management with V2G. With the marginal power plant method an approach is applied which considers short-term energy system effects, but does not necessitate additional simulation runs. However, as outlined in Subsection 5.4.1, if large-scale changes in electricity demand and a long-term perspective are to be considered, a more comprehensive approach is required.

5.5 End-of-Life: Ageing Processes

Moving from the use phase to the EoL phase, the lifetime extension of the battery in an SL application has been identified as a feasible CE approach in Section 4.2. In this context, the battery's state at its EoL in the vehicle and the battery's behaviour in the SL application become important. The following description and exemplary application of the method to integrate battery ageing modelling results into the environmental assessment of SL batteries builds on Regett and Fischhaber [61] and Fischhaber, Regett, Schuster and Hesse [33].

5.5.1 Overview: Life Cycle Assessment of Second-Life Batteries

As described in [33, p. 112], existing LCA studies on SL can be divided into two types. While [161] and [162] directly compare SL batteries with new batteries, the focus of other studies such as [163–165] is on the assessment of a new battery application and the comparison of SL batteries with other competing technologies. These two cases are also distinguished in the assessment by Richa et al. [166]. As outlined in [33, pp. 112–113], in principle, those studies considering a substitution of a new battery system disclose an environmental improvement through SL. If, on the contrary, the SL battery is applied in a new battery storage application, the saving potential is strongly dependent on the environmental benefit of the application itself, as well as the displaced technology.

The following analysis aims at determining the emission and resource saving potential of an SL battery resulting from the replacement of a new battery system. For this purpose, the Li and Co demand as well as the energy-related GHG emissions for the production of the battery system being substituted by the SL battery are to be identified. However, the prerequisite for these two systems to be comparable is that the functionality of the SL battery is equal to the functionality of the replaced new battery system. As the functionality of a battery is strongly dependent on the time in operation and the available capacity, which decreases dependent on time and usage, ageing processes need to be considered in the assessment. This is underlined by the overview in [33, p. 113] which points out that the emission saving potential of an SL battery does not only depend on the environmental footprint of the substituted technology, but also on the battery's ageing behaviour.

The available remaining capacity of a battery, being referred to as state of health (SoH), can be quantified using battery ageing models. As outlined by Groot [167], ageing models describe the decrease in capacity or the increase in impedance resulting from calendar and cyclic ageing of the battery cell. These ageing mechanisms are complex and strongly depend on the respective conditions, but can in principle be understood as side reactions leading to the consumption of cyclable Li, the reduction of accessible electrode material or the change in electrode structure [167, pp. 2–3]. As described by Schuster [168, pp. 31–32], the ageing process of a battery is in principle characterised by a short non-linear phase resulting from formation processes, followed by an almost linear decrease in SoH until eventually a sharp, non-linear capacity loss can be observed at low residual capacities. However, Schuster [168, p. 114] comes to the conclusion that non-linear ageing can be prevented for example by ageing-dependent load adaptation.

The idea of including battery ageing mechanisms into the LCA of SL applications has already been picked up for example in [163, 164, 169] by using SoH functions to determine the capacity decrease and the lifetime of SL batteries. But when directly comparing an SL battery with a new battery, also the ageing of the substituted stationary battery needs to be considered in detail. To this end, Kim et al. [161] introduce the concept of the substitutable nominal capacity which constitutes an approach to account for the difference in ageing of the SL battery and the substituted new battery. However, in the simplified approach applied in [161] no differentiation is made between applications and cell types.

5.5.2 Integration of Battery Ageing Modelling Results

To account for functionality losses in the assessment of SL batteries, in the following, a method is proposed combining the concept of the substitutable nominal capacity introduced in [161] with the use of ageing modelling results. For this purpose, different SoH curves are used to determine the substitutable capacity of an SL battery, thereby considering the dependency of the substitutable capacity on the SL application, cell technology and EoL criteria. Hereafter, each step of the developed methodological procedure for integrating battery ageing modelling results into the assessment of SL batteries is described.

Definition of input parameters: As outlined in [61], the ageing process of a battery depends, amongst others, on the cell type and the load profile. Therefore, first, the cell types of the traction battery and the substituted stationary battery system are specified. Furthermore, for each considered stationary application a load profile, serving as an input for the ageing model, is selected. As the battery lifetime strongly influences the provided function, also the years in operation both of the new and the SL battery are to be derived. For the SL battery this operating time depends on the defined EoL and End-of-Second-Life (EoSL) criteria. These criteria correspond to the share of capacity being left at the battery's EoL and EoSL, respectively, and are reflected by the SoH.

Simulation of battery ageing: For each stationary application and cell type the decrease of SoH over time results from the run of a cell type-specific battery ageing model which is fed with the corresponding load profile. Each model run results in a battery ageing function of type $SoH(t)$ with t being the year in use.

Translation into energy system service: So as to determine the functionality of the battery, for each stationary application an indicator is defined which translates the remaining capacity into the provided energy system service ess. This indicator is then linked to the ageing curve $SoH(t)$ to determine $ess(t)$. By this additional step of translating the SoH into an energy system service, also storage applications with a non-linear relationship between capacity decrease and provided functionality are properly represented.

Quantification of substitutable capacity: As outlined in Equation 5–17, the substitutable capacity sc depends on the application ap, the cell type of the traction battery ct_{tb}, the cell type of the substituted stationary battery ct_{sb} as well as the remaining capacity of the used traction battery $c_{\mathrm{eol,tb}}$. The substitutable capacity can be determined by multiplying the capacity of the used traction battery when entering the SL application $c_{\mathrm{eol,tb}}$ with the energy system service provided by the SL battery ess_{slb} compared to the energy system service ess_{sb}, which would have been provided by a stationary battery with the same capacity. Thus, by means of the second term in Equation 5–17 the difference in functionality and lifetime of the reused SL battery in comparison to a new stationary battery is taken into account.

$$sc(ap, ct_{\mathrm{tb}}, ct_{\mathrm{sb}}, c_{\mathrm{eol,tb}}) = c_{\mathrm{eol,tb}} \cdot \frac{\sum\limits_{t=t_{\mathrm{eol,tb}}}^{t_{\mathrm{eosl}}} ess_{\mathrm{slb}}(t, ap, ct_{\mathrm{tb}}, c_{\mathrm{eol,tb}})}{\sum\limits_{t=0}^{t_{\mathrm{eol,sb}}} ess_{\mathrm{sb}}(t, ap, ct_{\mathrm{sb}}, c_{\mathrm{eol,tb}})} \tag{5–17}$$

While for the new stationary battery the energy system service ess_{sb} is cumulated from the starting year to its defined year of EoL $t_{\mathrm{eol,sb}}$, for the SL battery ess_{slb} is added up over its time of use in the stationary application. This means from year $t_{\mathrm{eol,tb}}$, where the SoH is equal to the specified EoL criterion of the traction battery, until year t_{eosl}, in which the SoH equals the defined EoSL criterion for the SL battery. As the lifetime of a stationary battery is limited by $t_{\mathrm{eol,sb}}$, also for the SL battery a maximum operation time is introduced. This timespan results from the lifetime of the stationary battery less the lifetime of the SL battery in its first life in the vehicle.

The finally resulting substitutable capacity describes the capacity of the replaced stationary battery system which over its operation time would deliver the same energy system service as the used SL battery. Thus, it reflects the influence of battery ageing and lifetime on the provided function.

Quantification of critical metal and emission savings: In order to determine the critical metal and GHG emission savings of SL batteries, the quantified substitutable capacity is then multiplied with the critical metal demand (in this case Li and Co) and the GHG emissions associated with the production of the substituted stationary battery modules. In case a recycling of stationary batteries is considered, the respective critical metal demand needs to be reduced by the potentially recycled metals at the stationary battery's EoL.

5.5.3 Exemplary Application: Second-Life in Stationary Battery Applications

The described method is now applied to two exemplary SL applications which are selected based on the analysis and stakeholder process in the course of the study by Fischhaber, Regett, Schuster and Hesse [33]. The chosen applications, namely the use for primary control reserve (PCR) and as a home storage system (HSS), are not only of interest because of recent market developments, but also because they are characterised by different types of load profiles.

Definition of Scope

First, the system boundary as depicted in Figure 5–15 is defined. After its first life in the EV a traction battery with an original nominal capacity of 1 kWh is remanufactured and the modules are fed into an SL application. This prevents the production of new stationary battery modules, and thereby avoids energy-related GHG emissions as well as Li and Co demand.

Considering an EoL criterion of 70 % of the original nominal capacity, the used traction battery is entering the SL application with a capacity $c_{\mathrm{eol,TB}}$ of 0.7 kWh. This EoL criterion is derived from manufacturer warranties as well as [170]. After the remanufacturing process, entailing the disassembly of the traction battery, the testing and sorting of the modules and the assembly of the new battery system [98, pp. 25–29], the repurposed stationary battery system enters the stationary application.

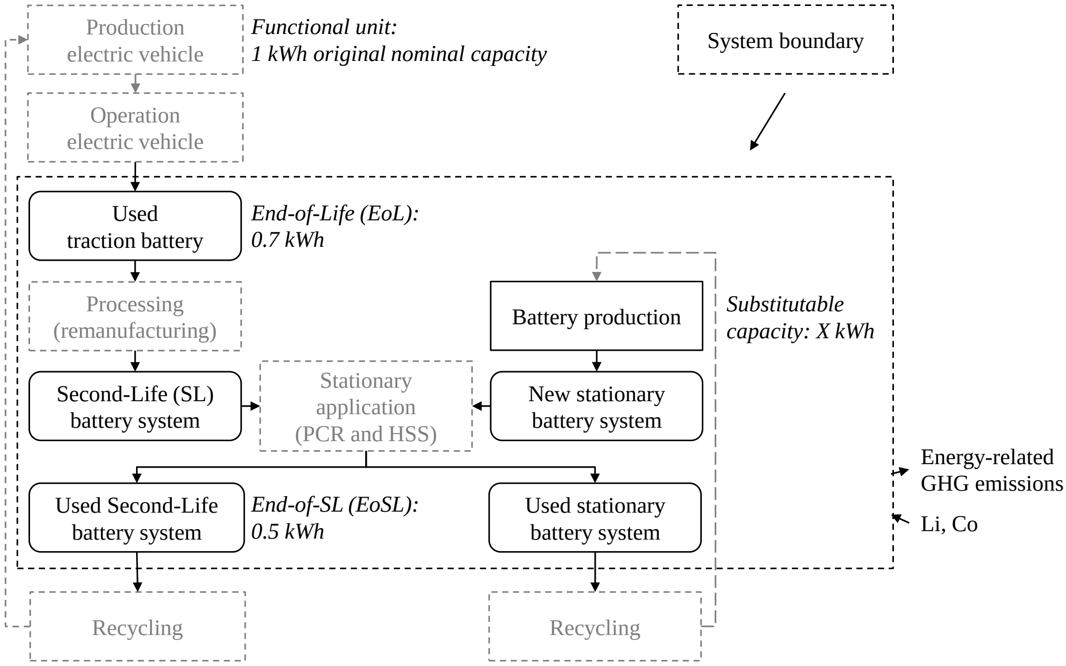

Figure 5–15: System boundary for the assessment of Second-Life applications

In this case, the SL battery is deployed for PCR or as an HSS. Control reserve is needed for the event of an imbalance between power supply and demand in order to stabilise network frequency. As described in [171, pp. 8–9], PCR is automatically activated in the event of a frequency deviation in a non-selective manner, meaning that the deployment of PCR is directly controlled by the network frequency. According to the German pre-qualification requirements, an activation of the complete PCR has to be performed within 30 seconds [171, p. 17]. Thus, as large power gradients in both directions are required, batteries constitute a viable option for delivering PCR. As explained in [126, pp. 142–143], the idea behind using batteries as HSSs is the increase of self-consumption from the rooftop PV system due to a temporal decoupling of PV generation and electricity demand. The increased self-consumption leads to a decrease of electricity demand from the grid and potentially a decrease of electricity costs.

As the SL battery has already aged during its use in the vehicle, its ageing process and operation time in the stationary application differ from those of a new battery. Hence, the method described in Subsection 5.5.2 is used to determine the substitutable capacity sc, based on which Li, Co and energy-related GHG emission savings are derived. In case of the PCR application the provided power is used to describe the energy system service ess. For the deployment as an HSS, on the contrary, the share of the household's total electricity demand supplied by PV electricity from the HSS is selected as an indicator to translate the remaining SoH into an energy system service. In the following, this share is referred to as "battery self-coverage share". Furthermore, the ageing process is dependent on the cell type. Here, for traction batteries the cell type NMC and for stationary batteries the cell types NMC and LFP are chosen for PCR and HSS, respectively. Reasons for the selection of these cell types are their currently large market shares (see Table 5–5) as well as the availability of ageing modelling results.

The final end of the operation time is in this case reached if either the SL system reaches 50 % of the traction battery's original nominal capacity, as defined in [170], or if the SL battery's maximum operation time is reached. For reasons of consistency, this maximum lifetime is derived from the lifetime of the stationary battery less the battery's operation time in the vehicle. While in this case the lifetime of the stationary battery is assumed to be 20 years according to the requirements specified in [172, pp. 4] and [32, p. 70], for the first life in the vehicle a minimum of 10 years as in Subsection 5.3.3 is assumed. This leads to a maximum operation time of the SL battery of 10 years.

As depicted in Figure 5–15, only GHG emission and critical metal savings resulting from preventing the production of a new battery system are included. The processing, use and recycling of the battery systems, on the contrary, are not included in the system boundaries of this analysis.

Input Data

In order to determine the substitutable capacity according to Equation 5–17, the SoH curve of an NMC battery used as an HSS and for PCR are required. As for the HSS application an LFP battery is substituted, furthermore, the capacity decrease of an HSS of type LFP is needed. Here, the SoH curves described in [33, pp. 78–81] and [61] are used.

The underlying load profiles and battery configurations, both for HSSs and for PCR, are described in detail in [33, pp. 53–64]. The PCR load profile stems from the EEBatt project [173] at the Institute for Electrical Energy Storage Technology (EES) of the Technical University of Munich and is valid for a storage system offering PCR in a pool. The load profile for the HSS application is taken from the e-GAP project of the FfE [174] and represents a single-family house with an EV, a PV system and an HSS in Garmisch-Partenkirchen. Using these load profiles, the SoH curves are an output of the NMC ageing model developed at the EES, which is described in [33, pp. 72–81], and the LFP ageing model developed at the FfE, which is summarised in [61].

The influence of the load profile on the SoH curves is shown in Figure 5–16, using the example of the NMC battery which ages much stronger in the HSS application. This is due to the deep charging and discharging cycles which have a great influence on the ageing of the considered NMC cell. Furthermore, it can be seen that the SoH is reduced in a non-linear pattern in the first years which can be explained by formation effects [168, p. 31]. Due to a lack of data, for the SL battery the prehistory in the vehicle is not considered. Instead the same SoH curves as for the new NMC battery are used, but starting in the year in which the SoH is just below 70 %.

As LFP batteries are characterised by a large cycle stability [69, p. 26], the decrease in capacity of the HSS is slower for an LFP than for an NMC system. For the considered LFP ageing model and the HSS load profile this leads to an SoH of just under 80 % after 20 years in use. However, it needs to be considered that these are only model results, while the actual ageing processes can vary strongly depending on the cell and the respective circumstances. Therefore, battery ageing model results need to be treated with caution, especially since the comparability between ageing models with different levels of complexity is limited [61].

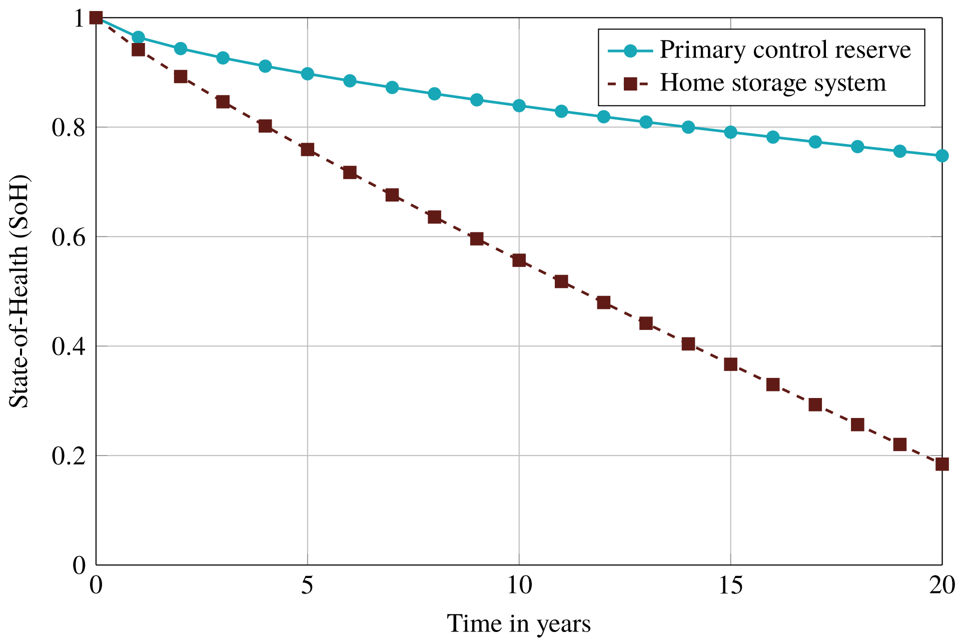

Figure 5–16: Capacity decrease for a battery with a nickel-manganese-cobalt cathode with a depth of discharge of 100 % (ageing curve of the Institute for Electrical Energy Storage Technology from [33, pp. 80–81])

For PCR the provided energy system service, in this case offered balancing power, is linearly reduced with the decrease in SoH to maintain the same Power-to-Energy (P/E) ratio. For HSSs the relationship between the decrease in battery self-coverage share and the remaining capacity is taken from [33, pp. 98–99] which builds on the methodology described in [175].

So as to determine the critical metal savings from the calculated substitutable capacity, for Li and Co the metal content in NMC622 and LFP battery systems from Table 3–2 is used. To calculate the energy-related GHG emission savings the same database as in Subsection 5.2.3 is applied, and expanded from NMC622 to LFP for the HSS application. However, in case of the chosen remanufacturing concept only the battery modules are substituted, therefore the energy-related GHG emissions of the module production excluding other components are determined. These amount to 93 kg CO_2 eq. per kWh for NMC622 modules and 78 kg CO_2 eq. per kWh for LFP modules.

Results and Discussion

The resulting Co, Li and GHG emission savings are depicted in Figure 5–17. It can be seen that the savings are smaller for the application of an SL battery as an HSS than for the case of using the SL battery for the provision of PCR. This can, on the one hand, be explained by the fact that in case of the HSS application LFP batteries are substituted which do not contain Co and are characterised by a lower specific Li content as well as lower production-related GHG emissions compared to NMC batteries. On the other hand, the considered NMC battery shows a stronger ageing behaviour in the HSS than in the PCR application (compare Figure 5–16), which results in a substitutable capacity for HSS of 0.21 kWh as compared to 0.39 kWh for PCR. This means that, per kWh traction battery, for the HSS application 21 % of the Li content and GHG emissions for a kWh of new LFP battery are saved through SL. For PCR, on the contrary, the savings amount to 39 % of Li and Co content as well as GHG emissions of a kWh of NMC battery.

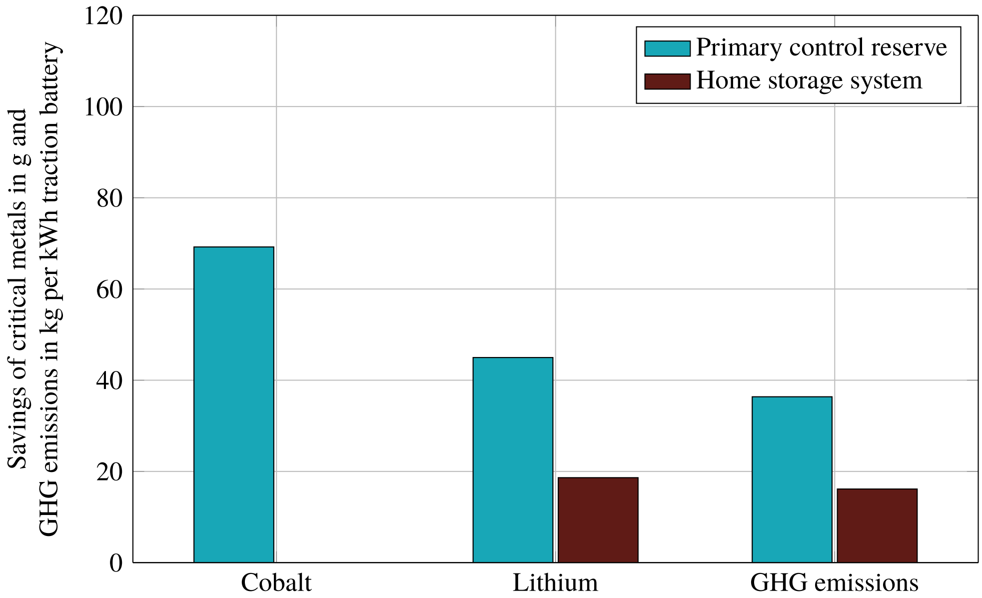

Figure 5–17: Critical metal and greenhouse gas emission savings per kilowatt hour original capacity of the traction battery resulting from the substitution of a new stationary battery through Second-Life

The larger substitutable capacity for PCR can be explained by the longer operation time of the SL battery in the PCR application due to a less pronounced ageing process. This shows that the used SoH curves and the assumptions about the maximum operation time have a decisive influence on the saving potential. Thus, the results can not be generalised, since the prehistory of the battery in the vehicle can have an impact on its performance in the SL application [176] and there are uncertainties regarding the battery ageing in actual operation.

It should also be noted that the GHG emission savings would decrease if the emissions occurring during the processing of SL modules are considered. However, in comparison to the electricity demand in battery manufacturing (see Subsection 5.2.3), the electricity demand for battery testing during remanufacturing is low, amounting to about 3 kWh per kWh battery capacity for the process described in Subsection 6.1.1. Another factor reducing the GHG emission saving potential of SL batteries is the efficiency loss resulting from the ageing process, as discussed in [165].

In this analysis only the battery production is considered. However, the environmental saving potential is dependent on the EoL treatment of the substituted battery. If for example recycling is considered, critical metal savings would decrease according to the recycling rate as this share of metals would have been recovered at the battery's EoL. Thus, Co savings would decrease by 94 % and Li savings by 56 %, if a 100 % collection rate and the future recycling rates defined in Subsection 5.6.3 are assumed. However, when including the recycling process in this type of analysis, it needs to be considered that the recycling process develops over time. This is relevant for SL batteries because the lifetime extension leads to a shift of the recycling process to a later point of time. Besides the recycling process, also the cell types of the batteries being substituted are dependent on time. Thus, when assessing SL applications and their interactions with recycling a more dynamic approach is required.

Summary

To determine emission and critical resource savings of SL batteries, functionality losses resulting from a capacity decrease over the battery's lifetime need to be considered. Here, a method was introduced and applied, which makes use of the concept of the substitutable capacity, while incorporating functionality losses dependent on application and cell type based on ageing modelling results. It is shown that Co, Li and GHG emission savings vary greatly depending on whether the SL battery is used for PCR provision or as an HSS. This is mainly due to the considered ageing behaviour of the NMC battery which differs for the two load profiles used. Since these results are strongly case-dependent, this assessment should be expanded to other batteries and applications, preferably using real data on battery ageing. Furthermore, the results indicate that the cell type of the substituted stationary battery greatly influences the saving potential, since the analysed cell types are characterised by different Co and Li contents as well as climate impacts. This means that the SL application should be selected in such a way that the load profile suits the ageing behaviour of the used EV battery and leads to a substitution of an emission- and critical resource-intensive battery.

If not only the production, but also the recycling of the substituted battery are to be included in the assessment, the time dependency of the recycling efficiency needs to be considered. Furthermore, also the substituted cell technology, which has a strong impact on the saving potential, depends on the development of the stationary battery market over time. Therefore, in Section 5.6 a model is developed which incorporates these time dependencies and substitution effects when assessing SL applications in combination with recycling.

5.6 End-of-Life: Time Dependencies and Substitution Effects

Apart from SL applications, also recycling constitutes a suitable CE approach for EV batteries (see Section 4.2). In the previous analysis, the consideration of time dependencies and substitution effects were identified as two challenges which need to be accounted for when assessing SL applications and their interactions with stationary battery markets as well as recycling processes. Therefore, in the following, based on an overview of existing dynamic modelling approaches for EV batteries in Subsection 5.6.1, a dynamic material flow model covering recycling and SL applications of batteries is developed. In Subsection 5.6.3 this model is then applied to a future scenario for Germany so as to examine the effect of EoL approaches for EV batteries on critical metal demand. The following description and illustrations are based on the method, model, input data and results by Regett et al. [105, 177, 178].

5.6.1 Overview: Dynamic Approaches for Resource Assessment of Batteries

Richa et al. [179] use an input-driven MFA approach to quantify future battery waste flows from EVs. This means that the annual waste stream is determined from the annual inflows of batteries, being derived from projected EV sales, as well as battery lifetimes. While the composition and material content of the battery waste flow is analysed, the effect of reuse and recycling is not assessed. The resulting composition of the waste stream in 2030 is then used in [30] for an environmental assessment of different EoL approaches. It is outlined that both recycling and SL applications of EV batteries offer a potential to reduce the environmental impact, but that this potential is dependent on boundary conditions such as the displaced technologies. However, since in this subsequent assessment the environmental indicators were not directly linked to the time-dependent battery flows, time dependencies are only considered to a limited extent.

To determine the impact of recycling of EV batteries on Li demand, Ziemann et al. [82] choose a stock-driven MFA approach which implies that battery inflows and outflows are derived from the development of the battery stock as well as battery lifetimes. It is shown that Li recycling can make an important contribution to future material availability if the quality of secondary Li is high enough to be reused in the production of EV batteries. With a focus on the recycling of Li from traction batteries, SL applications and stationary battery markets are not covered in this analysis. A similar approach is chosen by Weil et al. [72] who conduct a stock-driven dynamic MFA to determine the global demand for key metals from EV batteries. By including different recycling scenarios it is shown that recycling can significantly reduce the pressure on metal reserves, but that for some metals, such as Co, the cumulative primary metal demand until 2050 is still higher than current reserves.

As outlined in [180], MFA can be coupled with approaches from system dynamics to include feedback loops in the system. Novinsky et al. [181], for example, use a comprehensive system dynamics model to determine the effect of EV batteries on Co markets as well as the feedback of Co availability on the diffusion of technologies. Ziemann et al. [180], on the contrary, conduct a qualitative assessment based on causal loop diagrams to point out the importance of time delays in the assessment of battery reuse, while a quantification of these effects is not yet carried out.

Therefore, to quantify the impact of EoL approaches on critical metal demand, in the following, a stock-driven dynamic material flow model is developed which does not only include recycling, but also the reuse of EV batteries in stationary applications. To account for time-dependent substitution effects resulting from SL applications, the model also encompasses selected stationary battery markets. The demand and availability of Li and Co are directly linked to the calculated time-dependent battery flows so as to determine the potential of SL and recycling to reduce primary critical metal demand. Furthermore, a method for integrating LCA into the MFA model is proposed which can serve as starting point for a future dynamic assessment of GHG emission savings.

5.6.2 Dynamic Material Flow Model for Recycling and Second-Life of Batteries

Model Overview

The material flows are quantified based on a dynamic stock and flow model, which describes the stock of batteries in the system as well as the flows of batteries into the system (production) and out of the system (EoL) in each year of simulation (2015 to 2050). Knowing the annual battery stock, the annual production and EoL battery systems are determined using lifetime distribution functions. The general structure of the developed model resembles the consumption sector models developed in the course of the Dynamis project [10]. The model covers traction batteries used in passenger cars and stationary batteries used as HSSs and for PCR in Germany. The selection of stationary applications is based on [33], in which two applications were selected based on a detailed analysis of battery storage applications as well as stakeholder workshops (see Subsection 5.5.3).

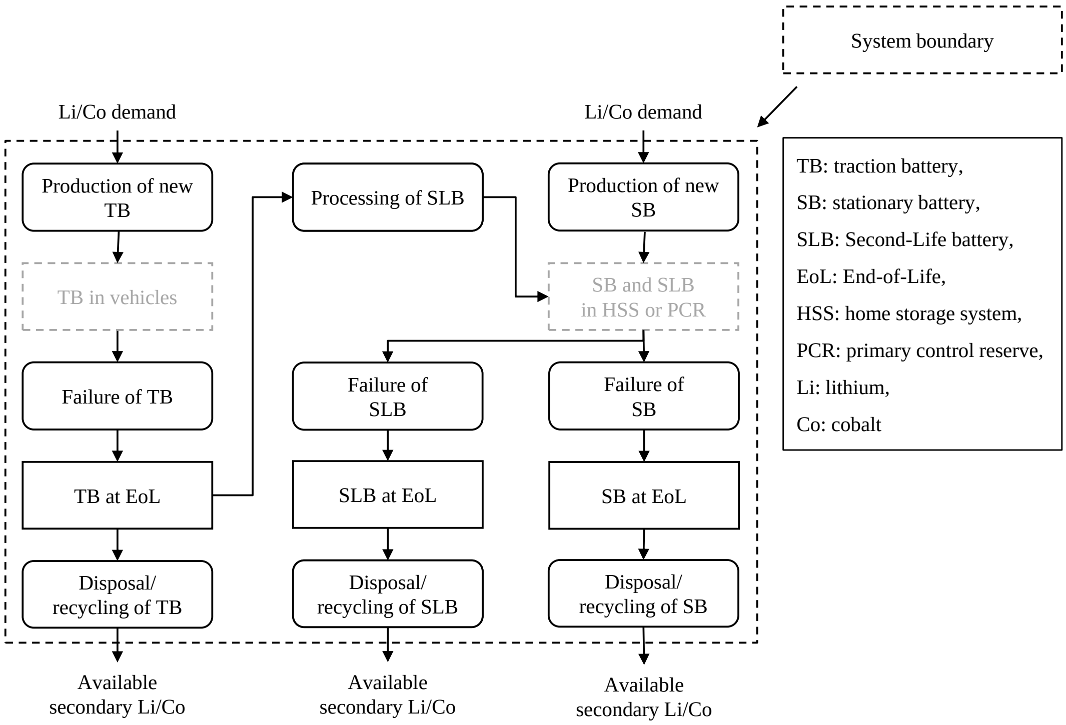

Figure 5–18: Overview of the dynamic material flow model to assess recycling and Second-Life applications of electric vehicle batteries

As shown in Figure 5–18, the resulting battery flows are directly linked to the corresponding Li and Co content to derive the demand for primary Li and Co, which results from the total metal demand less the available secondary metals from recycling. As the Li and Co demand is determined based on stoichiometry, a differentiation by cell type is made. When assessing the reuse of EV batteries in stationary applications, the formerly separate automotive and stationary markets are now connected via processed SL batteries which are deployed in stationary applications after their EoL in the vehicle. This leads, on one side, to a decrease in production of new stationary batteries, and, on the other side, to a shift of the recycling process to a later point of time because of an extension of the traction batteries' lifetime. While the production and EoL of batteries is included, the impact of the use phase, on the contrary, is not in the scope of this analysis.

Material Flow Modelling

The primary metal demand $\boldsymbol{d}_{\mathbf{pr,met}}$ of the previously described system can be quantified from the total metal demand less the available secondary metals as described by

$$\boldsymbol{d}_{\mathbf{pr,met}} = \boldsymbol{d}_{\mathbf{tot,met}} - \boldsymbol{s}_{\mathbf{sec,met}}. \tag{5–18}$$

In this context, $\boldsymbol{d}_{\mathbf{tot,met}}$ and $\boldsymbol{s}_{\mathbf{sec,met}}$ are vectors containing the annual total demand for the metal *met* (here: Li and Co) and the available mass of secondary metals from recycling per year, respectively.

As outlined by Equation 5–19, the total metal demand for battery production $\boldsymbol{d}_{\mathbf{tot,met}}$ is determined from the number of produced batteries, the share of cell technologies, the battery capacity and the metal content:

$$d_{\text{tot,met},t} = \sum_{bt} \sum_{ct} p_{bt,t} \cdot q_{bt,ct,t} \cdot c_{bt,t} \cdot m_{\text{met},ct,t}. \tag{5–19}$$

More precisely, the vector $\boldsymbol{q}_{\mathbf{bt,ct}}$ comprises the share of the respective cell technology *ct* (e.g. NMC, NCA, LFP) per battery type *bt* (in this case: traction and stationary batteries), $\boldsymbol{c}_{\mathbf{bt}}$ contains the average capacity per battery type and $\boldsymbol{m}_{\mathbf{met,ct}}$ the specific metal content per battery capacity depending on the cell technology in each year t. For the quantification of the battery production per battery type $\boldsymbol{p}_{\mathbf{bt}}$ not only the annual increase in battery stock needs to be included, but also the replacement of batteries reaching their EoL in the respective year.

Therefore, the production of traction batteries $\boldsymbol{p}_{\mathbf{tb}}$ is quantified by

$$p_{\text{tb},t} = st_{\text{tb},t} - st_{\text{tb},t-1} + \sum_{a} e_{\text{eol,tb},t,a} \tag{5–20}$$

and the production of stationary batteries $\boldsymbol{p}_{\mathbf{sb}}$ by

$$p_{\text{sb},t} = st_{\text{sb},t} - st_{\text{sb},t-1} + \sum_{a} e_{\text{eol,sb},t,a} + \sum_{a} e_{\text{eol,slb},t,a} - \sum_{a} e_{\text{eol,tb},t,a}. \tag{5–21}$$

In this regard, the vectors $\boldsymbol{st}_{\mathbf{tb}}$ and $\boldsymbol{st}_{\mathbf{sb}}$ are the year-dependent stock of traction and stationary batteries, respectively. To also account for the batteries reaching their EoL, the matrices $\mathbf{E}_{\text{eol,tb}}$, $\mathbf{E}_{\text{eol,sb}}$ and $\mathbf{E}_{\text{eol,slb}}$ are introduced. These are $m \times n$ matrices containing the number of EoL batteries per battery type (traction, stationary and SL batteries) depending on the year of EoL t (with $t \in [1, m]$) and the age at EoL a (with $a \in [1, n]$). The last term in Equation 5–21 indicates the number of available SL batteries for stationary applications, leading to a reduction in the production of stationary batteries. If the substitution takes place on a capacity basis, an additional conversion factor is required which translates the number of available SL batteries into the number of substitutable stationary batteries. Furthermore, an SL feasibility factor is used to account for the share of EoL traction batteries which can be reused in SL applications.

The elements of the battery EoL matrices $\mathbf{E}_{\mathrm{eol,bt}}$ in the previous equations are derived from

$$e_{\mathrm{eol,bt},t,a} = p_{\mathrm{eol,bt},t-a,t} \tag{5–22}$$

with $\mathbf{P}_{\mathrm{eol,bt}}$ being described by

$$p_{\mathrm{eol,bt},y,t} = p_{\mathrm{bt},y} \cdot f_{\mathrm{bt}}(t-y). \tag{5–23}$$

These so-called production-EoL matrices $\mathbf{P}_{\mathrm{eol,bt}}$ contain the number of batteries per battery type dependent on the year of production y and the year of EoL t. To create these matrices the lifetime probability density function per battery type f_{bt} is used to determine the number of battery's reaching their EoL in each year depending on the year of production.

However, to quantify the primary metal demand $\boldsymbol{d}_{\mathbf{pr,met}}$, apart from $\boldsymbol{d}_{\mathbf{tot,met}}$, also the available secondary metal supply $\boldsymbol{s}_{\mathbf{sec,met}}$ is required (see Equation 5–18). Basis for this is the amount of secondary metals contained in the batteries reaching their EoL, which is dependent on the share of cell technologies, the battery capacity and the metal content of the EoL batteries. As these parameters depend both on the year of EoL t and the age at EoL a, the vectors $\boldsymbol{q}_{\mathbf{bt,ct}}$, $\boldsymbol{c}_{\mathbf{bt}}$ and $\boldsymbol{m}_{\mathbf{met,ct}}$ (see Equation 5–19) are transformed into matrices of the same type as the battery EoL matrices $\mathbf{E}_{\mathrm{eol,bt}}$. In mathematical terms, the potentially available metals at the batteries' EoL $\boldsymbol{h}_{\mathbf{sec,met}}$ can then be quantified by

$$h_{\mathrm{sec,met},t} = \sum_{bt}\sum_{ct}\sum_{a} e_{\mathrm{eol},bt,t,a} \cdot q_{\mathrm{eol},bt,ct,t,a} \cdot c_{\mathrm{eol},bt,t,a} \cdot m_{\mathrm{eol,met},ct,t,a} \tag{5–24}$$

In this case, $\mathbf{Q}_{\mathrm{eol,bt,ct}}$, $\mathbf{C}_{\mathrm{eol,bt}}$ and $\mathbf{M}_{\mathrm{eol,met,ct}}$ are the created matrices containing the share of cell technology per battery type, the average capacity per battery type and the content of metal per cell technology at the batteries' EoL dependent on the year and age of EoL.

Finally, this potential supply of secondary metals contained in EoL batteries is translated into an actually available secondary metal supply $\boldsymbol{s}_{\mathbf{sec,met}}$ by

$$s_{\mathrm{sec,met},t} = h_{\mathrm{sec,met},t} \cdot cr_t \cdot rr_{\mathrm{met},t}, \tag{5–25}$$

where the vector $\boldsymbol{cr}$ describes the EoL collection rate and $\boldsymbol{rr}_{\mathbf{met}}$ the metal-dependent EoL recycling rate dependent on the year of EoL t.

Possible Extension by LCA

Originally, LCA methodology is a static method for assessing the environmental impact of a product or service given certain circumstances (see Subsection 5.1.1). However, with the described dynamic MFA model there is now data in annual resolution until 2050 available, which can be used for a more dynamic assessment of the environmental impact of batteries. While in [30] the dynamic MFA results from [179] are used as an input scenario for the following eco-efficiency assessment, a more integrated approach is proposed in Regett [178]. In this context, two possible links between dynamic MFA and LCA, as depicted in Figure 5–19, are suggested.

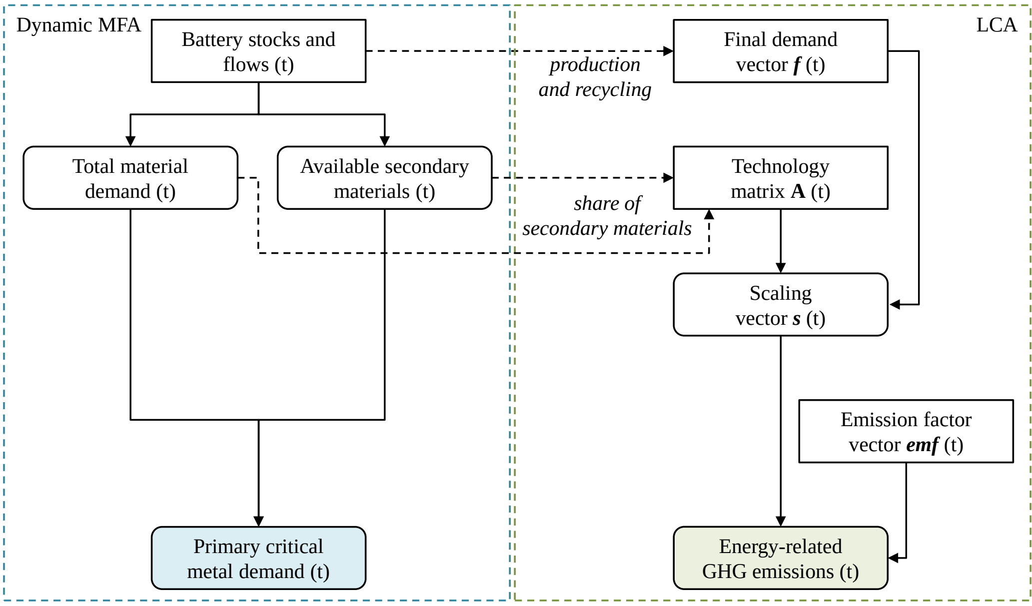

Figure 5–19: Coupling of the dynamic Material Flow Analysis with Life Cycle Assessment

First of all, the quantified flows of batteries, which need to be produced and recycled in each year t, can be used to define the final demand vector $\boldsymbol{f}$, specifying the demand for the processes of battery production and recycling contained in the technology matrix $\mathbf{A}$. Second, the technology matrix $\mathbf{A}$ contains the share of primary and secondary materials which can be dynamically modified based on the MFA results. For this purpose, the available secondary materials in each year are related to the total annual demand for the respective material. By multiplying the inverse of $\mathbf{A}$ with $\boldsymbol{f}$ for each year a year-dependent scaling vector $\boldsymbol{s}$ is obtained. To determine the energy-related GHG emissions associated with the provision of the final demand $\boldsymbol{f}$, finally, $\boldsymbol{s}$ is multiplied with the emission factor vector $\boldsymbol{emf}$, containing the carbon intensity of each energy carrier. As shown in Figure 5–19, there is a possibility for further dynamisation of the LCA by incorporating a year-dependent $\boldsymbol{emf}$. In this case, for example, the decreasing emission factor of electricity from Figure 5–6 could be incorporated into the assessment of battery production and recycling.

Due to data availability, in the following exemplary application in Subsection 5.6.3 only the impact of recycling and SL on critical metal demand is analysed. However, the results of the simplified application example presented in [178] indicate that total GHG emissions for the production of traction and stationary batteries can be reduced significantly by making use of recycled materials, and to a smaller extent by additionally considering SL applications. Furthermore, it is pointed out that SL applications can lead to trade-offs between GHG emission and critical metal savings.

5.6.3 Exemplary Application: Impact of Recycling and Second-Life on Critical Metals

Below, the described model is applied to determine the potential of recycling and SL to reduce the demand for primary Co and Li. For this purpose, first, the procedure as well as the initial scenario and input data are described. Then, the resulting critical metal savings for the initial scenario are shown and finally analysed with regard to sensitive parameters.

Procedure

To determine the critical metal savings through recycling and reuse of EV batteries several model runs are compared. In order to quantify the saving potential of recycling, first, a model run without recycling and SL is conducted, which is then compared to a run in which recycling is allowed. Second, a comparison between this "recycling only" run and a "recycling+SL" run of the model takes place to evaluate the impact of SL applications. These comparisons are first conducted for an initial scenario.

To identify critical parameters, which strongly impact the extent to which SL applications lead to critical metal savings, in a next step, a systematic sensitivity analysis is carried out. Starting from the critical metal savings through SL for the initial scenario, the development of one parameter is changed at a time and again a comparison of a "recycling only" and a "recycling+SL" simulation run takes place. The relative change in critical metal savings due to SL for this modified sensitivity scenario is then compared to the relative change in the initial scenario, so as to determine the influence of the changed parameter on the saving potential of SL applications.

Initial Scenario and Input Data

As the starting point of the assessment an initial scenario is defined, for which the input data is described in the following. In the "recycling only" run the batteries at EoL are recovered with the recycling rates described below. In case of the "recycling+SL" run the remanufacturing (reman) concept is applied, meaning that SL batteries substitute stationary battery systems on capacity basis, and the PCR application is prioritised over HSS due to a larger profitability (see Subsection 6.1.2).

To reduce complexity and enable a better interpretation, initially, for some of the following parameters constant or maximum values are applied. These are later varied in the sensitivity analysis in order to systematically examine the effects of selected parameters on the saving potential of SL applications. Thus, the described initial scenario does not claim to be a realistic development, but rather represents the starting point for the following analysis.

Battery stock and capacity: Apart from the stock and flow data on BEV and PHEV passenger cars, also the average battery capacity of traction batteries are obtained from the "Dynamis start" scenario [10]. The scenario is simulated with the FfE Transport Model (TraM), which is described in more detail in [127]. While the stock of EVs increases from under 0.1 million in 2015 to 2.8 million in 2030 and 8.8 million vehicles in 2050 (see Figure 3–6), the battery capacity, averaged over all classes and vehicle types, increases from 34 kWh in 2015 to about 44 kWh from 2027 on.

The stock of stationary batteries for PCR is derived from the implementation projects of large-scale battery storage systems from 2015 to 2018 listed in [182], which are linearly extrapolated until the maximum market potential of 600 MW (rounded up from historical PCR tenders in [183, p. 151]) is reached. The stock of stationary batteries for the HSS application is taken from [184, pp. 43–45]. This means that the stock is determined based on the development of the installed PV capacity in the "Dynamis start" scenario [10], which uses scenario B from [131, p. 23] as an input, and the method to derive the number of HSSs depending on installed PV outlined in [185]. According to this procedure, the probability for the equipment with an HSS amounts to 0.6 % per year for the PV stock and 41 % for a new PV system. Due to expiring feed-in tariffs, PV systems built before the time horizon under consideration are also upgraded with an HSS after 20 years of operation, using the same probability of 41 %. This results in an increase of HSSs from around 34 thousand in 2015 to 1.0 million in 2030 and 2.3 million in 2050.

The historical battery capacity and the P/E ratio for HSSs in 2015 to 2017 is derived from [186, pp. 72, 86], assuming a ratio of usable to installed capacity of 0.9. For the HSS built in the following years, a battery capacity of 7 kWh and a P/E ratio of 1 [135, p. 112] is applied. The capacity and P/E ratio for PCR systems from 2015 to 2018 are deducted from the currently installed batteries for PCR summarised in [182]. The average values for the installed battery systems for PCR in 2018 (capacity of 9.7 MWh and a P/E ratio of 0.91) are used to describe PCR batteries built in the following years.

Lifetime: For each battery type, a lifetime probability density function is determined using a lognormal distribution which, according to [187], is suitable to describe the lifetime of batteries. To determine the parameters of the lifetime function a mean age and a failure starting point is required. The mean age of stationary batteries is set to 20 years (see Subsection 5.5.3). The mean age for traction batteries is in this case assumed to equal the average lifetime of the EVs modelled in TraM, amounting to 12.8 years. This is in line with the required minimum lifetime of about 10 years stated in [32, p. 14, 70]. There are large uncertainties with regard to the lifetime of SL batteries because the lifetime depends amongst others on the cell type and application, as shown in Section 5.5. Here, a mean age of 8.5 years is considered based on the simplified assumption of a linear ageing process across both first and second life, as well as an EoL criterion of 70 % and an assumed EoSL criterion of 50 % (see Subsection 5.5.3). These criteria describe the share of original nominal capacity being left at the battery's EoL and EoSL, respectively. As the EoL criterion corresponds to a large number of recently issued warranties of car manufacturers, the failure starting points are also determined based on warranties of original equipment manufacturers (OEMs), amounting to 10 years for stationary batteries [188, pp. 7–28] and about 8 years for traction batteries. Analogous to traction batteries, for SL batteries also a warranty of two thirds of the expected mean age, in this case 5 years, is adopted. To determine the lifetime function, a maximum failure before warranty expiry of 1 % of the batteries is tolerated, which is assumed due to a lack of data, but has a negligible effect on the results described below.

Cell technologies: To determine the share of cell technology per battery type in Table 5–5, for each battery type the current sales figures are analysed with regard to sales numbers, installed power, capacities and cell technologies. For traction batteries this data is obtained from [18, p. 8], [189], [190], [191] and OEM data sheets. As described in [184, pp. 47–48], the data for HSSs comes from [188, p. 3] and [192, pp. 7–28], while for PCR the storage systems from [182] are used. These are complemented with technical data on installed capacity, power and cell manufacturer from [193]. The share of cell technology is then determined by weighting the cell technologies by the sold capacity for traction batteries and HSSs, and by the installed power for PCR. As in Subsection 3.2.2, for NMC batteries the type NMC622 is chosen. For the initial scenario it is assumed that the share of batteries stay constant until 2050.

Table 5–5: Share of cell technologies per battery type

Cell technology	Share for traction batteries	Share for HSSs	Share for PCR
NMC622	0.56	0.60	0.94
LFP	0.02	0.40	0.02
LMO	0	0	0.04
LMO-NMC333	0.18	0	0
NCA	0.24	0	0

Recycling efficiency and collection rates: To better point out the effects of recycling and SL applications on Li and Co demand, a maximum scenario with a collection rate and SL feasibility of used EV batteries of 100 % is defined. With regard to battery recycling, for Co the recycling efficiency of the Umicore/LiBRi process of 94 % is used (see Subsection 3.2.2) and assumed for the whole time horizon under consideration. The recycling of Li, on the contrary, is currently only in exceptional cases carried out on an industrial scale [85, p. 67], therefore, the Li recycling efficiency is first set to 0 %. Given rising Li prices, it is assumed that the Li recovery from slag starts on a large scale once the return flows of EoL traction batteries are steeply increasing, which in this scenario occurs around the year 2025. The Li recycling efficiency is then set to the efficiency of the Umicore/LiBRi process of 56 % (see Subsection 3.2.2). These efficiencies are valid for materials in battery-grade quality [57, p. 2].

Metal content: For each cell technology the specific metal content per battery capacity is determined based on the mass balance and battery system specifications from [70] as well as the stoichiometry of the cathode materials (see Section 5.2).

Results

The impact of recycling on primary Li and Co demand for the analysed battery systems in Germany is depicted in Figure 5–20. As expected, a large reduction is achieved especially for

Co. However, even in the recycling scenario the demand for primary metals increases due to an increasing stock of traction and stationary batteries. Only for Co, the primary demand decreases in the long-term once a large number of batteries reaches its EoL and enters the recycling process. This leads to an increasing availability of secondary Co, which is recovered with a high recycling rate, and therefore a reduction in demand for primary Co. This effect is less visible for Li because of a lower recycling rate.

Overall, despite large recycling rates, the annual primary Co demand still totals more than 2 000 t a^{-1} in 2050 due to an increasing stock of batteries especially for EVs. This corresponds to about 1.5 % of recent global Co production of 140 000 t a^{-1} [194]. It needs to be considered that these results hold true for a relatively conservative EV scenario of 8.8 million BEVs and PHEVs in 2050. The demand for Li and Co would rise significantly for an ambitious electrification scenario such as the "fuEL scenario" with about 31 million EVs, as depicted in Figure 3–6. Therefore, the question arises to what extent SL applications can lead to additional Li and Co savings.

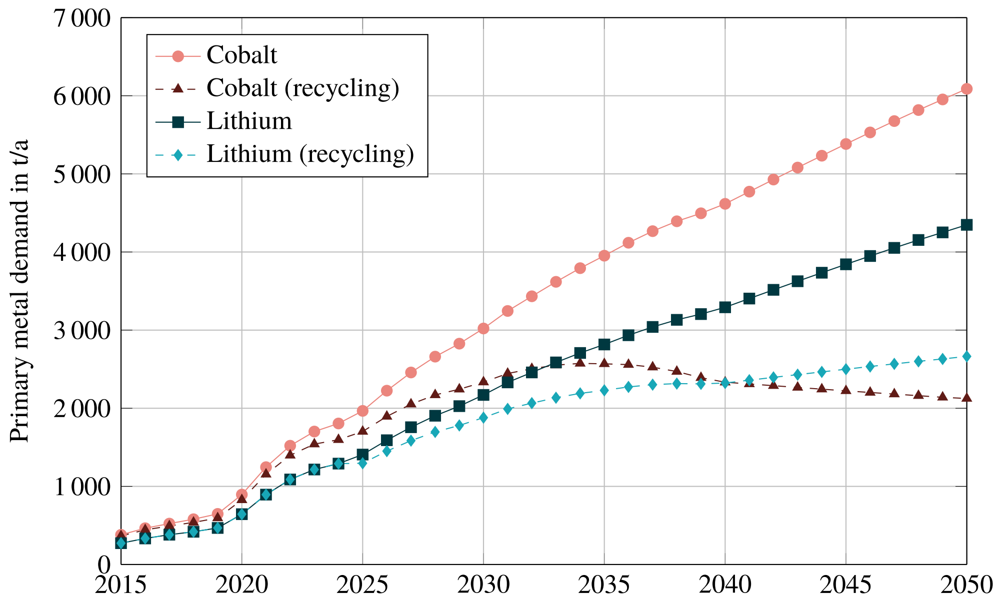

Figure 5–20: Impact of recycling on annual primary lithium and cobalt demand for electric vehicle batteries and stationary batteries in home storage and primary control reserve applications in Germany

By comparing the "recycling only" with the "recycling+SL" simulation run the Li and Co savings through SL applications can be determined. From the results in Figure 5–21 it can be seen that for Li in each year of simulation a reduction in Li demand takes place in case batteries from EVs are reused in stationary applications. For Co, on the contrary, an increase in Co demand (negative savings) is observed in the time horizon under consideration.

For Li the savings increase until 2020 due to an increasing availability of SL batteries substituting the production of new Li-containing stationary batteries. In 2025 a decrease in savings can be

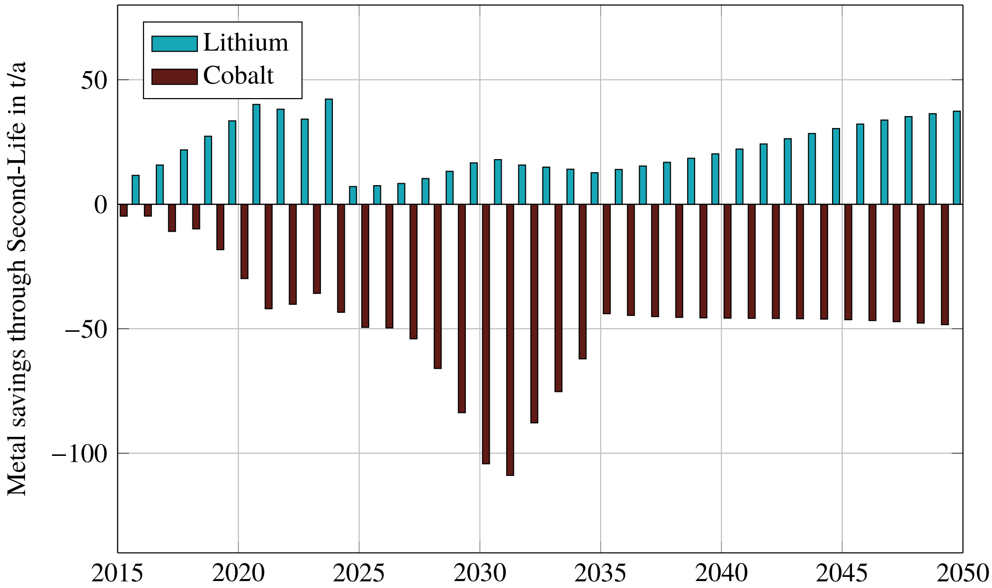

Figure 5–21: Annual lithium and cobalt savings through a Second-Life in home storage and primary control reserve applications compared to a "recycling only" scenario

observed because the Li recycling rate rises from 0 % to 56 %. This has a negative effect on the saving potential because the Li contained in the used SL batteries reaches the recycling system at a later point of time, corresponding to a later availability of secondary Li. The peak in Li savings in the early 2030s results from the large demand in SL batteries due to the upgrade of old PV systems with HSSs. The increasing Li savings in the long-term can be explained by a still increasing stock of HSSs as well as the fact that a large number of SL batteries gradually reaches the recycling system, leading to an availability of secondary Li. In total, for Li the positive effect resulting from the substitution of new stationary batteries always outweighs the negative effect of a temporal shift of the recycling process through SL applications. Under the described boundary conditions this leads in sum to positive savings in every year of investigation.

For Co, on the contrary, the demand for primary Co increases in case of SL applications, which can mainly be traced back to three effects. First of all, due to the ageing in the vehicle the available capacity of an SL battery is lower (EoL criterion: 70 % of original capacity) than the original capacity of a new stationary battery. This results in the substitution of a smaller stationary battery, while an oversized SL battery (factor 1.4) is bound in the stationary market. This effect is independent of the metal and therefore also reduces the saving potential for Li. Second, Co-rich traction batteries replace less Co-containing stationary batteries, since the share of Co-free cell types (such as LFP) is larger for stationary than for traction batteries, due to less stringent requirements with regard to energy density. Third, Co is characterised by a high recycling rate so that the extension of the traction battery's lifetime leads to a temporal shift of large amounts of secondary Co available from recycling. In the long-term, the increase in annual Co demand is reduced as Co-intensive SL batteries reach their EoL, leading to a larger availability of secondary Co.

Overall, in 2050 about 37 t of Li can be saved through SL, which corresponds to 1.4 % of the annual Li demand in the "recycling only" scenario. Over the considered time horizon the primary Li demand is reduced by approximately 800 t, which compares to 1.3 % of the total cumulative primary Li demand of about 64 000 t. On the contrary, the increase in cumulative primary Co demand due to SL amounts to around 1 700 t.

Sensitivity Analysis and Discussion

From the results of the initial scenario it can be seen that there are several mechanisms affecting the critical metal saving potential through SL. As these mechanism are influenced by the selected boundary conditions, in the following, a sensitivity analysis is conducted to identify critical parameters on the saving potential of SL applications. Table 5–6 gives an overview of the defined sensitivity scenarios. For each of these scenarios one or two parameters are changed compared to the initial scenario. Then, for each of these scenarios again the "recycling only" calculation run is compared to the "recycling+SL" run.

Reducing the *SL feasibility* to 50 % leads to a decrease in critical metal saving potential because less SL batteries are deployed, leading to lower positive savings for Li, but also lower negative savings for Co. In this case, the full coverage of the stationary battery markets by SL batteries, for example, is only reached in 2023, as compared to 2021 for the initial scenario. However, once the market is fully covered by SL batteries, the course of the saving potential is the same as for the initial scenario in Figure 5–21. The smaller *collection rate* for EV batteries of 17 % does not only reduce the number of available SL batteries (full market coverage in 2034), but also reduces the availability of secondary materials in the "recycling only" case. Thus, the decrease in collection rate leads, on the one hand, to a shift of savings through SL to a later point of time and, on the other hand, to smaller relative savings for Li and to a smaller relative increase for Co than for the initial scenario.

At this point it needs to be mentioned that the basis for the evaluation of SL applications change if the varied parameter influences the "recycling only" run of the respective sensitivity scenario. In this case, comparing the absolute savings of the sensitivity scenario with the absolute savings of the initial scenario is not meaningful. Instead the relative savings of "recycling+SL" in relation to the corresponding "recycling only" run need to be compared both for the sensitivity and the initial scenario.

As outlined in Subsection 3.2.2, there is potential for improvement with regard to the recovery of especially Li from EoL batteries. The sensitivity of the saving potential on the recycling efficiency has already been briefly discussed for the initial scenario. In Figure 5–22 this effect is clarified by showing the relative Li savings through SL for the initial scenario (Li recycling rate: 56 % from 2025 on) and the two sensitivity scenario *"recycling efficiency min"* and *"recycling efficiency max"*. It can be seen that under the chosen boundary conditions the recycling rate decides whether Li savings through SL become positive or negative. Also for Co, the saving potential becomes positive if the minimum recycling efficiency is assumed. This shows that, from a critical metal perspective, SL is a more useful approach for metals with low recycling rates, since for these metals the temporal shift of the recycling process does not lead to binding large amounts of valuable secondary materials in stationary applications. This effect is reinforced by the oversizing of SL batteries due to the previous ageing in the vehicle. If an hypothetical *EoL*

Table 5–6: Overview of the sensitivity scenarios for analysing the impact of Second-Life on critical metal demand

Name	Changed parameter	Motivation
"SL feasibility"	SL feasibility factor: 50 %	Considering restrictions for the technical feasibility of SL applications as in [166]
"Collection rate"	Collection rate: 17 %	Assuming an equally low collection rate for EVs as for conventional vehicles due to vehicle export [78, p. 39]
"Recycling efficiency min"	Recycling efficiency for Li and Co: 0 %	Illustrating the impact of the recycling efficiency by an extreme scenario
"Recycling efficiency max"	Recycling efficiency for Li und Co: 100 %	Illustrating the impact of the recycling efficiency by an extreme scenario
"EoL criterion"	EoL criterion: 100 %	Showing the impact of the EoL criterion by an extreme scenario
"Same technology"	Share of cell technologies for stationary batteries: same shares as for traction batteries	Eliminating the substitution effect resulting from different shares of cell technologies for traction and stationary batteries
"Lifetime"	Mean age SL batteries: 4.25 years (halved)	Demonstrating the effect of shorter lifetimes of SL batteries because of strong uncertainties with regard to battery ageing
"Constant stock"	Stock of HSS and PCR : stagnating from 2020 on	Illustrating the effects of SL in a saturated market
"Constant stock+half lifetime"	Stock of HSS and PCR: stagnating from 2020 on; mean age of stationary and SL batteries: halved	Illustrating the effects of SL in a "closed" system, in which the saturated stationary battery market is continuously covered by SL batteries (for this purpose, lifetimes are reduced)
"Reuse"	SL concept: reuse	Determining the impact of the SL concept (processing on system instead of module level)

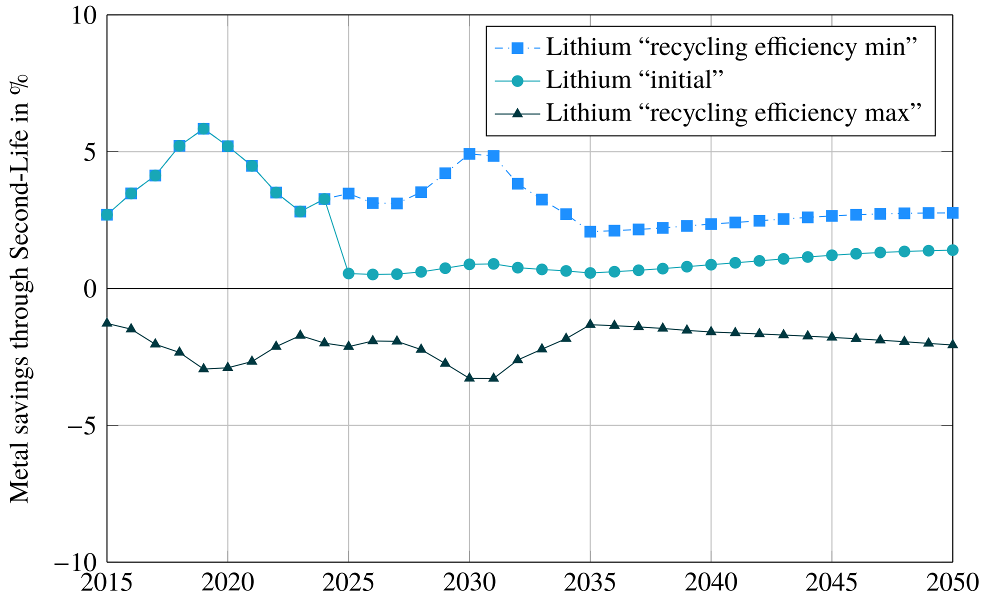

Figure 5–22: Impact of the recycling efficiency on relative lithium savings through Second-Life

criterion of 100 % is assumed, Li savings are more than doubled compared to the initial scenario and the increase in primary Co demand is more than halved.

Furthermore, as described for the initial scenario, the shares of cell technologies for traction and stationary batteries have an impact on the substitution effect of SL batteries. If for stationary batteries the *same technology* (same market shares of cell technologies) is assumed as for traction batteries, relative Li savings through SL are increased in the long-term by a factor of about 1.2 and, more importantly, the relative increase in Co demand is about halved compared to the initial scenario. Halving the *lifetime* of the SL batteries in the stationary application, on the contrary, does not have a large impact on critical metal savings. However, it needs to be considered that the dynamic MFA model does not include a detailed modelling of ageing processes. This means that, in contrast to Subsection 5.5.3, the differences in functionality loss of new and SL batteries, resulting from the battery ageing process, are not accounted for.

The course of savings through SL for the initial scenario described above is also strongly influenced by the fact that battery markets are still growing in the time horizon under consideration. Therefore, in Figure 5–23 it is illustrated how critical metal savings develop if a saturated market (no stock increase from 2020 on) is assumed. Here, the scenario *"constant stock+half lifetime"* is depicted, since lifetimes need to be reduced to actually reach a "closed" system until 2050 in which the stationary battery market is continuously covered by SL batteries. It can be seen that, once this type of system is established, in the long-term SL leads to positive savings for both Li and Co. In a system, for which only the existing stock is renewed by the same type of battery, SL leads to an increase in the time period between recycling processes and therefore a decrease in recycling losses. As recycling losses are higher for Li than for Co, for Li larger savings are observed.

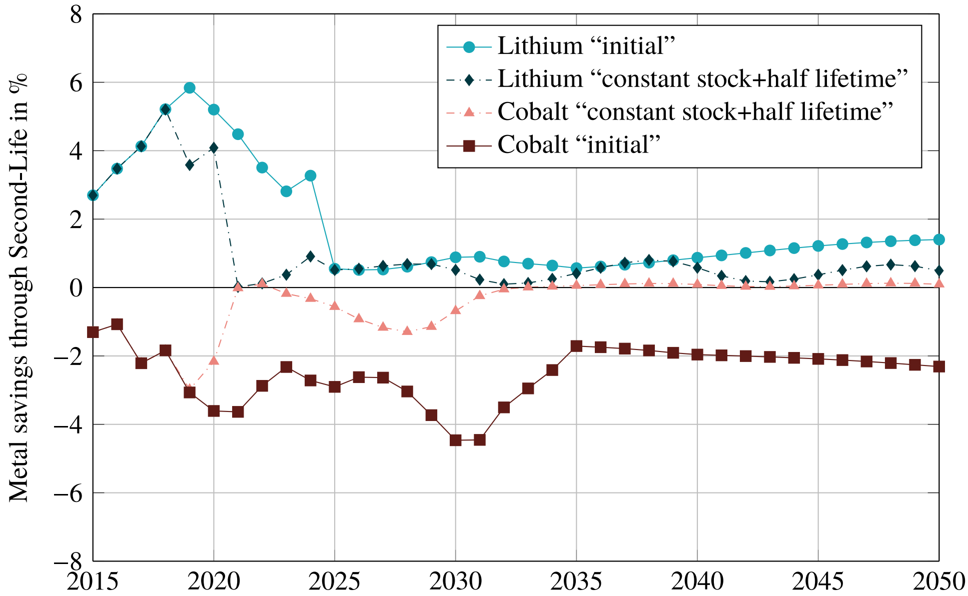

Figure 5–23: Impact of a market saturation on relative critical metal savings through Second-Life

Figure 5–24 shows that the choice of the *reuse* instead of the reman concept, leads to a strong increase in primary metal demand. This is due to the substitution of small HSSs (7 kWh) by large SL batteries (around 34 kWh to 44 kWh), leading to a reinforcement of the substitution effects described above. Thus, large amounts of Li and Co from traction batteries are bound in stationary applications and are available for recycling at a later point of time.

If, in addition, two recent trends, namely the increase in battery capacities of EVs and the increase in energy densities, are considered, the following effects on absolute critical metal savings are observed. While larger capacities of traction batteries lead to an increase in positive Li and negative Co savings in the first years, similar absolute savings as in the initial scenario occur once the stationary markets are fully covered by SL batteries. A decrease in energy density, on the contrary, leads to a reduction in specific critical metal demand per kWh battery capacity, which in return leads to a proportional decrease in critical metal demand and absolute critical metal savings.

Summary

It is often taken for granted that the CE leads to resource savings. The present analysis shows that the reuse of EV batteries in stationary applications can offer critical metal savings. However, it is clearly outlined that this is not the case under all circumstances. Furthermore, it is shown that the savings through SL are strongly dependent on the considered time horizon as they vary over time. Thus, when pushing forward SL approaches for EV batteries, the potential negative effects over the course of time need to be considered.

In the analysed scenario the reuse of EV batteries leads to savings of primary Li, but an increase

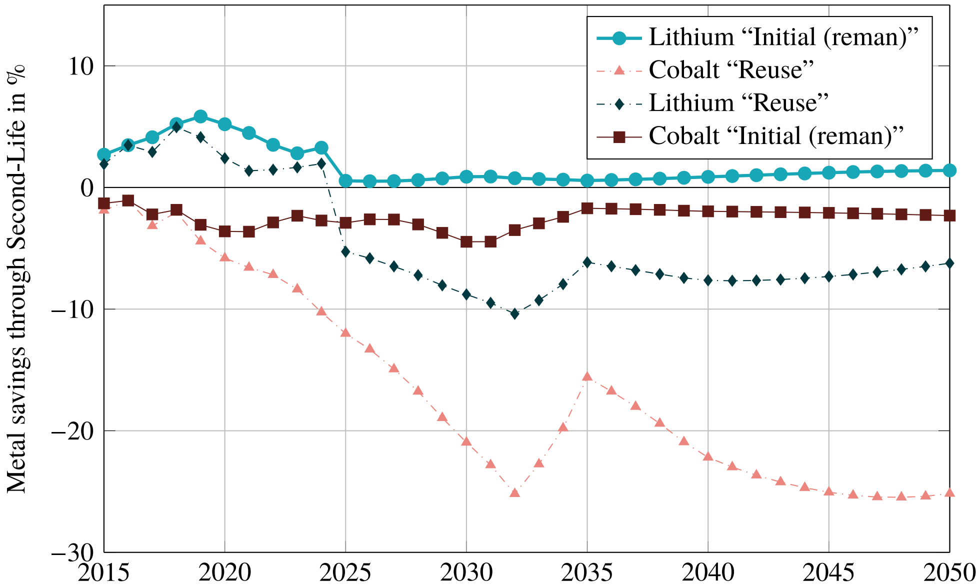

Figure 5–24: Impact of the Second-Life concept on relative critical metal savings through Second-Life

in primary Co demand. By using the developed dynamic modelling approach it is shown that the time delay of the recycling process and the substitution effects on stationary markets have a strong impact on the critical metal saving potential. As SL applications lead to a postponement of the recycling process and therefore a delay of secondary metal availability, SL is more effective for metals with low recycling rates. When substituting the production of new stationary batteries by SL batteries both the oversizing as well as the share of cell technologies affect the saving potential. Because of the ageing in the vehicle an SL battery is always oversized compared to a new battery because only a certain share of the original capacity is available. This effect is further enhanced in case the reuse concept is chosen for HSSs as largely oversized traction batteries substitute smaller HSSs. This reinforces the effect resulting from the temporal shift of the recycling process, since even larger amounts of secondary materials are bound in stationary applications. As traction and stationary batteries have different requirements with regard to energy density, stationary markets are dominated by less Co-intensive batteries. Thus, in case of a substitution of new stationary batteries by SL batteries more Co is bound than being displaced.

The absolute saving potential depends both on the availability of SL batteries and on the battery demand. It is shown that the availability of SL batteries is not only dependent on the available EoL batteries from EVs, but that the collection rate and the technical feasibility also have a strong impact on the actual saving potential through SL. In case SL is applied in a saturated market in which battery demand is stagnating, also Co savings would eventually become positive due to a decrease in recycling losses, resulting from the establishment of longer life cycles.

5.7 Resulting Set of Instruments

Based on the selection of technically feasible CE approaches in Section 4.2, in Section 5.2 to Section 5.6 for each life cycle phase of EV batteries challenges for an emission and resource assessment of the respective CE approaches were identified based on recent literature. Then, for each challenge a suitable instrument was developed, which was subsequently deployed in an exemplary application. These instruments, which extent, refine and combine existing approaches, are of different nature. They include methodological procedures, methods for integrating energy system modelling results into emission accounting, the combination of environmental assessment methods with ageing modelling results and a dynamic stock and flow model. Figure 5–25 gives an overview over the developed instruments to assess CE approaches in the different life cycle phases of an EV battery.

In the battery production phase, efficiency and renewable energy supply were identified as relevant CE approaches for the reduction of GHG emissions. But to assess the potential of these approaches for an emerging technology such as Li-ion batteries, the dealing with uncertainties about future improvement potentials poses a major challenge. To address this challenge a step-wise procedure was specified, according to which, first, the processes with the largest contribution to GHG emissions are identified based on a contribution analysis. Subsequently, for those of the identified processes which are characterised by large uncertainties or a large variability a subsequent sensitivity analysis is conducted. In the course of the sensitivity analysis the uncertain parameters are varied with upper and lower boundaries derived from the current state of the art and technical limits, so as to quantify the possible potential for GHG emission reduction. This procedure was then applied to battery production, resulting in a variation of electricity demand for battery manufacturing and its carbon intensity. By means of this analysis the potential of reducing the carbon footprint of battery production through energy efficiency and renewable energy supply in the manufacturing process could be identified.

Also for the use phase, renewable energy supply was identified as an important CE approach for GHG emission reduction. However, in contrast to the production phase, which takes place in a specific year, in the use phase the temporal course of the carbon intensity of electricity over the battery's lifetime becomes relevant. Therefore, the incorporation of the development of an increasingly complex energy system into emission assessment was identified as an important challenge. This challenge was addressed by the development of an accounting method for determining time-resolved emission factors of energy carriers in future multi-energy systems. The developed method takes into account the increasing linkages between the different energy carriers by setting up a linear equation system balancing incoming and outgoing emissions for all of the modelled energy carriers. The application of the developed method to the "Dynamis start" scenario, which is a result of the energy system model ISAaR, delivers amongst others year-dependent emission factors of the electricity mix. These average emission factors were then used to assess the climate impact over the lifetime of a BEV dependent on the year of purchase. The comparison with ICEVs demonstrates that the incorporation of temporal developments of the energy system further improves the advantage of BEVs. If sufficient input data and scenario results are made available, the developed method can in principle not only be deployed to other scenario of the ISAaR model, but also to future scenarios resulting from other energy system models.

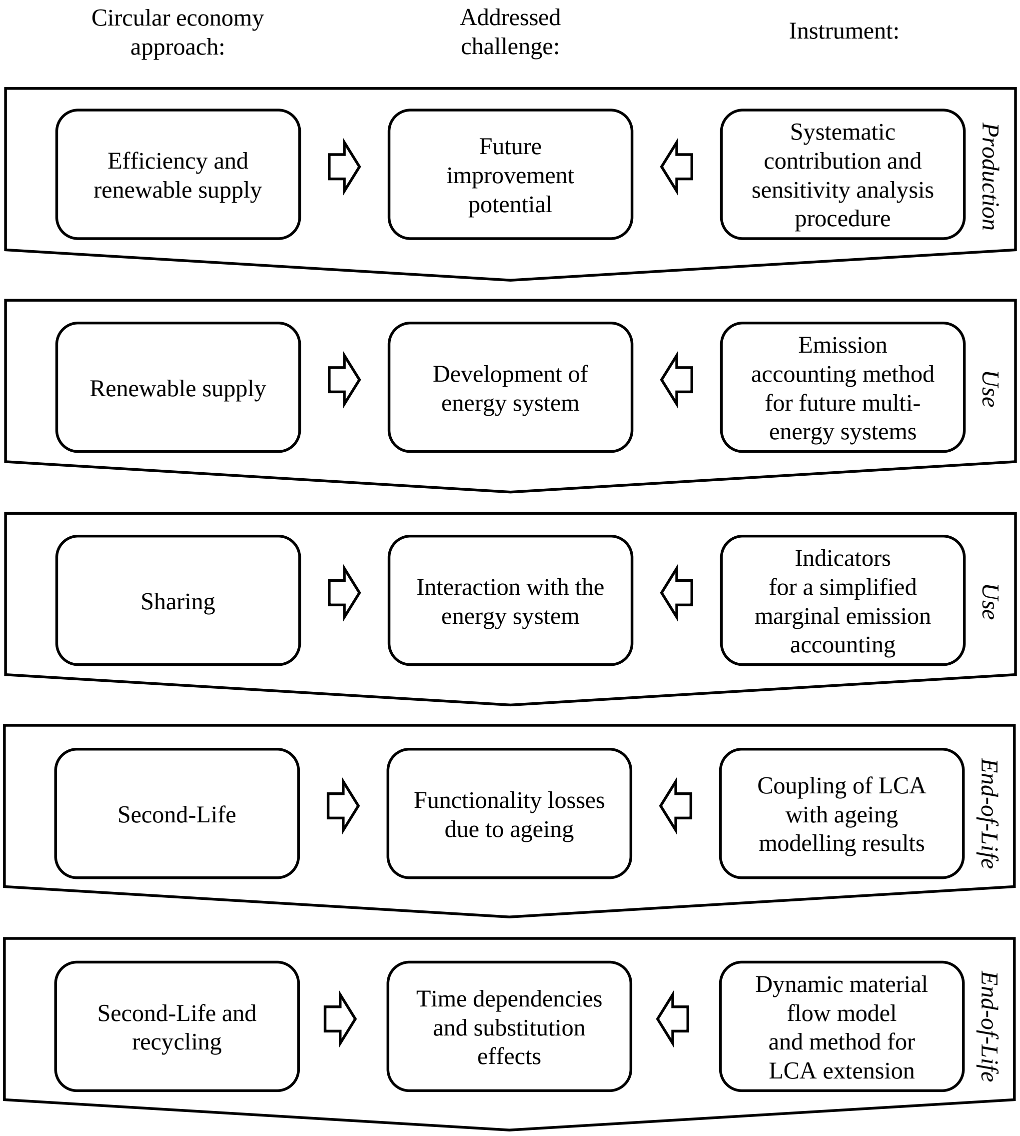

Figure 5–25: Developed set of instruments for the emission and resource assessment of circular economy approaches over the life cycle of electric vehicle batteries

Apart from the future development of the electricity system, in the use phase, the interaction of the battery with the energy system was identified as another major challenge. This is also relevant when assessing GHG emission savings of sharing concepts, such as multi-use cases for batteries, which lead to a change of the load profile. To assess the effect of a change in load, an average emission factor of the annual electricity mix is not sufficient, but time-resolved, marginal emission factors are required. Based on a comparison of different emission accounting methods for electricity, which make use of existing energy system modelling results in hourly resolution, indicators for a simplified assessment of short-term marginal effects through load shifting are proposed. The resulting time series of average and marginal emission factors were then applied to the sharing concept of load management with V2G for peak load reduction. However, these indicators can not only be used for load management strategies, but also for the assessment of electrification and efficiency measures. To account for long-term effects, on the contrary, a more comprehensive approach including new optimisation runs of the energy system model is required.

Functionality losses and shorter operation times due to ageing processes during the first life in the vehicle need to be considered when assessing CE approaches aiming at the lifetime extension at the traction battery's EoL. To address this challenge a method is suggested which integrates ageing modelling results into the LCA of SL batteries. In this context, SoH curves resulting from ageing models are used to determine the provided energy system service over the battery's lifetime by linking the loss of battery capacity to a decrease in provided function. Then, the provided energy system services of a new and an SL battery are compared, so as to determine the equivalent battery capacity being substituted by a used SL battery. Due to the special characteristics of the battery ageing process the concrete methodological procedure is battery-specific, however, the general principle is transferable to other technologies with different ageing mechanisms.

Finally, to include time dependencies and substitution effects on stationary battery markets into the assessment of CE approaches in the battery's EoL phase, a dynamic material flow model was developed. This model was then applied, so as to determine critical metal savings through SL applications and recycling as well as the sensitivity of savings to different parameters. Furthermore, an approach to extend the dynamic material flow model by LCA is proposed. The proposed coupling of dynamic MFA with LCA includes three elements, namely the definition of the final demand based on the resulting battery flows in each year, the adaptation of the share of secondary materials depending on the resulting material flows per year as well as the use of year-dependent emission factors for energy carriers. The application of this methodological extension, however, is subject of further research.

6 Implementation Potential of the Circular Economy

To understand the opportunities and challenges for a practical implementation of CE approaches for EV batteries, first, the economic feasibility is analysed in Section 6.1, using the example of SL applications. Then, in Section 6.2, in addition to economic aspects, also other barriers and drivers for the implementation of circular business models for EV batteries are identified and translated into critical success factors.

6.1 Economic Feasibility of Second-Life Applications

The results in Chapter 5 show that the GHG emission and critical metal savings through SL applications strongly depend on battery ageing, substitution effects and time delays. Since these aspects can also be of importance for the economic feasibility, the following assessment focuses on SL applications. Furthermore, the remanufacturing and reuse of traction batteries in stationary applications is of particular interest because it links the transport sector and the energy industry.

With regard to the economic feasibility of SL applications, on the one hand, the cost savings resulting from the avoided production of new battery systems are relevant and, on the other hand, the profitability for the implementing stakeholders. Therefore, in Subsection 6.1.1, first, the cost savings from a system perspective are quantified for the two selected SL applications. Then, in Subsection 6.1.2 the profitability of these SL applications from a stakeholder perspective is determined using the net present value method.

6.1.1 System Perspective: Cost Savings through Second-Life Applications

To determine cost savings through SL applications the dynamic material flow model described in Subsection 5.6.2 is extended by costs. Analogous to the procedure in Subsection 5.6.3, the cost savings are determined by comparing a “recycling only” with a “recycling+SL” model run. Starting with the initial scenario described in Subsection 5.6.3, the sensitivities of these costs savings are identified by means of several sensitivity scenarios, for which again the “recycling only” and “recycling+SL” run are compared. The following description and illustrations of the modelling approach, input data and results are based on the analysis by Regett and Bangoj [177].

Cost Modelling

While for the quantification of critical metal savings the flows of battery production and recycling are linked to the specific stoichiometric Li and Co content per battery capacity (compare Subsection 5.6.2), an extension of the model is required to determine the impact of SL applications on costs for stationary batteries. Therefore, the previously described dynamic material flow model is modified and extended in the sense that the main components of stationary batteries are modelled separately. Next to battery modules, a modelling of the periphery and power electronics is required. This is due to the facts that, on the one hand, different SL concepts (reuse or reman)

Table 6–1: Need for battery components depending on stationary application and Second-Life concept

Component	HSS "new"	HSS "reuse"	HSS "reman"	PCR "new"	PCR "reuse"	PCR "reman"
Modules	X			X		
Processing		X	X		X	X
Power electronics	X	X	X	X	X	X
Periphery	X		X	X	X	X

require different components, and, on the other hand, different components are characterised by different lifetimes. The different lifetimes of these components need to be accounted for, since the lifetime does not only determine the time of substitution, but also the battery component's annuity. This annuity is used to evenly distribute the investment over the component's lifetime. By applying this modelling approach, in each year the simulated production of stationary battery components can be linked to the respective annualised investments, and the simulated capacity of processed SL batteries can be linked to the corresponding processing costs.

As described in [138, pp. 30–31], the annuity A of an investment I can be quantified by

$$A = I \cdot anf \tag{6–1}$$

where the annuity factor anf is defined by

$$anf = \frac{(1+i)^n \cdot i}{(1+i)^n - 1} \tag{6–2}$$

with i being the discount rate and n being the lifetime.

When modelling costs, furthermore, a differentiation needs to be made between applications and SL concepts, since they require different components as illustrated in Table 6–1. While "reuse" means that the traction battery is used as a whole in the stationary application, "reman" refers to the case that the traction battery is first broken down into modules before being remanufactured into a stationary battery. This also has an impact on the amount of stationary batteries being substituted by SL batteries as the substitution takes place on the basis of numbers of batteries in case of reuse, and on capacity basis in case of reman.

For new battery systems *module costs* are considered which take into account cell costs and the costs for their installation in the modules. In case of an SL system, instead of module costs, the *costs for processing* of the used traction battery for stationary use are included. The amount of processing costs depends on the SL concept considered. While the *power electronics costs* include the costs for the inverter, the *periphery costs* comprise other components such as thermal management, housing and grid connection [195, p. 39]. All of these costs only reflect the costs occurring due to the production of the components, and therefore include neither margins of the manufacturer nor costs for battery assembly and operation.

Input Data

For this analysis the same initial scenario and input data as for the resource assessment is used, which are described in detail in Subsection 5.6.3. The additionally required cost data by component is summarised below.

Module costs: The module costs of new Li-ion batteries are based on the mean cost development for pouch/prismatic cells in the roadmap by Thielmann et al. [32, p. 15]. To transfer these costs to the module level 10 % of the battery cell costs are added. This value is an approximation derived from the total costs on the cell and module level in [196, p. 30].

Processing costs: The costs associated with the preparation of traction batteries for stationary use are determined by Bangoj [184, pp. 37–41] for a processing plant at a German location, using the tool from [197], supplemented with data from [10, 70, 198, 199]. The processing includes transport, storage and repurposing of the traction batteries for stationary use. In the initial scenario, a maximum utilisation of the processing plants is assumed and kept constant over the considered time horizon. As described above, a distinction is made between processing at the system level (reuse) and the module level (reman).

While the costs for the transport and storage of the traction battery are independent of the processing concept and amount to 4.8 € kWh^{-1}, the repurposing costs depend on the level of processing. The calculated repurposing costs for the reuse concept are 6.5 € kWh^{-1} and therefore lower than for the reman concept, for which they add up to 17.3 € kWh^{-1}. The differences in costs are due to the greater amount of work involved in disassembling the traction battery down to the module level. Furthermore, the costs for additional elements need to be considered which are charged at 5.7 € kWh^{-1} for the reuse and at 32.3 € kWh^{-1} for the reman concept. Overall the processing costs sum up to 17.1 € kWh^{-1} for the reuse and 54.4 € kWh^{-1} for the reman concept, respectively. The resulting values are in line with the range stated by Neubauer et al. [200, p. 46].

Power electronics costs: The cost development for power electronics until 2030 is taken from the input parameters in [201] using the 2016 exchange rate from dollars to euros of 0.9. While for the year 2015 the 2016 value from [201] is assumed, for the years until 2050 a linear extrapolation is conducted. A distinction is made between inverters for small and large storage systems, so that different costs are assumed for HSS and PCR storage systems, respectively. Because the costs for power electronics refer to the battery's installed power, the battery flows on capacity basis are converted using the P/E ratio from Subsection 5.6.3.

Periphery costs: As the cost development for the periphery, which consists of several components, is difficult to foresee, the development is linked to the cell costs by means of the ratio from [202]. As a result, for HSS the periphery costs amount to about 48 % of the cell costs and for large storage systems, in this case PCR, to around 111 %.

The described cost assumptions finally lead to the cost development summarised in Table 6–2. For the years between, a linear interpolation is performed. As the discount rate from a system

Table 6–2: Cost development per battery component

Components	2015	2020	2025	2030	2035	2040	2045	2050
Modules in € kWh^{-1}	336	212	151	94	94	94	94	94
Processing "reuse" in € kWh^{-1}	17	17	17	17	17	17	17	17
Processing "reman" in € kWh^{-1}	54	54	54	54	54	54	54	54
Power electronics HSS in € kW^{-1}	140	112	80	57	41	29	21	15
Power electronics PCR in € kW^{-1}	95	81	62	48	37	28	22	17
Periphery HSS in € kWh^{-1}	146	92	66	41	41	41	41	41
Periphery PCR in € kWh^{-1}	340	215	153	95	95	95	95	95

perspective the social discount rate of 3.5 % for developed countries discussed in [203, pp. 16–17] is chosen.

Results

The costs savings through SL are determined by several developments. One decisive factor is the difference in costs between the production of new battery modules and the processing of SL battery modules. In the initial scenario these differential costs are decreasing because prices for new modules are falling, while processing costs are assumed to stay constant. The decreasing module prices and the smaller lifetime of SL batteries lead to a tipping point in 2029, in which the annuity of a new HSS is smaller than the annuity of an SL battery. Furthermore, the cost savings are determined by the availability of SL batteries, which in this case can cover the total demand for the two analysed stationary applications from 2021 on. And finally, the saving potential is strongly influenced by the demand for stationary batteries. This demand is not only dependent on the development of the stock, but also on the lifetime of the deployed stationary and SL batteries, since they need to be replaced after reaching their EoL.

For the described scenario, these developments lead to the annual cost savings for stationary batteries depicted in Figure 6–1. With the increasing use of SL batteries in stationary applications, first, growing savings of investments in stationary batteries can be observed. However, in 2029 the annuity of new HSS is smaller than the annuity of SL batteries, leading to a decrease in cost savings. These savings eventually become negative as the SL batteries deployed prior to 2029 gradually reach their EoL. As for critical metal savings, the exact course of the costs savings depends on the demand for HSS and the resulting demand for SL batteries (see Subsection 5.6.3).

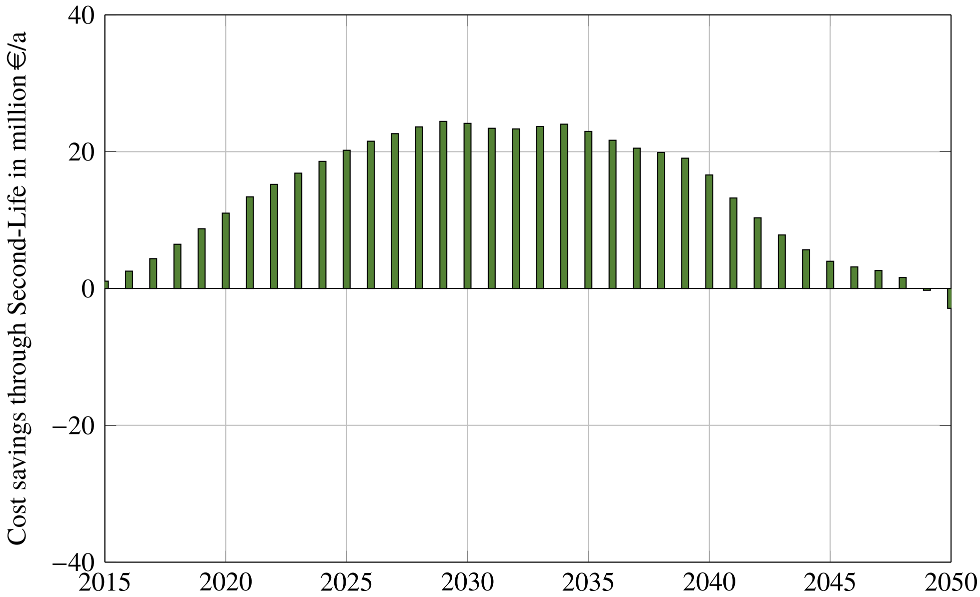

Figure 6–1: Cost savings through a Second-Life in home storage and primary control reserve applications

Sensitivity Analysis and Discussion

For identifying the sensitivity of the cost savings through SL the same sensitivity scenarios as for critical metals are applied, which are described in detail in Subsection 5.6.3 and are summarised in Table 5–6. In addition, a *"Reuse (PCR)"* scenario is analysed, in which only the PCR application is considered, to explore whether the favourable SL concept depends on the stationary application. Furthermore, a *"processing costs"* scenario is introduced, in which the utilisation of processing plants for SL batteries is assumed to be only 10 % in 2015 and then increases to 40 % in 2020, 70 % in 2025 and 100 % in 2030. This sensitivity outlines the impact of the availability of SL batteries, since the availability affects the utilisation of processing plants and therefore processing costs. As the costs savings also depend on the development of new battery prices, also a sensitivity with regard to *"module prices"* is conducted. In this scenario it is assumed that the prices for battery modules fall even faster so that the prices in 2025 and 2030 from Table 6–2 are reached five years earlier.

The results in Figure 6–2 show that the choice of SL concept strongly influences the cost saving potential. In case the reuse concept is applied for both applications, (HSS and PCR), cost savings turn negative in 2024. If, however, only the PCR application is considered in the assessment, cost savings stay positive over the whole time horizon. This is due to the fact that for PCR the reuse concept leads to lower annuities for SL batteries because of lower processing costs compared to the reman concept. Furthermore, in contrast to HSS, for large PCR storage systems several SL batteries are required, which means that for PCR the choice of SL concept does not lead to the oversizing issue described Subsection 5.6.3. Thus, if in both applications SL batteries are being reused instead of remanufactured, cost savings turn negative as soon as the positive

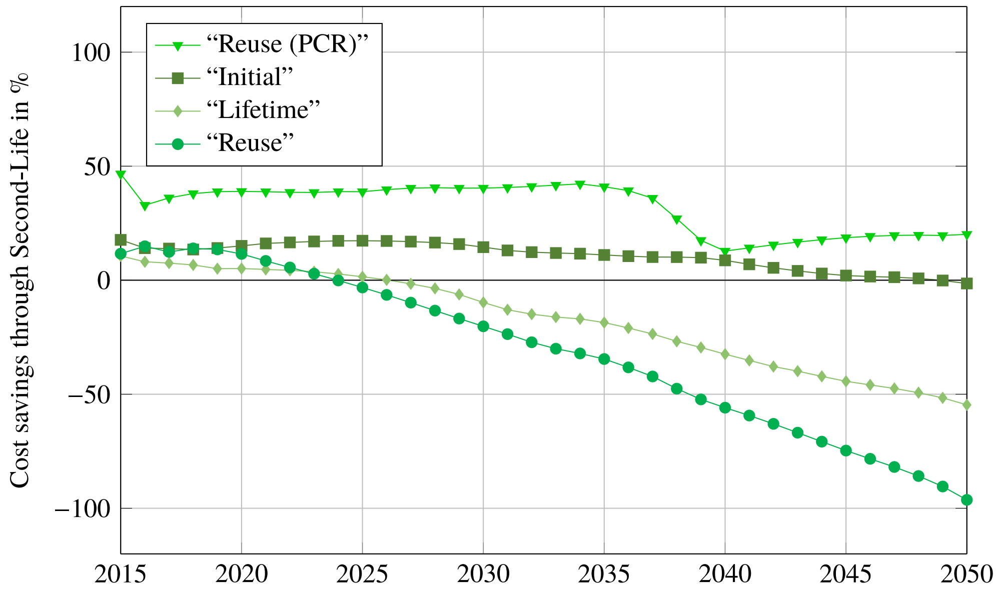

Figure 6–2: Impact of the Second-Life concept and the lifetime in the stationary application on relative cost savings through Second-Life

cost savings of the prioritised PCR application are balanced out by the negative savings for the HSS application. Furthermore, the lifetime of SL batteries has an impact on the cost savings. In case the lifetime is halved, for example due to strong ageing processes in the SL application, the annuity for SL batteries increases. This leads to a tipping point compared to the annuity of a new HSS as early as 2022, and therefore negative savings already from 2027 on.

Apart from the SL concept and the lifetime, also the development of processing costs and prices for new battery modules affect the cost savings (see Figure 6–3). If instead of a 100 % utilisation, an increasing utilisation of the SL processing plant over time is assumed, first negative cost savings occur as the annuity of SL batteries is larger than the annuity of new HSS. With an increasing utilisation the cost savings eventually turn positive. Once a 100 % utilisation is reached in 2030 a similar course of savings as for the initial scenario can be observed. A stronger decline in module prices, on the contrary, leads to considerably lower cost savings compared to the initial scenario as the break-even between the annuities of remanufactured SL modules and new modules is already reached in 2024.

Finally, it needs to be considered that these results only include investment costs for stationary batteries. However, assuming decreasing recycling costs, the temporal shift of the recycling process would lead to a reduction in costs for battery recycling. In addition, the postponement of the recycling process has an impact on the availability of secondary metals (see Subsection 5.6.3), which in return effects metal procurement costs.

Summary

It is shown that in the short- to medium-term SL applications, such as HSS and PCR, can potentially lead to a reduction in investment costs for stationary batteries. But the development

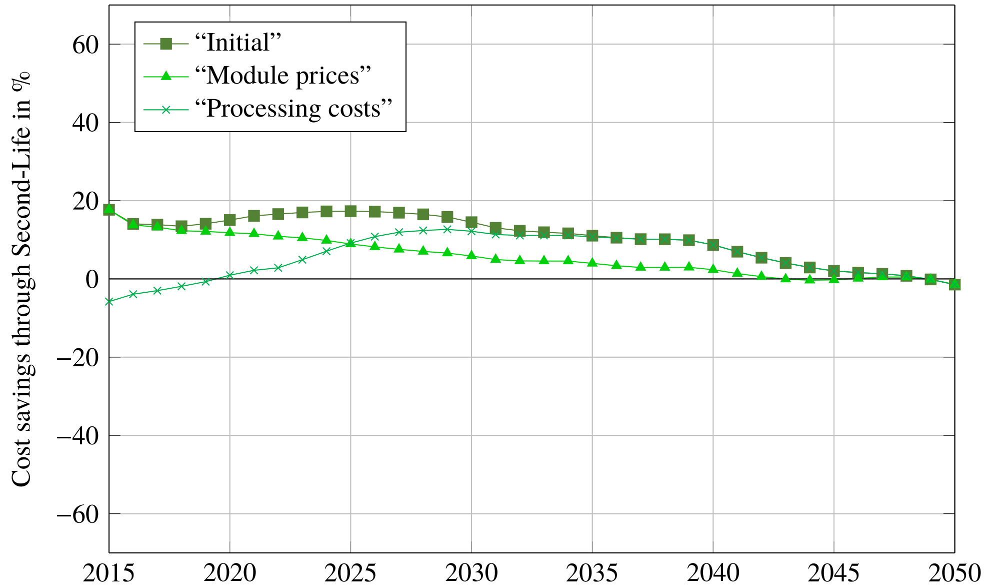

Figure 6–3: Impact of the development of processing costs and prices for new battery modules on cost savings through Second-Life

of new battery prices, the utilisation of SL processing plants and the chosen SL concept strongly influence the cost savings as well as the tipping point, at which SL batteries are no longer cost-efficient compared to new stationary batteries. The results point out that the relative development of new module prices and SL processing costs is crucial for the economic viability of SL batteries from a system perspective. Furthermore, it is demonstrated that the preferable SL concept depends on the application. Under the described boundary conditions, for PCR the reuse concept is economically more attractive. For the HSS application, on the contrary, remanufacturing is the preferable option, not only from a critical metal perspective, but also from a cost point of view. In the future, this analysis should be extended by evaluating the effect of the temporal shift of the recycling process on metal procurement and recycling costs.

6.1.2 Stakeholder Perspective: Profitability of Second-Life Batteries

While the focus of Subsection 6.1.1 was on the cost savings through SL batteries from a system perspective, here, the profitability from the perspective of the implementing stakeholders is assessed. For this purpose, a dynamic investment calculation for the deployment of an SL battery instead of a new battery system is conducted, both for an HSS and a PCR application.

Methodological Approach

In an investment calculation the various cash flows occurring during the lifetime of an investment need to be taken into account. In the following, analogously to [33, pp. 93–104], the net present value (NPV) method is used to determine the profitability of an investment into an SL battery compared to an investment into a new battery system. By translating future expenditures and revenues into net present values, the time of payments and the associated interest are taken into account.

As outlined in [138, pp. 23–24], the investment's net present value NPV at the reference year ($t = 0$) can be determined by

$$NPV(0) = \sum_{t=0}^{n} \frac{(-I(t) - E(t) + R(t))}{(1 + i)^t}, \tag{6–3}$$

with I, E and R describing the investments, expenditures and revenues in each year t until the end of the calculatory lifetime n is reached. All of these cash flows are discounted using the discount rate i. As outlined in [138, p. 24], the NPV constitutes a criterion for the profitability of an investment in the sense than an absolute profitability exists in case of a positive NPV. When comparing two competing investments, a relative profitability is given for the investment with the larger NPV.

In this case, the NPV of the investment in an SL battery is compared to the NPV of a new battery system. This is done separately for HSS and for PCR, since ageing profiles, costs and revenues strongly depend on the storage application. In the case of battery systems, the investment consists of the capital expenditures (CAPEX) for modules, periphery and power electronics (see Subsection 6.1.1). On the expenditure side, fixed operational expenditures (OPEX) as well as variable OPEX for electricity losses due to the charging and discharging processes during PCR provision are considered. On the revenue side, for the provision of PCR, the renumeration for the provided power is accounted for. The revenues for the HSS application, on the contrary, correspond to the electricity cost savings resulting from on-site consumption of PV electricity. These savings are quantified from the decrease in costs for electricity from the grid less the missed feed-in tariff, which results from the decreased supply of PV electricity to the grid.

As for new battery systems, also for SL batteries the investments in power electronics I_{pow} and periphery I_{per} are taken into account. However, instead of the investment for new battery modules, the salvage value of used EV batteries SV_{slb} and the processing costs C_{proc} are considered, when determining the investment of an SL battery system I_{slb} in the respective year t as outlined by

$$I_{\text{slb}}(t) = I_{\text{pow}}(t) + I_{\text{per}}(t) + SV_{\text{slb}}(t) + C_{\text{proc}}(t). \tag{6–4}$$

The salvage value, which corresponds to the costs to purchase used EV batteries, reflects the fact that the used batteries have already aged during their first life in the vehicle. In Subsection 6.1.1 it is shown that the additional processing costs depend on whether the modules are remanufactured (for HSS) or reused (for PCR). While for the initial investment all four cost components in Equation 6–4 are considered, for the replacement investments only the salvage value and the processing costs are accounted for. A replacement investment is needed if the SL modules reach their final EoL during the calculatory lifetime. As defined in Section 5.5, the final EoL is either determined by the EoSL criterion or the maximum age.

Input Data

For the following analysis the results of the study by Fischhaber, Regett et al. [33, pp. 93–101] are updated with recent data from [177, 184, 204, 205] to ensure a consistency of input parameters with the previous analyses. This holds true for the EoL and EoSL criteria as well as battery parameters, load profiles, resulting ageing profiles and maximum operation times of stationary and SL batteries described in Subsection 5.5.3. For modules, periphery and power electronics as well as the processing of SL modules the same cost values as in Subsection 6.1.1 are used. The considered time horizon (calculatory lifetime) is set to 20 years in accordance with the lifetime of new stationary batteries defined in Subsection 5.5.3. For the profitability assessment from a stakeholder perspective additional economic input parameters are required, which are summarised in Table 6–3.

Table 6–3: Additional economic input parameters for the profitability assessment

Parameter	Value	Sources
Remuneration for PCR provision in € kW^{-1} a^{-1}	110	Average PCR price in 2018 [206], availability of storage system [207, p. 31]
Price for electricity losses during PCR provision in € MWh^{-1}	45	Average intraday price in 2018 [208]
Feed-in tariff € kWh^{-1}	0.12	Renewable Energy Sources Act (EEG)
Household electricity price in 2020/2040 in € kWh^{-1}	0.31/0.29	Costs for procurement and sales from “Dynamis start” scenario [10], EEG levy [209], other price components [210, p. 8]
Discount rate of households (for HSS) in %	4	[11, part B, p. 51]
Discount rate of industry (for PCR) in %	8	[11, part B, p. 51]
Fixed OPEX as share of investment of new battery in % a^{-1}	1.5	[211, p. 32]
Value added tax for HSS in %	19	Value Added Tax Act (UStG)

In addition, as outlined in Equation 6–4, the salvage value of the SL battery needs to be included. In this context, it should be considered that the salvage value is dependent on the price development for new battery modules. To take this interrelation into account, first, the ratio between the salvage value of an SL battery and the price of a new battery from [200, p. 40] is determined, resulting in a range of 16 % to 52 %. Due to large uncertainties, in the following, the upper value of 52 % is used as a conservative default value. This value is then multiplied with the price for battery modules in the respective year from Table 6–2, so as to determine the time-dependent salvage value of SL modules linked to the price development of new modules.

Results and Discussion

In Figure 6–4, Figure 6–5 and Figure 6–6 the results of the profitability assessment are depicted for the two selected SL applications. From Figure 6–4 it can be seen that for PCR the NPV of the SL battery is larger than for the new battery system, implying a larger profitability in case SL batteries are deployed. This is due to the lower initial investment as well as slightly larger revenues from PCR provision (see Figure 6–5). The larger revenues for the SL system can be explained by the fact that the new battery is subject to a non-linear ageing process in the beginning of its use phase, as described in Subsection 5.5.3. The decrease in cash flow in 2029 is due to a replacement of the SL battery modules after 10 years in operation (see Subsection 5.5.3). Compared to the initial investment, this replacement investment is relatively low. This can be explained by the facts that only the modules are replaced, that module prices and therefore also the salvage value of SL modules fall sharply (see Table 6–1) and that future cash flows are discounted. Overall, for the described boundary conditions, at the end of the calculatory lifetime an increase in NPV of 28 % can be observed, making the PCR application more profitable when using SL batteries.

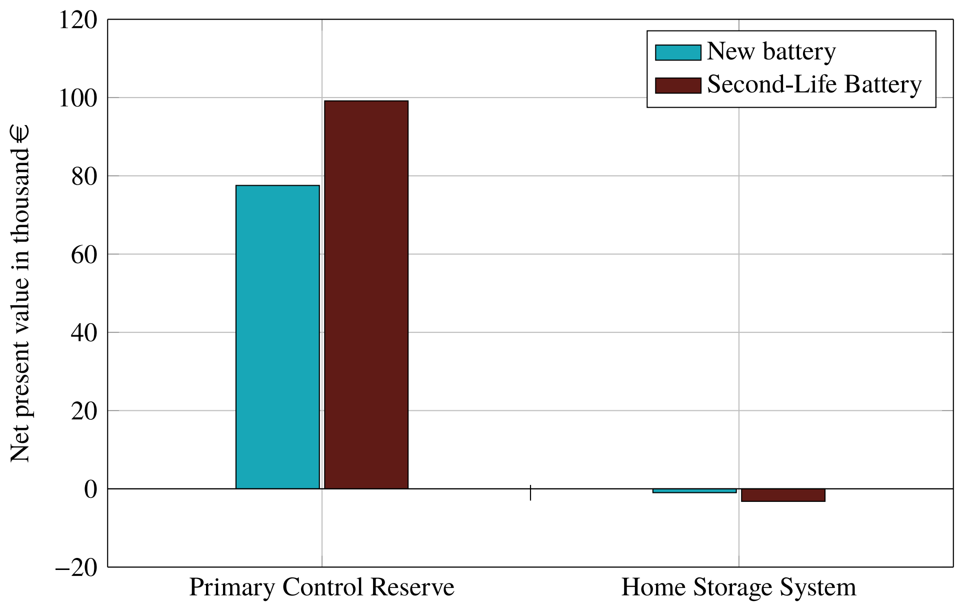

Figure 6–4: Net present value of the investments into a new and a Second-Life battery in 2019 over the calculatory lifetime of 20 years

For the HSS application, on the contrary, a different picture emerges. Despite larger processing costs for remanufacturing, the initial investment of the SL battery is still lower than for a new battery (see Figure 6–6). But due to the strong ageing process of used NMC in the HSS application, as described in Subsection 5.5.3, the revenues from self-consumption are lower in case an SL battery is used. Furthermore, making use of the ageing curves from Subsection 5.5.3, the final EoSL criterion is already reached after six years of operation, leading to three investments for the replacement of SL battery modules in the considered time horizon, as depicted in Figure 6–6. This leads to a further reduction of the already negative NPV of about 1 000 € by around factor 3.3.

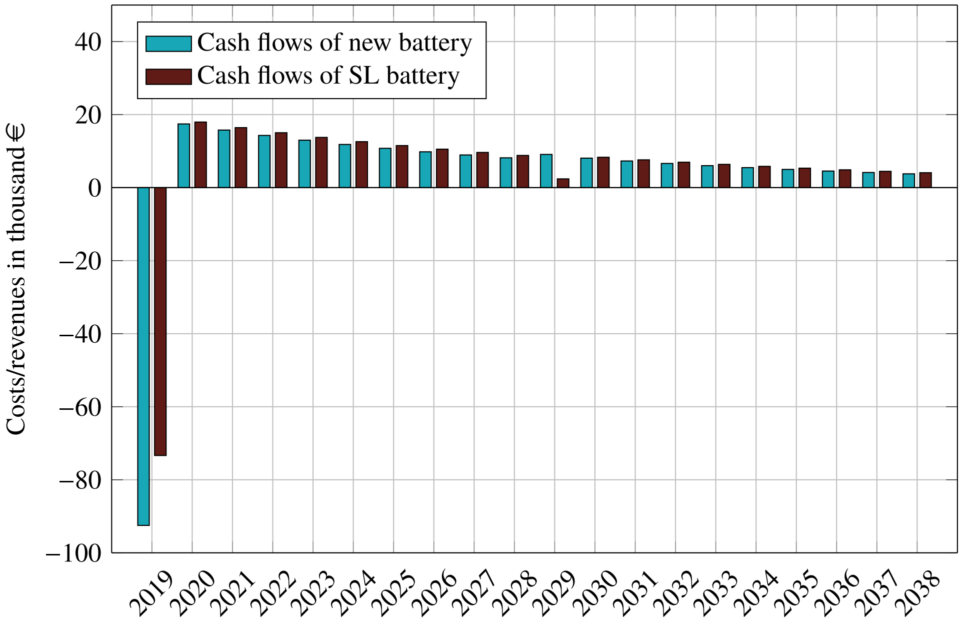

Figure 6–5: Cash flows for the investments into a new and a Second-Life battery for primary control reserve

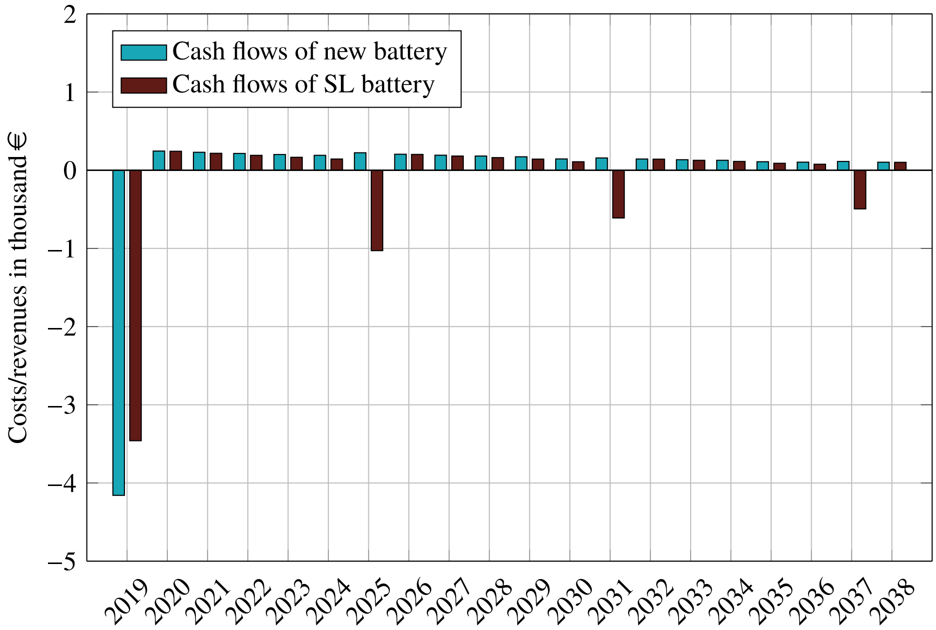

Figure 6–6: Cash flows for the investments into a new and a Second-Life battery for the application as a home storage system

The results show that under the considered boundary conditions an absolute profitability is only given for PCR, while the HSS application does not lead to a positive NPV. However, an increase in electricity prices for households and a decrease in feed-in tariff for PV electricity would lead to a larger profitability of the HSS application in the future. For the PCR application, on the contrary, recent developments show a decrease in PCR prices [206], due to an increasing number of market participants, which would lead to a reduction in NPV. Further, it needs to be considered that the market for PCR in Germany is limited to about 600 MW (see Subsection 5.6.3).

The analysis of the NPV also points out that the relative profitability of an SL battery compared to a new battery system mainly depends on the savings in initial investment and the need for replacement investments during the considered time horizon. The reduction of the initial investment is dependent on the share of battery modules in total battery system costs, since only this share is addressed by SL batteries while the other components are required in both cases. Further, the price for SL batteries, consisting of the salvage value and the processing costs, plays a decisive role and is still subject to large uncertainties. Therefore, a sensitiviy analysis is conducted by using a salvage value of 16 % of new module price, corresponding to the lower boundary derived from [200], instead of 52 %. The SL battery then leads to an increase in NPV for the PCR application by 55 %, as compared to 28 % in the previous case. Also for HSS the profitability of the SL battery is considerably improved when assuming the lower salvage value, with the NPV now lying in the same order of magnitude as the NPV of the new battery. Furthermore, the results for HSS show that there is a strong dependency of the profitability of SL batteries on the operation time in the stationary application which is dependent on the chosen EoL criteria, the underlying ageing curves and the assumed maximum operation times.

Summary

The economic assessment from a stakeholder perspective shows that the absolute profitability of SL batteries in stationary battery applications is strongly dependent on the revenues from the respective storage application. While under the chosen boundary conditions PCR provision constitutes a positive business case, the use of an HSS is not profitable. In the future, due to rising electricity prices and decreasing feed-in tariffs the prospects for the HSS application are increasingly positive, while for PCR a decrease in revenues is observed.

However, for the assessment of SL batteries especially the relative profitability compared to a new battery system is relevant. It is shown that the profitability of SL batteries mainly depends on whether the advantage of the lower initial investment is outweighed by replacement investments needed due to the shorter operation time. Hence, the ratio of the price for SL modules and the price for new modules is decisive for the business case. Here, it needs to be considered that these values are time-dependent and that SL module prices are determined both by processing costs as well as the salvage value of used modules, which in turn is linked to the development of new module prices. Early-state procurement deals for SL batteries constitute one option to meet these uncertainties about future price developments.

But also the ageing behaviour, which is dependent on the application and the battery type, is key to a profitable business case as it determines the need for replacement investments. In this context, uncertainties can be met by obtaining information on the battery state after its first life. Furthermore, the monitoring of the battery state and the optimisation of the operation strategy in the specific application are an option to increase the operation lifetime of SL batteries and therefore their profitability. In this context, strategies such as ageing-dependent load adaptation [168, p. 114] and deploying hybrid systems consisting of both new and SL battery modules [212] can be viable options.

6.2 Critical Success Factors for Implementing Circular Business Models

The results above show that the CE can offer ecological and economic saving potentials for EV batteries. As outlined in [26], there are already some implementation examples in place, but the full potential has not yet been exploited. This raises the question, which barriers currently hinder the practical implementation of circular business models for EV batteries, and which drivers and technologies (so-called digital enablers) can pave the way for stakeholders along the value chain. From these insights critical success factors from a stakeholder perspective can be identified, which are essential for the practical implementation of a CE for electric mobility. The following description and illustrations originate from Regett, Buschle and Stuchtey [213], building on the work by Buschle [204] who provides a detailed description of the methodological procedure, input data and results.

Methodological Procedure

To assess the practical implementation potential of circular business models for EV batteries, a three-part methodology was applied which is summarised in Figure 6–7.

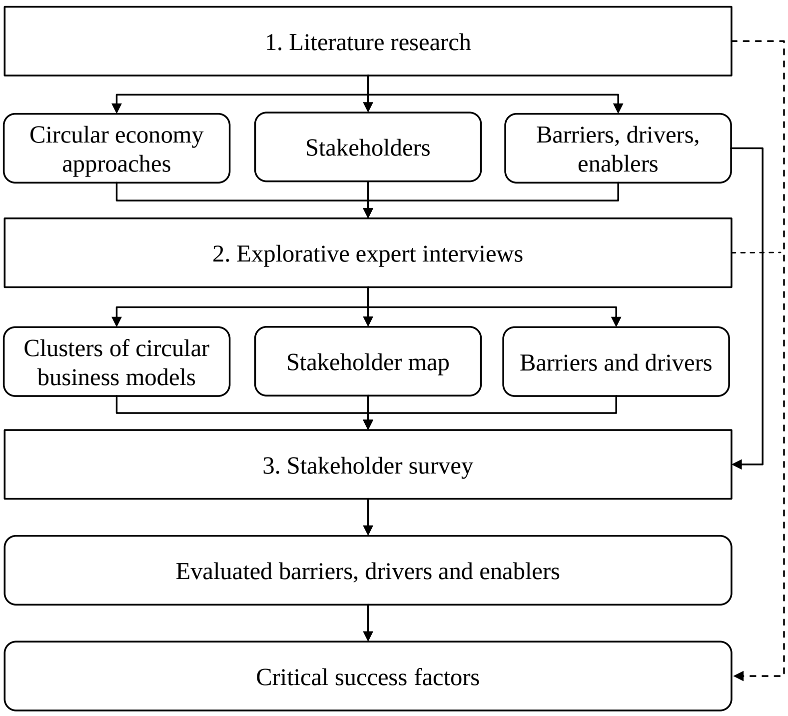

Figure 6–7: Overview of the methodological procedure for identifying critical success factors for circular business models for electric vehicle batteries

Based on a *literature research*, first, stakeholders and CE approaches along the value chain of EV batteries, as well as general and battery-specific drivers, barriers and enablers of the CE are identified. For this purpose, starting from the identification of CE approaches in Chapter 4, supplementary publications such as [27, 29, 89, 200, 214–218] are considered.

The results of the literature research are then validated and supplemented using four *explorative expert interviews*. Based on these interviews a stakeholder map is created, the CE approaches are classified into clusters of circular business models and more drivers and barriers are added. The expert interviews with two representatives from the automotive industry (B. Gohla-Neudecker, BMW and an expert for second-use from Daimler), a specialist from the recycling industry (Dr. C. Hagelüken, Umicore), and an university professor (Prof. Dr. A. Reller, University of Augsburg) were conducted by Buschle [204].

The generated results are then used in a written *stakeholder survey* to validate the previous findings and to assess the significance of the identified drivers, barriers and enablers. To this end, in the context of [204], a questionnaire was developed consisting of the following parts: evaluation of the relevance of general drivers and barriers of the CE for EV batteries, assessment of battery-specific drivers and barriers, evaluation of concrete drivers and barriers per circular business model, analysis of the regulatory framework and digital enablers as well as a final classification of the practical implementation potential. The questionnaire was answered by a total of 26 experts, covering a large share of the value chain of EV batteries in Germany. In addition to experts from the scientific community, these include experts from the automotive and recycling industries, SL battery suppliers, manufacturers of battery packs and components, battery analysts, representatives from reverse logistics and grid operators. The number of participants is considered to be sufficiently large, since this survey aims at providing information based on expert knowledge in a small field rather than generating representative results.

To evaluate the survey results on drivers and barriers of circular business models for EV batteries, the answers are translated into point values (strong barrier: -1; barrier: -0.5; neutral: 0; driver: 0.5; strong driver: 1) and then weighted according to the proportion of answers. This results in a so-called "impact score" for each barrier or driver queried. Finally, the critical success factors for a circular value chain are derived from the highest rated barriers, while considering the information obtained from the explorative expert interviews and literature research. By means of the identified critical success factors the need for action is pointed out and assigned to the actors along the battery value chain.

Results and Discussion

The stakeholder mapping process across the value chain of EV batteries shows that circular business models increase the number of actors involved, especially in the use and EoL phases of the EV battery. In addition, the use of EV batteries for energy system services, for example in the context of V2G and SL concepts, is increasingly linking the mobility sector and the energy industry. In view of a new competitive situation this poses a challenge, but also offers new business opportunities for two sectors that are currently undergoing a transformation process.

For the further evaluation of circular business models in the questionnaire, the multitude of CE approaches (see Chapter 4) were aggregated into three clusters of battery-specific circular business models, based on the findings from the explorative expert interviews. In the sense of *battery as a service (BaaS)*, leasing, sharing or swapping concepts allow access to the EV battery, while the manufacturer remains in possession of the battery and the materials contained. The main source of income is in this case the payment for the use of the battery. For the second cluster of *Second-Life applications*, used batteries from EVs are processed and used in a second use phase for the provision of energy system services. *Recycling*, on the contrary, includes the dismantling and treatment of spent batteries as well as the recovery of the contained resources. Similar to BaaS concepts, recycling can be offered as a service to battery producers, whereby the producer remains the owner of the materials and the recycling company earns revenue from the service offered.

The results from the stakeholder survey show that some of the overarching drivers and barriers of the CE derived from literature are also considered important for circular business models for EV batteries. The most important drivers include:

- the increased availability of data across the entire supply chain as a result of increasing digitalisation;
- new business opportunities due to growing awareness about sustainability;
- the increasing importance of the use of secondary raw materials when carrying out sustainability assessments (e.g. LCA) in companies.

Furthermore, the following major barriers to the CE were also classified as relevant for EV batteries:

- the risk of cannibalisation of the current product portfolio through increased competition between existing linear and new circular product offerings;
- the lack of transparency about the content and origin of resources as well as the lack of standardisation of products;
- uncertain profitability and financial risks due to uncertain markets for the CE, e.g. high upfront investments and uncertainties about return on investment.

After identifying the general drivers and obstacles of the CE, which are also of relevance for EV batteries, Figure 6–8 shows the assessment results for battery-specific obstacles using the impact score (selection criterion: absolute value of impact score >0.25). It can be seen that battery design is identified as a barrier for circular business models, especially at the EoL. This includes both the lack of standardisation of modules and packs as well as connections which are difficult to disassemble. In addition, experts rate the lack of cooperation between stakeholders in the energy industry and the mobility sector as a critical barrier to the implementation of circular business models. However, the barriers shown in Figure 6–8 are currently being countered by a number of drivers. For instance, almost 80 % of the respondents see urbanisation and the associated new mobility concepts as a trend that increases the demand for circular business models. With a share of above 90 %, the majority also evaluates the energy transition ("Energiewende") as one of the most important drivers, since it is accompanied not only by an increasing demand for EVs, but also for stationary storage systems and thus potential SL applications.

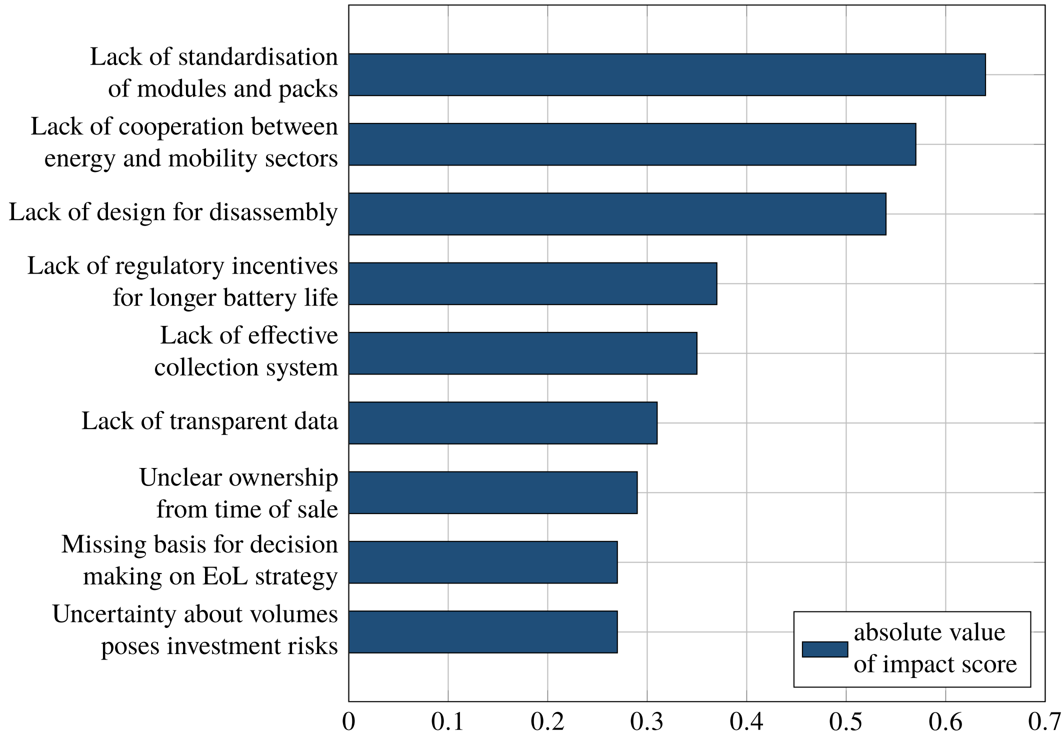

Figure 6–8: Assessment of battery-specific barriers of the circular economy using the impact score (maximum: absolute value of impact score = 1, number of answers > 21)

Then, the regulatory framework, which is regarded as an important obstacle to the implementation of circular business models for EV batteries, was queried in more detail. According to the survey participants, the European Directive 2006/66/EC (short: "batteries directive") turns out to be particularly inhibiting. As pointed out by the recent evaluation report [219], it does not provide any material-specific incentives and no incentives to increase collection and recycling rates beyond the current minimum. In addition, the batteries directive does not take the implementation of innovative approaches such as SL applications and technological developments sufficiently into account [219, p. 35]. More than half of the respondents also see regulations on hazardous substances and chemicals such as REACH (EC 1907/2006) as a regulatory obstacle. As discussed in [89, p. 19], these could hamper the use of innovative materials and the use of remanufactured components due to the unpredictability of future restrictions. Furthermore, uncertainties about the ownership and liability of batteries at the EoL represent a barrier for more than half of the respondents. The extended producer responsibility, for example, which holds the producer responsible for the EoL treatment, does not properly address possible SL applications [219, p. 36]. At the same time, however, there are already a number of drivers that favour the implementation of circular activities. These include, for instance, the innovation deals introduced by the European Commission, in the course of which regulatory obstacles to innovation are identified and made visible by affected players. One example is the already signed innovation deal [220] on the reuse and recycling of EV batteries.

Finally, the analysis of the detailed survey results for the three types of circular business models leads to the most important barriers and digital enablers summarised in Table 6–4. These digital technologies do not only support the implementation of circular business models, but may, in the future, also themselves be at the centre of disruptive business models.

Table 6–4: Overview of the most important barriers and enablers for the implementation of circular business models for electric vehicle batteries

Category	Battery as a Service[a]	Second-Life[b]	Recycling[b]
Economic barriers	Uncertain business case for manufacturers due to the need for rethinking of customers and the establishment of new (sales) structures	Uncertainty with regard to potential of and revenues on stationary battery markets Decreasing battery prices and recycling costs as well as uncertain development of resource prices Costs for processing of Second-Life batteries	Risks for investments in mostly automatised processes due to technological uncertainties
Organisa-tional barriers	Lack of control over battery use phase	Unresolved design of warranties for end customers	
Technical barriers	Lack of data about battery ageing in the use phase Uncertainty concerning ageing due to improper use	Security concerns with regard to battery processing and Second-Life applications	Currently low technological maturity and therefore high costs for recycling plants
Digital enablers[c]	Use of big data analyses for better decision making in circular systems Modelling of batteries as digital twins to control and optimise the life cycle Linking of batteries in the internet of things for product and material tracking and recording of usage behaviour Machine learning for process and system optimisation Use of product life cycle management systems for data integration across the value chain		

[a] Selection based on multiple answers in survey and coverage with explorative interviews
[b] Selection criterion: absolute value of impact score >0.3
[c] Selection criterion: classified as a potential enabler by more than 80 % of respondents

Despite the numerous barriers identified, the survey also indicates that the experts do not expect these barriers to prevent the implementation of circular business models for EV batteries. The likelihood of implementation in 4 years, for example, is rated at 55 %, 67 % and 74 % for recycling, BaaS and SL, respectively. In addition, the survey results show that the respondents expect these probabilities to rise to 74 %, 87 % and 87 % in 8 years, indicating that a removal of barriers is expected by the experts in the field. Nevertheless, with 83 % a large proportion of those surveyed believe that the implementation of circular business models requires new partnerships along the value chain. Furthermore, 35 % of the respondents point out the need for new financial support mechanisms. However, it should be noted that these values can not be generalised, since the respondents are experts with an interest in the field of study.

Finally, from the results of the expert interviews, the survey as well as the underlying background literature, the following critical factors for the successful implementation of a circular value chain for EV batteries are derived:

1. Design for disassembly and standardisation: The design of traction batteries must take into account the EoL already in the design process. To this end, minimum standards must be introduced that define a common denominator with regard to battery housing and connectors, so that remanufacturing, reuse and recycling can be carried out economically.
2. Cooperation and data transparency: It must be made possible for companies along the battery value chain and between the mobility and energy sectors to cooperate sufficiently with each other. In this context, there is a need to establish new partnerships and platforms to enable cross-sectoral and cross-company cooperation and data exchange.
3. Extended ownership, take-back systems and warranties: Global take-back systems must be established to ensure the necessary battery volumes for SL and recycling. One way to achieve this is the development of new ownership models, in which manufacturers or other companies keep the ownership beyond the point of sale. This can potentially also contribute to providing sufficient warranty on SL batteries.
4. Regulatory incentives at End-of-Life: The regulator must provide stronger incentives for the remanufacturing and reuse of batteries and promote higher recycling rates. This necessity has also been recognised by the European Commission so that the batteries directive is currently already undergoing a revision process, with expert circles assuming that the revised version contains stronger incentives for a CE.

The key stakeholders and the identified critical success factors for circular business models along the value chain of EV batteries are summarised in the schematic illustration in Figure 6–9.

Summary

Based on a literature review, explorative interviews and an expert survey four critical success factors for the practical implementation of circular business models for EV batteries were identified. These encompass not only regulatory incentives at the EoL, but also an incorporation of the whole life cycle into the design process. Furthermore, sufficient return volumes of EoL batteries need to be ensured, for which new ownership models constitute one possibility. Lastly, the basis for a practical implementation of circular business models are new forms of cooperation and data exchange across the whole value chain. In this context, especially the newly

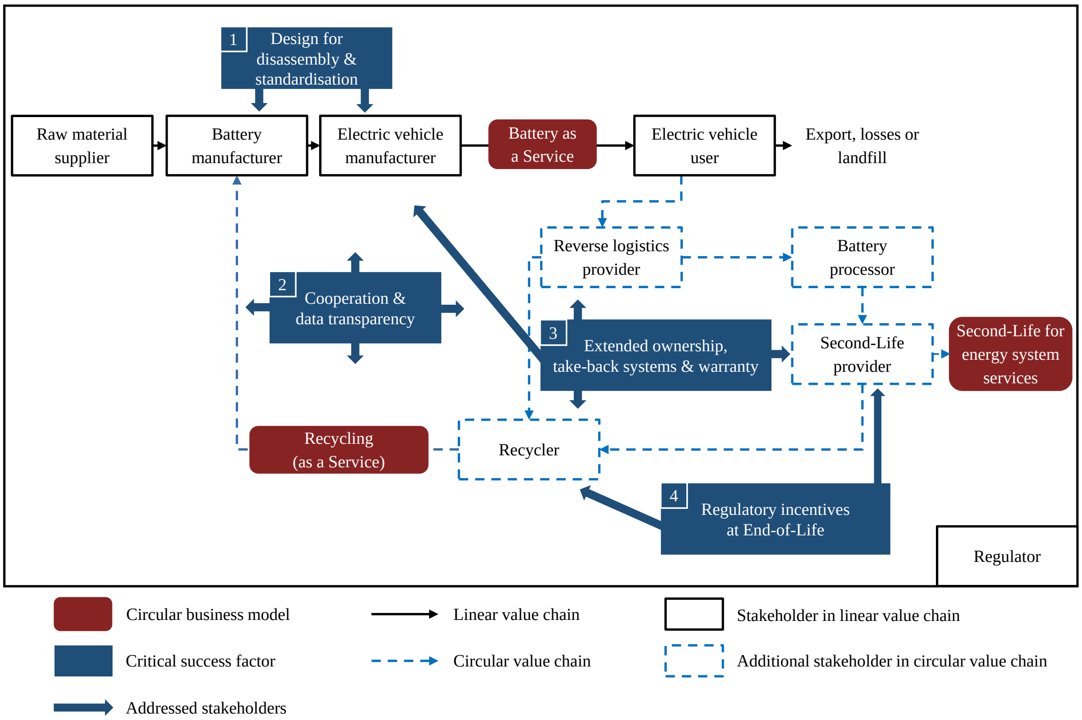

Figure 6–9: Critical success factors for the implementation of circular business models for electric vehicle batteries

emerging interfaces between the energy industry and mobility sector pose a challenge, but also an opportunity for two sectors currently undergoing a transition process. Overall, the removal of the identified technical, regulatory, organisational and economic barriers forms the prerequisite for a practical implementation of circular business models, which again are the basis for raising the environmental and economic potential of CE approaches for EV batteries.

7 Conclusion and Outlook

Starting with the identification of current hot spots with regard to the climate impact and critical metal demand for lithium-ion (Li-ion) traction batteries, technically feasible approaches from the circular economy (CE) were identified for each phase of the battery's life cycle. To quantify the potential of CE approaches to reduce the demand for primary lithium (Li) and cobalt (Co) as well as energy-related greenhouse gas (GHG) emissions, a set of instruments was developed and applied to selected CE approaches for electric vehicle (EV) batteries. Additionally, the potential for a practical implementation of the CE for EV batteries was discussed by means of an economic assessment and an analysis of the drivers and barriers from the stakeholders' perspective. Thus, a method to systematically assess the potential of CE approaches to reduce critical resource demand and GHG emissions was developed and applied to EV batteries. This procedure resulted not only in a set of instruments to include future developments and energy system effects into emission and resource assessments, but also quantitative results for the selected application examples. In the future, this set of instruments could be further extended, since the developed and applied instruments do neither cover all possible CE approaches for EV batteries nor all identified challenges for an emission and resource assessment. Furthermore, this set of instruments could be adapted for the assessment of other key technologies such as wind power plants, photovoltaic systems and Power-to-X technologies.

Overall, based on the developed instruments and generated results, the following six core issues for the assessment of the climate and resource impact of EV batteries and the improvement potential through the CE were identified:

Since the scale and energy supply of the production plant are important determinants of the battery's climate impact, there is great potential for improvement through energy efficiency and the use of renewable energy.

The comparisons of battery-electric vehicles (BEVs) with conventional combustion engine vehicles, which were extensively discussed in the media, are usually based on current or even outdated data for battery production. Considering that Li-ion traction batteries and the corresponding production process are still undergoing a development, a step-wise procedure for dealing with uncertainties in the assessment of emerging technologies was applied. Thereby it was shown that the climate impact of battery production is strongly sensitive to the energy efficiency of the production plant, which is going to improve on an industrial scale, as well as the carbon intensity of the plant's energy supply. This means that the choice of location, as well as a proper design of the energy supply, play a key role in the development of new battery production sites. It can be expected that through energy efficiency measures as well as renewable energy supply, in the future a significant reduction of the initial disadvantage of BEVs, which results from the energy-intensity of battery production, is achieved.

In view of rapidly increasing energy densities, starting from [113] future research should further focus on analysing the sensitivity of the environmental impact of battery production on the development of the battery's energy density. Furthermore, as pointed out in [32], apart from current Li-ion batteries, in the future, other battery technologies such as solid state and Li-sulphur batteries might emerge. To estimate the environmental impact of these technologies prospective Life Cycle Assessment (LCA) studies, such as for example [113], are required. However, the basis for all of these assessments is an increasing availability and transparency of input data which can be supported by initiatives such as the Environmental Footprint Pilots of the European Commission [221].

When designing climate mitigation strategies for the mobility sector, future developments of the energy system must be taken into account. This requires methods for emission balancing which consider the increasing linkages between different energy carriers as well as the expansion of fluctuating renewable energy systems.

As GHG abatement measures such as EV will operate in a future energy system, also for the battery's use phase, future developments need to be considered in the emission assessment. For the electricity system this refers, on the one hand, to the expansion of renewable electricity systems leading to an increasing volatility of electricity generation. On the other hand, the roll-out of sector-coupling Power-to-X technologies leads to stronger linkages between energy carriers. To account for these developments, an emission assessment method for multi-energy carrier system was developed, which results in hourly emission factors for the different energy carriers for each year covered by the modelled energy system scenario. By making use of the year-dependent emission factors of electricity in a vehicle comparison, it was demonstrated that the advantage of BEVs during operation is reinforced when taking into account the future improvement of the background electricity system.

As outlined in [141], the resulting hourly emission factors for electricity can also be used to determine the potential of different load management strategies to further reduce the environmental impact of EVs. Apart from EVs, the time series of emission factors can, furthermore, be used to assess other drive trains such as fuel cell electric vehicle as well as renewable fuels. This is for example subject of the BEniVer project whose approach is described in [222]. In this context, the effect of the level of decarbonisation of the energy system on the environmental impact of different vehicle types is also of interest. To address this issue, the application of the emission accounting method should be extended to other energy system scenarios.

Due to the feedback with the electricity system, the expansion of electric vehicles must be considered together with the expansion of renewable energy systems and optimised load management strategies to fully exploit the advantages of electric mobility in the use phase.

The high efficiency of the electric drive train leads to an advantage of EVs compared to conventional vehicles in the use phase. This holds true even for a large share of electricity demand still being covered by conventional power plants. The comparison of different emission accounting methods for electricity showed that the applied short-term marginal approach leads to higher emission factors than the electricity mix method. This underlines the need to complement measures leading to an increase in load, such as EV, by an expansion of renewable electricity. This will ensure that the GHG abatement effect is further improved in the mid- to long-term. While the advantage of EVs in the use phase can be further pronounced by load management strategies, in this context the choice of indicator poses a challenge. The so-called merit order dilemma for example leads to a discrepancy between price- and emission-optimised strategies, which can be partly solved by higher prices for CO_2 certificates, leading to a fuel switch between coal- and gas-fired power plants. However, using time series of emission factors for load optimisation is not sufficient when aiming at an increased integration of renewable surpluses. In this case further indicators, such as the residual load, need to be incorporated.

Based on the work in [141], in the future, trade-offs resulting from different optimisation targets (e.g. emissions, system costs or stakeholder costs) should be evaluated in more detail, so as to derive a balanced strategy for load management of EVs for further practical implementation. Also, to enable an integration of a large number of EVs into the energy system, there is a need to look deeper into the interaction of electric mobility and the energy system using dynamic approaches accounting for large-scale changes, as for example described in [158].

Since battery ageing can be crucial for critical metal and emission savings as well as the profitability of Second-Life batteries, the selection of suitable storage applications is a prerequisite for a successful implementation of Second-Life approaches.

By including the functionality loss of the battery into the assessment of Second-Life (SL) batteries, it was outlined that emission, resource and cost savings strongly depend on the selected stationary application. This is, on the one hand, due to the dependency of the battery ageing process on the considered load profile and, on the other hand, due to the difference in substituted cell technologies, which strongly impacts critical metal savings. Thus, SL applications should be selected in such a way that they are characterised by mild load profiles as well as a substitution of technologies with a large carbon footprint and critical metal demand.

The basis for a suitable matching of SL batteries and stationary battery applications is a deeper knowledge about the state of the EV battery at its EoL in the vehicle. According to [168] state of health (SoH) quick tests as well as interface standardisation, are possible solutions for providing better insight into battery history. Furthermore, options for increasing the lifetime of SL batteries need to be further investigated. In this context, in [168] an ageing-dependent load adaptation is proposed to prevent non-linear ageing, while [212] pursue the strategy of reducing the stress on SL batteries through a combination with new batteries.

Due to a temporal shift of the recycling process and substitution effects on stationary markets, Second-Life approaches do not automatically lead to a reduction in critical metal demand. In point of fact, potential trade-offs between different environmental indicators need to be considered.

When the CE is discussed, it is often taken for granted that circular approaches lead to a reduction of the environmental and resource impact. But by means of a dynamic Material Flow Analysis (MFA) it was shown that SL concepts do not automatically lead to critical metal savings, if temporal delays and substitution effects on stationary battery markets are included. Instead it was demonstrated that SL applications can lead to trade-offs between different indicators, in this case primary Li and Co demand. Thus, it needs to be considered that through SL applications valuable metals such as Co are bound in stationary markets, which otherwise would be available for recycling and therefore for the production of new, potentially more resource-efficient batteries.

It was further shown that recycling leads to a significant reduction in primary metal demand, but overall critical metal demand remains high due to growing battery markets.

To provide insights into the impact of recycling and SL applications on GHG emissions and into possible trade-offs with critical metal demand, the proposed extension of the dynamic MFA model by LCA should be conducted. Furthermore, as the focus of this thesis was on Li-ion batteries, the effect of breakthroughs in battery technologies, as in [82], could be further analysed, for example by means of additional scenarios.

If the identified critical success factors for an implementation of circular business models for electric vehicle batteries are addressed, the circular economy offers new business opportunities for the energy and mobility sectors, which are currently undergoing a transition process.

Using the example of SL batteries, it was shown that CE approaches can potentially lead to cost savings and an increased profitability from a stakeholder perspective. The achievable economic benefit, however, is not only strongly dependent on the lifetime of the SL battery, but also on the costs for processing of SL batteries and the development of costs for new batteries, which have fallen sharply in recent years. The stakeholder analysis revealed that representatives of the battery value chain expect CE approaches to be implemented in the future, but not as a matter of course since first existing barriers need to be removed. As the interface between the mobility sector and the energy industry increases in a circular battery supply chain, one of the key success factors is a closer cooperation between these two sectors. If a cooperation succeeds, this can potentially lead to the emergence of new business opportunities for two sectors currently facing a profound transition process.

To exploit the potential of CE approaches for critical metal and GHG emission savings, in the future, the identified critical success factors need to be addressed by policy makers. This includes creating the boundary conditions for an increased cooperation between sectors, a design for disassembly through standardisation, an establishment of functioning take-back systems and an increase in material-specific recycling rates. For this purpose, partnerships such as the global battery alliance [223] and the working group on EV batteries in the context of the German CE initiative [21] form a good starting point. Furthermore, for a practical implementation of circular business models for EV batteries, case-specific assessments are required to point out the economic potential for the implementing stakeholders.

Overall, it can be concluded that the CE offers potentials to reduce the carbon footprint and critical metal demand for EV batteries if current barriers are removed. However, the actual impact of CE approaches on GHG emissions and critical metal demand is strongly dependent on energy system effects and future developments. Therefore, the assessment of GHG abatement technologies such as EVs, as well as the saving potential through CE approaches, can not be carried out from today's point of view, but needs to include a future perspective over the technology's entire life cycle.

Bibliography

[1] F. Asdrubali, G. Baldinelli, F. D'Alessandro and F. Scrucca. "Life Cycle Assessment of Electricity Production from Renewable Energies: Review and Results Harmonization". In: *Renewable and Sustainable Energy Reviews* 42, 2015, pp. 1113–1122.

[2] R. Frischknecht et al. "LCA of Key Technologies for Future Electricity Supply - 68th LCA Forum, Swiss Federal Institute of Technology, Zurich, 16 April, 2018". In: *The International Journal of Life Cycle Assessment* 23 (8), 2018, pp. 1716–1721.

[3] G. Angerer, P. Buchholz, J. Gutzmer, C. Hagelüken, P. Herzig, R. Littke, R. Thauer and F. Wellmer. *Rohstoffe für die Energieversorgung der Zukunft - Geologie - Märkte - Umwelteinflüsse*. München: acatech - Deutsche Akademie der Technikwissenschaften, 2016.

[4] R. Kleijn. *Materials and Energy: A Story of Linkages (PhD Thesis)*. Leiden: Leiden University, 2012.

[5] D. T. Blagoeva, P. Aves Dias, A. Marmier and C. C. Pavel. *Assessment of Potential Bottlenecks along the Materials Supply Chain for the Future Deployment of Low-Carbon Energy and Transport Technologies in the EU - Wind Power, Photovoltaic and Electric Vehicles Technologies, Time Frame: 2015-2030*. JRC Science for Policy Report. Petten: European Commission, 2016.

[6] P. Viebahn, K. Arnold, J. Friege, C. Krüger, A. Nebel, S. Samadi, O. Soukup, M. Ritthof, J. Teubler and K. Wiesen. *KRESSE - Kritische mineralische Ressourcen und Stoffströme bei der Transformation des deutschen Energieversorgungssystems*. Wuppertal: Wuppertal Institut für Klima, Umwelt, Energie, 2014.

[7] R. L. Moss, E. Tzimas, P. Willis, J. Arendorf and L. Tercero Espinoza. *Critical Metals in the Path towards the Decarbonisation of the EU Energy Sector*. JRC Science for Policy Report. Petten: European Commission, 2013.

[8] T. Graedel, E. M. Harper, N. T. Nassar, P. Nuss and B. K. Reck. "Criticality of Metals and Metalloids". In: *Proceedings of the National Academy of Sciences of the United States of America (PNAS)* 112 (14), 2015, pp. 4257–4262.

[9] S. Pichlmaier, A. Regett and A. Guminski. "Development of Application-Related Emissions in the Course of the German Energy Transition". In: *11. Internationale Energiewirtschaftstagung (IEWT)*. Wien, 2019.

[10] J. Conrad, S. Fattler, A. Regett, F. Böing, A. Guminski, S. Greif, T. Hübner, F. Jetter, T. Kern, B. Kleinertz, A. Murmann, A. Ostermann, C. Pellinger, S. Pichlmaier, T. Schmid and S. von Roon. *Dynamis – Dynamische und intersektorale Maßnahmenbewertung zur kosteneffizienten Dekarbonisierung des Energiesystems – Abschlussbericht*. München: Forschungsstelle für Energiewirtschaft, 2019.

[11] *dena-Leitstudie Integrierte Energiewende - Impulse für die Gestaltung des Energiesystems bis 2050 - Teil A: Ergebnisbericht und Handlungsempfehlungen (dena) - Teil B: Gutachterbericht (ewi Energy Research & Scenarios gGmbH)*. Berlin: Deutsche Energie-Agentur (dena), 2018.

[12] D. Hall and N. Lutsey. *Effects of Battery Manufacturing on Electric Vehicle Life-Cycle Greenhouse Gas Emissions*. Washington: International Council on Clean Transportation, 2018.

[13] F. Cerdas, P. Egede and C. Herrmann. "LCA of Electromobility". In: *Life Cycle Assessment*. Cham: Springer, 2018, pp. 669–693.

[14] A. Nordelöf, M. Messagie, A.-M. Tillman, M. Ljunggren Söderman and J. Van Mierlo. "Environmental Impacts of Hybrid, Plug-in Hybrid, and Battery Electric Vehicles - What Can We Learn from Life Cycle Assessment?" In: *The International Journal of Life Cycle Assessment* 19 (11), 2014, pp. 1866–1890.

[15] M. Wietschel, M. Kühnbach and D. Rüdiger. *Die aktuelle Treibhausgasemissionsbilanz von Elektrofahrzeugen in Deutschland*. Karlsruhe: Fraunhofer Institut für System- und Innovationsforschung, 2019.

[16] B. Reuter, A. Hendrich, J. Hengstler, S. Kupferschmid and M. Schwenk. *Rohstoffe für innovative Fahrzeugtechnologien - Herausforderungen und Lösungsansätze*. Stuttgart: e-mobil BW, 2019.

[17] H. Helms, K. Biemann and K. Meyer. *Klimabilanz von Elektroautos - Einflussfaktoren und Verbesserungspotenzial*. Berlin: Agora Verkehrswende, 2019.

[18] M. Romare and L. Dahllöf. *The Life Cycle Energy Consumption and Greenhouse Gas Emissions from Lithium-Ion Batteries - A Study with Focus on Current Technology and Batteries for Light-Duty Vehicles*. Stockholm: IVL Swedish Environmental Research Institute, 2017.

[19] C. Buchal, H.-D. Karl and H.-W. Sinn. *Kohlemotoren, Windmotoren und Dieselmotoren: Was zeigt die CO_2-Bilanz?* München: ifo Institut, 2019.

[20] T. Kroher. "Prima fürs Klima?" In: *ADAC Motorwelt* 4, 2018, pp. 18–22.

[21] T. Weber, M. Stuchtey, S. Kadner, K. Schweitzer, S. Buttkereit, A. Marm, T. Vahle and R. Wolf. *Pathways towards a German Circular Economy - Lessons from European Strategies - Preliminary Study*. München: acatech - Circular Economy Initiative Deutschland, SYSTEMIQ, 2019.

[22] *Closing the Loop - An EU Action Plan for the Circular Economy*. Brussels: European Commission, 2015.

[23] D. E. MacArthur, K. Zumwinkel and M. R. Stuchtey. *Growth Within: A Circular Economy Vision for a Competitive Europe*. Cowes: Ellen MacArthur Foundation, Deutsche Post Foundation, McKinsey Center for Business and Environment, 2015.

[24] P. Lacy, J. Keeble, R. McNamara, J. Rutqvist, K. Eckerle, T. Haglund, P. Buddemeier, M. Cui, A. Sharma, A. Cooper, T. Senior and C. Pettersson. *Circular Advantage - Innovative*

Business Models and Technologies to Create Value in a World without Limits to Growth. Dublin: Accenture, 2014.

[25] V. Rizos, K. Tuokko and A. Behrens. *The Circular Economy - A Review of Definitions, Processes and Impacts*. Brussels: CEPS, 2017.

[26] N. Hill, D. Clarke, L. Blair and H. Menadue. *Circular Economy Perspectives for the Management of Batteries Used in Electric Vehicles*. Seville: European Commission, 2019.

[27] *Electric Vehicles from Life Cycle and Circular Economy Perspectives*. Luxembourg: European Environment Agency, 2018.

[28] L. Olsson, S. Fallahi, M. Schnurr, D. Diener and P. Van Loon. "Circular Business Models for Extended EV Battery Life". In: *Batteries* 4 (4), 2018, p. 57.

[29] E. Drabik and V. Rizos. *Prospects for Electric Vehicle Batteries in a Circular Economy*. Brussels: CEPS, 2018.

[30] K. Richa, C. W. Babbitt and G. Gaustad. "Eco-Efficiency Analysis of a Lithium-Ion Battery Waste Hierarchy Inspired by Circular Economy". In: *Journal of Industrial Ecology* 21 (3), 2017, pp. 715–730.

[31] M. Kurdve, M. Zackrisson, M. I. Johansson, B. Ebin and U. Harlin. "Considerations When Modelling EV Battery Circularity Systems". In: *Batteries* 5 (2), 2019, p. 40.

[32] A. Thielmann, C. Neef, T. Hettesheimer, H. Döscher, M. Wietschel and J. Tübke. *Energiespeicher-Roadmap (Update 2017) - Hochenergie-Batterien 2030+ und Perspektiven zukünftiger Batterietechnologien*. Karlsruhe: Fraunhofer-Institut für System- und Innovationsforschung, 2017.

[33] S. Fischhaber, A. Regett, S. Schuster and H. Hesse. *Second-Life-Konzepte für Lithium-Ionen-Batterien aus Elektrofahrzeugen - Analyse von Nachnutzungsanwendungen, ökonomischen und ökologischen Potenzialen - Ergebnispapier 18*. Frankfurt am Main: Begleit- und Wirkungsforschung Schaufenster Elektromobilität, 2016.

[34] T. Hübner, A. Guminski and S. von Roon. "Die Rolle synthetischer Brennstoffe zur Erreichung der klimapolitischen Ziele". In: *BWK* 70 (10), 2018, pp. 32–35.

[35] P. Mancarella, G. Andersson, J. A. Peças-Lopes and K. R. W. Bell. "Modelling of Integrated Multi-Energy Systems: Drivers, Requirements, and Opportunities." In: *2016 Power Systems Computation Conference (PSCC)*. Genoa, 2016, pp. 1–22.

[36] *Klimaschutzplan 2050 - Klimaschutzpolitische Grundsätze und Ziele der Bundesregierung*. Berlin: German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety, 2016.

[37] *Report of the Conference of the Parties on Its Twenty-First Session, Held in Paris from 30 November to 13 December 2015*. Paris: United Nations Framework Convention on Climate Change, 2015.

[38] *Zweiter Fortschrittsbericht zur Energiewende - Die Energie der Zukunft - Berichtsjahr 2017*. Berlin: German Federal Ministry for Economic Affairs and Energy, 2019.

[39] M. Rasch, A. Regett, S. Pichlmaier, J. Conrad, A. Guminski, E. Rouyrre, C. Orthofer and T. Zipperle. “Eine anwendungsorientierte Emissionsbilanz - Kosteneffiziente und sektorenübergreifende Dekarbonisierung des Energiesystems”. In: *BWK* 69 (3), 2017, pp. 38–42.

[40] *Energiebilanz der Bundesrepublik Deutschland 2016*. Berlin: Arbeitsgemeinschaft Energiebilanzen, 2018.

[41] *Submission under the United Nations Framework Convention on Climate Change and the Kyoto Protocol 2018 - National Inventory Report for the German Greenhouse Gas Inventory 1990 – 2016*. Dessau-Roßlau: Umweltbundesamt, 2018.

[42] *Zahlen und Fakten Energiedaten - Nationale und Internationale Entwicklung*. Berlin: German Federal Ministry for Economic Affairs and Energy, 2018.

[43] J. Conrad and S. Greif. “Dynamik der Energiewende - Wie lassen sich Maßnahmen zur Reduktion von Treibhausgasemissionen quantifizieren?” In: *10. Internationale Energiewirtschaftstagung (IEWT)*. Wien, 2017.

[44] P. Gniffke. *National Trend Tables for the German Atmospheric Emission Reporting 1990-2017 - Final Version Reporting Period 2019*. Dessau-Roßlau: Umweltbundesamt, 2019.

[45] *ADAC EcoTest*. 2019. URL: `www.adac.de/infotestrat/tests/eco-test/` (visited on 08/28/2019).

[46] D. A. Notter, M. Gauch, R. Widmer, P. Wäger, A. Stamp, R. Zah and H.-J. Althaus. “Contribution of Li-Ion Batteries to the Environmental Impact of Electric Vehicles”. In: *Environmental Science & Technology* 44 (17), 2010, pp. 6550–6556.

[47] J. B. Dunn, L. Gaines, J. C. Kelly and K. Gallagher. “Life Cycle Analysis Summary for Automotive Lithium-Ion Battery Production and Recycling”. In: *REWAS 2016*. Cham: Springer, 2016, pp. 73–79.

[48] T. R. Hawkins, B. Singh, G. Majeau-Bettez and A. H. Strømman. “Comparative Environmental Life Cycle Assessment of Conventional and Electric Vehicles”. In: *Journal of Industrial Ecology* 17 (1), 2013, pp. 53–64.

[49] *Kurzbericht - Verkehr in Kilometern, Jahr 2017*. Flensburg: Kraftfahrt-Bundesamt, 2018.

[50] *The Ecoinvent Database (Version 3.5)*. ecoinvent. Zurich, 2018.

[51] *Submission under the United Nations Framework Convention on Climate Change and the Kyoto Protocol 2016 - National Inventory Report for the German Greenhouse Gas Inventory 1990 – 2014*. Dessau-Roßlau: Umweltbundesamt, 2016.

[52] B. Marmiroli, M. Messagie, G. Dotelli and J. Van Mierlo. “Electricity Generation in LCA of Electric Vehicles: A Review”. In: *Applied Sciences* 8 (8), 2018, p. 1384.

[53] L. A.-W. Ellingsen, C. R. Hung and A. H. Strømman. “Identifying Key Assumptions and Differences in Life Cycle Assessment Studies of Lithium-Ion Traction Batteries with Focus on Greenhouse Gas Emissions”. In: *Transportation Research Part D: Transport and Environment* 55, 2017, pp. 82–90.

[54] J. F. Peters, M. Baumann, B. Zimmermann, J. Braun and M. Weil. “The Environmental Impact of Li-Ion Batteries and the Role of Key Parameters – A Review”. In: *Renewable and Sustainable Energy Reviews* 67, 2017, pp. 491–506.

[55] Q. Dai, J. Dunn, J. C. Kelly and A. Elgowainy. *Update of Life Cycle Analysis of Lithium-Ion Batteries in the GREET Model*. Chicago: Argonne National Laboratory, 2017.

[56] L. A.-W. Ellingsen, G. Majeau-Bettez, B. Singh, A. K. Srivastava, L. O. Valøen and A. H. Strømman. “Life Cycle Assessment of a Lithium-Ion Battery Vehicle Pack”. In: *Journal of Industrial Ecology* 18 (1), 2014, pp. 113–124.

[57] M. Buchert, W. Jenseit, C. Merz and D. Schüler. *Verbundprojekt: Entwicklung eines realisierbaren Recyclingkonzepts für die Hochleistungsbatterien zukünftiger Elektrofahrzeuge - LiBRi - Teilprojekt: LCA der Recyclingverfahren*. Freiburg: Öko-Institut, 2011.

[58] M. Buchert, W. Jenseit, C. Merz and D. Schüler. *Ökobilanz zum "Recycling von Lithium-Ionen-Batterien" (LithoRec)*. Freiburg: Öko-Institut, 2011.

[59] M. Buchert and J. Sutter. *Aktualisierte Ökobilanzen zum Recyclingverfahren LithoRec II für Lithium-Ionen-Batterien (Stand 09/2016)*. Freiburg: Öko-Institut, 2016.

[60] F. Cerdas, S. Andrew, S. Thiede and C. Herrmann. “Chapter 16 - Environmental Aspects of the Recycling of Lithium-Ion Traction Batteries”. In: *Recycling of Lithium-Ion Batteries - The LithoRec Way*. Sustainable Production, Life Cycle Engineering and Management. Cham: Springer, 2018, pp. 267–288.

[61] A. Regett and S. Fischhaber. “Reduction of Critical Resource Consumption through Second Life Applications of Lithium Ion Traction Batteries”. In: *10. Internationale Energiewirtschaftstagung (IEWT)*. Wien, 2017.

[62] S. Glöser and M. Faulstich. “Analyse kritischer Rohstoffe durch Methoden der multivariaten Statistik”. In: *3. Symposium Rohstoffeffizienz und Rohstoffinnovationen*. Nürnberg, 2014.

[63] *Report on Critical Raw Materials for the EU - Report of the Ad Hoc Working Group on Defining Critical Raw Materials*. Brussels: European Commission, 2014.

[64] *Critical Raw Materials for the EU - Report of the Ad-Hoc Working Group on Defining Critical Raw Materials*. Brussels: European Commission, 2010.

[65] L. Erdmann, S. Behrendt and M. Feil. *Kritische Rohstoffe für Deutschland*. Berlin: Institut für Zukunftsstudien und Technologiebewertung, adelphi, 2011.

[66] *Energiekonzept für eine umweltschonende, zuverlässige und bezahlbare Energieversorgung*. Berlin: German Federal Ministry for Economic Affairs and Energy, German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety, 2010.

[67] *Zwischenbericht 03/2019 - Wege zur Erreichung der Klimaziele 2030 im Verkehrssektor - Arbeitsgruppe 1 Klimaschutz im Verkehr*. Berlin: Nationale Plattform Zukunft der Mobilität, 2019.

[68] S. M. Simon. *Szenarien nachhaltiger Bioenergiepotenziale bis 2030 - Modellierung für Deutschland, Polen, Tschechien und Ungarn (PhD Thesis)*. München: Fakultät Wissenschaftszentrum Weihenstephan für Ernährung, Landnutzung und Umwelt, Technische Universität München, 2007.

[69] E. Rahimzei, K. Sann and M. Vogel. *Kompendium: Li-Ionen-Batterien - Grundlagen, Bewertungskriterien, Gesetze und Normen*. Frankfurt am Main: Verband der Elektrotechnik Elektronik Informationstechnik, 2015.

[70] P. Nelson, K. Gallagher, I. Bloom, D. Dees and S. Ahmed. *BatPac (Version 3.1)*. UChicago Argonne, LLC under Contract No. DE-AC02-06CH11357 with the Department of Energy. 2017.

[71] *Commission Staff Working Document - Report on Raw Materials for Battery Applications*. Brussels: European Commission, 2018.

[72] M. Weil, S. Ziemann and J. Peters. “The Issue of Metal Resources in Li-Ion Batteries for Electric Vehicles”. In: *Behaviour of Lithium-Ion Batteries in Electric Vehicles.* Green Energy and Technology. Cham: Springer, 2018, pp. 59–74.

[73] C. Helbig, A. M. Bradshaw, L. Wietschel, A. Thorenz and A. Tuma. “Supply Risks Associated with Lithium-Ion Battery Materials”. In: *Journal of Cleaner Production* 172, 2018, pp. 274–286.

[74] S. Al Barazi, T. Brandenburg, T. Kuhn, M. Schmidt and S. Vetter. *Rohstoffrisikobewertung - Kobalt - DERA Rohstoffinformationen 36*. Berlin: Deutsche Rohstoffagentur in der Bundesanstalt für Geowissenschaften und Rohstoffe, 2018.

[75] M. Schmidt. *Rohstoffrisikobewertung - Lithium - DERA Rohstoffinformationen 33*. Berlin: Deutsche Rohstoffagentur in der Bundesanstalt für Geowissenschaften und Rohstoffe, 2017.

[76] T. E. Graedel, J. Allwood, J.-P. Birat, M. Buchert, C. Hagelüken, B. K. Reck, S. F. Sibley and G. Sonnemann. “What Do We Know About Metal Recycling Rates?” In: *Journal of Industrial Ecology* 15 (3), 2011, pp. 355–366.

[77] T. E. Graedel, J. Allwood, J.-P. Birat, B. K. Reck, S. F. Sibley, G. Sonnemann, M. Buchert and C. Hagelüken. *Recycling Rates of Metals - A Status Report, A Report of the Working Group on the Global Metal Flows to the International Resource Panel*. United Nations Environmental Programme, 2011.

[78] *Jahresbericht über die Altfahrzeug-Verwertungsquoten in Deutschland im Jahr 2015 nach Art. 7 Abs. 2 der Altfahrzeug-Richtlinie 2000/53/EG*. Dessau-Roßlau: Umweltbundesamt, 2017.

[79] G. Angerer, F. Marscheider-Weidemann, M. Wendl and M. Wietschel. *Lithium für Zukunftstechnologien - Nachfrage und Angebot unter besonderer Berücksichtigung der Elektromobilität*. Karlsruhe: Fraunhofer Institut für System- und Innovationsforschung, 2009.

[80] C. Hanisch, J. Diekmann, A. Stieger, W. Haselrieder and A. Kwade. “Chapter 27 - Recycling of Lithium-Ion Batteries”. In: *Handbook of Clean Energy Systems*. Volume 5 Energy Storage. Hoboken: John Wiley & Sons, Ltd., 2015, pp. 2865–2888.

[81] S. Rothermel, M. Winter and S. Nowak. “Chapter 1 - Background”. In: *Recycling of Lithium-Ion Batteries - The LithoRec Way*. Sustainable Production, Life Cycle Engineering and Management. Cham: Springer, 2018, pp. 1–31.

[82] S. Ziemann, D. B. Müller, L. Schebek and M. Weil. “Modeling the Potential Impact of Lithium Recycling from EV Batteries on Lithium Demand: A Dynamic MFA Approach”. In: *Resources, Conservation and Recycling* 133, 2018, pp. 76–85.

[83] J. Diekmann, S. Rothermel, S. Nowak and A. Kwade. “Chapter 2 - The LithoRec Process”. In: *Recycling of Lithium-Ion Batteries - The LithoRec Way*. Sustainable Production, Life Cycle Engineering and Management. Cham: Springer, 2018, pp. 33–38.

[84] C. Hagelüken. “Recycling of Li-Ion Batteries - Imperative for Sustainable e-Mobility (Presentation)”. In: *Advanced Automotive Battery Conference (AABC) Europe*. Mainz, 2018.

[85] H. Stahl, Y. Baron, D. Hay, A. Hermann, G. Mehlhart, L. Baroni, K. Rademaekers, R. Williams and S. Pahal. *Study in Support of Evaluation of the Directive 2006766/EC on Batteries and Accumulators and Waste Batteries and Accumulators - Final Report*. Rotterdam: Trinomics, 2018.

[86] *Report on the Implementation of the Circular Economy Action Plan*. Brussels: European Commission, 2019.

[87] J. Kirchherr, D. Reike and M. Hekkert. “Conceptualizing the Circular Economy: An Analysis of 114 Definitions”. In: *Resources, Conservation and Recycling* 127, 2017, pp. 221–232.

[88] *Towards the Circular Economy - Economic and Business Rationale for an Accelerated Transition*. Cowes: Ellen MacArthur Foundation, 2013.

[89] V. Rizos, A. Behrens, E. Drabik, D. Rinaldi and K. Tuokko. *The Role of Business in the Circular Economy - Markets, Processes and Enabling Policies*. Brussels: CEPS, 2018.

[90] C. K. Yamakawa, F. Qin and S. I. Mussatto. “Advances and Opportunities in Biomass Conversion Technologies and Biorefineries for the Development of a Bio-Based Economy”. In: *Biomass and Bioenergy* 119, 2018, pp. 54–60.

[91] *Deutsches Ressourceneffizienzprogramm (ProgRess) - Programm zur nachhaltigen Nutzung und zum Schutz der natürlichen Ressourcen*. Berlin: German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety, 2012.

[92] C. Yuan, Y. Deng, T. Li and F. Yang. “Manufacturing Energy Analysis of Lithium Ion Battery Pack for Electric Vehicles”. In: *CIRP Annals* 66 (1), 2017, pp. 53–56.

[93] A. Kampker, H. Heimes, C. Deutskens, M. Ordung, E. Maiser and S. Michaelis. *Produktionsprozess einer Lithium-Ionen-Batteriezelle*. Aachen: RWTH Aachen, 2015.

[94] *Elektroantrieb: Komponenten und Funktionen*. 2019. URL: www.adac.de/rund-ums-fahrzeug/e-mobilitaet/antrieb/elektroantrieb/ (visited on 05/10/2019).

[95] F. Un-Noor, S. Padmanaban, L. Mihet-Popa, M. N. Mollah and E. Hossain. “A Comprehensive Study of Key Electric Vehicle (EV) Components, Technologies, Challenges, Impacts, and Future Direction of Development”. In: *Energies* 10 (8), 2017, p. 1217.

[96] J. Gayko. *Der Technische Leitfaden - Ladeinfrastruktur Elektromobilität - Version 2*. Frankfurt am Main: DKE Deutsche Kommission Elektrotechnik Elektronik Informationstechnik in DIN und VDE, 2015.

[97] E. Martinez-Laserna, I. Gandiaga, E. Sarasketa-Zabala, J. Badeda, D.-I. Stroe, M. Swierczynski and A. Goikoetxea. “Battery Second Life: Hype, Hope or Reality? A Critical Review of the State of the Art”. In: *Renewable and Sustainable Energy Reviews* 93, 2018, pp. 701–718.

[98] E. Cready, J. Lippert, J. Pihl, I. Weinstock, P. Symons and R. G. Jungst. *Technical and Economic Feasibility of Applying Used EV Batteries in Stationary Applications - A Study for the DOE Energy Storage Systems Program*. Albuquerque, Livermore: Sandia National Laboratories, 2003.

[99] R. Heijungs and S. Suh. *The Computational Structure of Life Cycle Assessment*. Dordrecht: Kluwer Academic Publishers, 2002.

[100] P. H. Brunner and H. Rechberger. *Practical Handbook of Material Flow Analysis*. Boca Raton: CRC Press LLC, 2004.

[101] E. Müller, L. M. Hilty, R. Widmer, M. Schluep and M. Faulstich. “Modeling Metal Stocks and Flows: A Review of Dynamic Material Flow Analysis Methods”. In: *Environmental Science & Technology* 48 (4), 2014, pp. 2102–2113.

[102] S. Cucurachi, C. van der Giesen and J. Guinée. “Ex-Ante LCA of Emerging Technologies”. In: *25th CIRP Life Cycle Engineering (LCE) Conference*. Vol. 69. Copenhagen, 2018, pp. 463–468.

[103] R. Arvidsson, A.-M. Tillman, B. A. Sandén, M. Janssen, A. Nordelöf, D. Kushnir and S. Molander. “Environmental Assessment of Emerging Technologies: Recommendations for Prospective LCA”. In: *Journal of Industrial Ecology* 22 (6), 2018, pp. 1286–1294.

[104] A. Mendoza Beltran, B. Cox, C. Mutel, D. P. van Vuuren, D. F. Vivanco, S. Deetman, O. Y. Edelenbosch, J. Guinée and A. Tukker. “When the Background Matters: Using Scenarios from Integrated Assessment Models in Prospective Life Cycle Assessment”. In: *Journal of Industrial Ecology*, 2018.

[105] A. Regett, U. Wagner, W. Mauch and J. Bangoj. “Environmental Impact of Electric Vehicles: Potential of the Circular Economy?” In: *Der Antrieb von Morgen 2019*. Wiesbaden: Springer Vieweg, 2019, pp. 121–140.

[106] A. Regett, W. Mauch and U. Wagner. *Klimabilanz von Elektrofahrzeugen - Ein Plädoyer für mehr Sachlichkeit*. München: Forschungsstelle für Energiewirtschaft, 2018.

[107] A. Elgowainy, D. Dieffenthaler, V. Sokolov, R. Sabbisetti, C. Cooney and A. Anjum. *Software GREET (Version 1.3.0.13239)*. UChicago Argonne, LLC as Operator of Argonne National Laboratory under Contract No. DE-AC02-06CH11357 with the Department of Energy. Chicago, 2017.

[108] P. Stolz and R. Frischknecht. *Life Cycle Inventories of Aluminium and Aluminium Profiles*. Uster: treeze, 2016.

[109] S. Glöser, M. Soulier and L. A. Tercero Espinoza. "Dynamic Analysis of Global Copper Flows. Global Stocks, Postconsumer Material Flows, Recycling Indicators, and Uncertainty Evaluation". In: *Environmental Science & Technology* 47 (12), 2013, pp. 6564–6572.

[110] *World Steel Recycling in Figures 2012-2016 - Steel Scrap - a Raw Material for Steelmaking*. Brussels: Bureau of International Recycling, 2017.

[111] A. Guminski and S. von Roon. "Transition Towards an "All-Electric World" - Developing a Merit-Order of Electrification for the German Energy System". In: *10. Internationale Energiewirtschaftstagung (IEWT)*. Wien, 2017.

[112] *The Ecoinvent Database (Version 3.4)*. ecoinvent. Zurich, 2017.

[113] F. Cerdas, P. Titscher, N. Bognar, R. Schmuch, M. Winter, A. Kwade and C. Herrmann. "Exploring the Effect of Increased Energy Density on the Environmental Impacts of Traction Batteries: A Comparison of Energy Optimized Lithium-Ion and Lithium-Sulfur Batteries for Mobility Applications". In: *Energies* 11 (1), 2018, p. 150.

[114] J. Conrad, S. Greif, A. Regett and B. Kleinertz. "Evolution und Vergleich der CO_2-Bewertungsmethoden in Wärmepumpen (Presentation)". In: *3. Dialogplattform Power to Heat*. Berlin, 2017.

[115] N. A. Ryan, J. X. Johnson and G. A. Keoleian. "Comparative Assessment of Models and Methods To Calculate Grid Electricity Emissions". In: *Environmental Science & Technology* 50 (17), 2016, pp. 8937–8953.

[116] B. A. Sandén, K. M. Jonasson, M. Karlström and A.-M. Tillman. "LCA of Emerging Technologies: A Methodological Framework". In: *LCM 2005 - Innovation by Life Cycle Management*. En. Barcelona, 2005, pp. 37–41.

[117] J. Günther, H. Lehmann, U. Lorenz and K. Purr. *Den Weg zu einem treibhausgasneutralen Deutschland ressourcenschonend gestalten*. Dessau-Roßlau: Umweltbundesamt (UBA), 2017.

[118] P. Gerbert, P. Herhold, J. Burchardt, S. Schönberger, F. Rechenmacher, A. Kirchner, A. Kemmler and M. Wünsch. *Klimapfade für Deutschland*. München: Boston Consulting Group, prognos, 2018.

[119] B. Pfluger, B. Tersteegen and B. Franke. *Langfristszenarien für die Transformation des Energiesystems in Deutschland - Modul 3: Referenzszenario und Basisszenario*. Karlsruhe, Aachen, Heidelberg: Fraunhofer Institut für System- und Innovationsforschung, Consentec, Institut für Energie- und Umweltforschung Heidelberg, 2017.

[120] P. Capros, L. L. Höglund-Isaksson, S. Frank and H. P. Witzke. *EU Reference Scenario 2016 - Energy, Transport and GHG Emissions Trends to 2050*. Brussels: European Commission, 2016.

[121] C. Ripp and F. Steinke. "A First Shot at Time-Dependent CO_2 Intensities in Multi-Modal Energy Systems". In: *15th International Conference on the European Energy Market (EEM)*. Lodz, 2018.

[122] P. Jochem, S. Babrowski and W. Fichtner. "Assessing CO_2 Emissions of Electric Vehicles in Germany in 2030". In: *Transportation Research Part A: Policy and Practice* 78, 2015, pp. 68–83.

[123] F. Böing and A. Regett. "Hourly CO_2 Emission Factors and Marginal Costs of Energy Carriers in Future Multi-Energy Systems". In: *Energies* 12, 2019, p. 2260.

[124] C. Pellinger. *Mehrwert Funktionaler Energiespeicher aus System- und Akteurssicht (PhD Thesis)*. München: Fakultät für Elektrotechnik und Informationstechnik, TU München, 2016.

[125] S. Köppl, F. Samweber, A. Bruckmeier, F. Böing, M. Hinterstocker, B. Kleinertz, C. Konetschny, M. Müller, T. Schmid and A. Zeiselmaier. *Grundlage für die Bewertung von Netzoptimierenden Maßnahmen - Teilbericht Basisdaten*. München: Forschungsstelle für Energiewirtschaft, 2017.

[126] C. Pellinger and T. Schmid. *Merit Order der Energiespeicherung im Jahr 2030 - Hauptbericht*. München: Forschungsstelle für Energiewirtschaft, 2016.

[127] S. Pichlmaier, S. Fattler and C. Bayer. "Modelling the Transport Sector in the Context of a Dynamic Energy System". In: *Transforming Energy Markets, 41st IAEE International Conference*. Groningen, 2018.

[128] A. Guminski, T. Hübner, A. Gruber and S. von Roon. "Model Based Evaluation of Industrial Greenhouse Gas Abatement Measures". In: *11. Internationale Energiewirtschaftstagung (IEWT)*. Wien, 2019.

[129] J. Conrad and S. Greif. "Modelling the Private Households Sector and the Impact on the Energy System". In: *Transforming Energy Markets, 41st IAEE International Conference*. Groningen, 2018.

[130] M. Schlesinger, D. Lindenberger and C. Lutz. *Entwicklung der Energiemärkte - Energiereferenzprognose - Projekt Nr. 57/12 Studie im Auftrag des Bundesministeriums für Wirtschaft und Technologie*. Basel, Köln, Osnabrück: Prognos, Energiewirtschaftliches Institut an der Universität Köln, Gesellschaft für Wirtschaftliche Strukturforschung, 2014.

[131] *Szenariorahmen für den Netzentwicklungsplan Strom 2030 (Version 2019) - Entwurf der Übertragungsnetzbetreiber*. Berlin, Dortmund, Bayreuth, Stuttgart: 50Hertz Transmission GmbH, Amprion GmbH, TenneT TSO GmbH, TransnetBW GmbH, 2018.

[132] *Ten-Year Network Development Plan 2018 (TYNDP)*. Brussels: European Network of Transmission System Operators for Electricity, 2018.

[133] *Final Report: Commission on Growth, Structural Change and Employment*. Berlin: German Federal Ministry for Economic Affairs and Energy, 2018.

[134] T. Schmid. *Dynamische und kleinräumige Modellierung der aktuellen und zukünftigen Energienachfrage und Stromerzeugung aus Erneuerbaren Energien (PhD Thesis)*. München: Fakultät für Elektrotechnik und Informationstechnik, TU München, 2019.

[135] *Genehmigung des Szenariorahmens 2019-2030*. Bonn: Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen, 2018.

[136] T. Tereshchenko and N. Nord. "Uncertainty of the Allocation Factors of Heat and Electricity Production of Combined Cycle Power Plant". In: *Applied Thermal Engineering* 76, 2015, pp. 410–422.

[137] *Energy Statistics Manual*. Paris: International Energy Agency, 2005.

[138] P. Konstantin. *Praxisbuch Energiewirtschaft – Energieumwandlung, -transport und -beschaffung, Übertragungsnetzausbau und Kernenergieausstieg*. 4th ed. Berlin: VDI Verlag, 2017.

[139] B. Tranberg, O. Corradi, B. Lajoie, T. Gibon, I. Staffell and G. B. Andresen. "Real-Time Carbon Accounting Method for the European Electricity Markets". In: *Energy Strategy Reviews* 26, 2019.

[140] P. Icha and G. Kuhs. *Entwicklung der spezifischen Kohlendioxid-Emissionen des deutschen Strommix in den Jahren 1990 - 2018*. Dessau-Roßlau: Umweltbundesamt, 2019.

[141] S. Fattler and A. Regett. "Environmental Impact of Electric Vehicles: Influence of Intelligent Charging Strategies (Submitted)". In: *Grid Integration of Electric Mobility - 4. Internationale ATZ-Fachtagung*. Mannheim, 2019.

[142] J. Knodt. *Analyse und Vergleich des Kumulierten Energieaufwandes (KEA) der Antriebsstränge für konventionelle und elektrische Automobile (Diploma Thesis)*. Bayreuth, München: Universität Bayreuth, Forschungsstelle für Energiewirtschaft, 2011.

[143] *Klimabilanz von E-Fahrzeugen & Life Cycle Engineering*. Wolfsburg: Volkswagen, 2019.

[144] C. Kranner. *Emissionsbewertung von industriellem Spitzenlastmanagement durch Traktionsbatterien in Elektrofahrzeugen unter Berücksichtigung des Merit-Order-Effekts (Master Thesis)*. München: Technische Universität München, Forschungsstelle für Energiewirtschaft, 2018.

[145] W. Plege. *Integration von dezentralen Power2Gas-Anlagen in Verteilnetze - Untersuchung der netztechnischen Auswirkungen und Analyse der Emissionsbilanz (Master Thesis)*. München: Technische Universität München, Forschungsstelle für Energiewirtschaft, 2017.

[146] C. Taylor. *Development of LCA Methodology for Incorporating Energy Market Developments into the Life Cycle-Based Assessment of Load Flexibilisation - A Case Study on Power-to-Chemistry (Master Thesis)*. München: Technische Universität München, Forschungsstelle für Energiewirtschaft, 2014.

[147] A. Regett, F. Böing, J. Conrad, S. Fattler and C. Kranner. “Emission Assessment of Electricity: Mix vs. Marginal Power Plant Method”. In: *15th International Conference on the European Energy Market (EEM)*. Lodz, 2018.

[148] C. Pellinger and S. Fattler. “Möglichkeiten und Grenzen des europäischen Verbundsystems - Eine empirische Analyse für den deutschen Kraftwerkspark - Basisjahr 2013 (Presentation)”. In: *VDI-Wissensforum Leittechnik in Kraftwerken*. Nürnberg, 2014.

[149] *Kraftwerksliste der Bundesnetzagentur*. Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen, 2016.

[150] *World Electric Power Plants Database (Europe)*. S&P Global Platts, 2014.

[151] *Kraftwerke in Deutschland (ab 100 Megawatt elektrischer Leistung)*. Umweltbundesamt, 2013.

[152] I. Ellersdorfer, N. Hundt and A. Voß. *Preisbildungsanalyse des deutschen Elektrizitätsmarktes*. Stuttgart: Institut für Energiewirtschaft und Rationelle Energieanwendung, Universität Stuttgart, 2008.

[153] N. Sun. *Modellgestützte Untersuchung des Elektrizitätsmarktes - Kraftwerkseinsatzplanung und -investitionen (PhD Thesis)*. Stuttgart: Institut für Energiewirtschaft und Rationelle Energieanwendung, Universität Stuttgart, 2013.

[154] F. Böing, A. Murmann, C. Pellinger, A. Bruckmeier, T. Kern and T. Mongin. “Assessment of Grid Optimisation Measures for the German Transmission Grid Using Open Source Grid Data”. In: *Journal of Physics: Conference Series* 977, 2018, p. 012002.

[155] A. Regett, A. Zeiselmaier, K. Wachinger and C. Heller. *Merit Ordner Netz-Ausbau 2030 - Teilbericht 1: Szenario-Analyse*. München: Forschungsstelle für Energiewirtschaft, 2017.

[156] *Ten-Year Network Development Plan 2016 (TYNDP)*. Brussels: European Network of Transmission System Operators for Electricity, 2015.

[157] F. Böing, A. Regett, C. Kranner, C. Pellinger, S. Fattler and J. Conrad. *Das Merit-Order-Dilemma der Emissionen - Eine Diskussionsgrundlage zur klimapolitischen Debatte (Working Paper)*. München: Forschungsstelle für Energiewirtschaft, 2019.

[158] J. Conrad, A. Regett, S. Fattler and F. Jetter. “Von statischen CO_2-Verminderungskosten zur dynamischen Bewertung von Klimaschutzmaßnahmen”. In: *Energiewirtschaftliche Tagesfragen* 69 (10), 2019, pp. 47–52.

[159] A. Regett, C. Kranner, S. Fischhaber and F. Böing. “Using Energy System Modelling Results for Assessing the Emission Effect of Vehicle-to-Grid for Peak Shaving”. In: *Progress in Life Cycle Assessment*. Sustainable Production, Life Cycle Engineering and Management. Cham: Springer, 2018, pp. 115–123.

[160] A. Regett, S. Fischhaber and C. Kranner. “Environmental Saving Potential of Circular Approaches for Traction Batteries (Poster)”. In: *NTNU Sustainability Science Conference*. Trondheim, 2017.

[161] D. Kim, A. Geissler, C. Menn and D. Hengevoss. “Quantifizierung des Umweltnutzens von gebrauchten Batterien aus Elektrofahrzeugen als gebäudeintegrierte 2nd-Life Stromspeichersysteme”. In: *Bauphysik* 37 (4), 2015, pp. 213–222.

[162] K. N. Genikomsakis, C. S. Ioakimidis, A. Murillo, A. Trifonova and D. Simic. “A Life Cycle Assessment of a Li-Ion Urban Electric Vehicle Battery”. In: *World Electric Vehicle Symposium and Exhibition (EVS27)*. 2013, pp. 1–11.

[163] R. Faria, P. Marques, R. Garcia, P. Moura, F. Freire, J. Delgado and A. T. de Almeida. “Primary and Secondary Use of Electric Mobility Batteries from a Life Cycle Perspective”. In: *Journal of Power Sources* 262, 2014, pp. 169–177.

[164] R. Sathre, C. D. Scown, O. Kavvada and T. P. Hendrickson. “Energy and Climate Effects of Second-Life Use of Electric Vehicle Batteries in California through 2050”. In: *Journal of Power Sources* 288, 2015, pp. 82–91.

[165] L. Ahmadi, A. Yip, M. Fowler, S. B. Young and R. A. Fraser. “Environmental Feasibility of Re-Use of Electric Vehicle Batteries”. In: *Sustainable Energy Technologies and Assessments* 6, 2014, pp. 64–74.

[166] K. Richa, C. W. Babbitt, N. G. Nenadic and G. Gaustad. “Environmental Trade-Offs across Cascading Lithium-Ion Battery Life Cycles”. In: *The International Journal of Life Cycle Assessment* 22 (1), 2017, pp. 66–81.

[167] J. Groot. *State-of-Health Estimation of Li-Ion Batteries: Ageing Models (PhD Thesis)*. Göteborg: Division of Electric Power Engineering, Chalmers University of Technology, 2014.

[168] S. F. Schuster. *Reuse of Automotive Lithium-Ion Batteries: An Assessment from the Cell Aging Perspective (PhD Thesis)*. München: Fakultät für Elektrotechnik und Informationstechnik, Technische Universität München, 2016.

[169] L. Casals Canals, B. García Amante, F. Aguesse and A. Iturrondobeitia. “Second Life of Electric Vehicle Batteries: Relation between Materials Degradation and Environmental Impact”. In: *The International Journal of Life Cycle Assessment* 22 (1), 2017, pp. 82–93.

[170] S. Thein and Y. S. Chang. “Decision Making Model for Lifecycle Assessment of Lithium-Ion Battery for Electric Vehicle – A Case Study for Smart Electric Bus Project in Korea”. In: *Journal of Power Sources* 249, 2014, pp. 142–147.

[171] *Description of Load-Frequency Control Concept and Market for Control Reserves - Study Commissioned by the German TSOs (Ordered by 50Hertz Transmission GmbH)*. Aachen: Consentec, 2014.

[172] A. Thielmann, A. Sauer and M. Wietschel. *Gesamt-Roadmap Lithium-Ionen-Batterien 2030*. Bonn: Fraunhofer-Institut für System- und Innovationsforschung, 2015.

[173] M. Müller and A. Jossen. “Research Project - EEBatt - Distributed Stationary Battery Storage Systems for the Efficient Use of Renewable Energies and Support of Grid Stability”. In: *Batterieforum Deutschland*. Berlin, 2015.

[174] P. Nobis, S. Fischhaber, J. Habermann and F. Samweber. *e-GAP – Modellkommune Elektromobilität Garmisch-Partenkirchen*. München: Forschungsstelle für Energiewirtschaft, 2012.

[175] T. Staudacher and S. Eller. "Dezentrale Stromversorgung eines Einfamilienhauses". In: *BWK* 64 (6), 2012, pp. 38–45.

[176] E. Martinez-Laserna, E. Sarasketa-Zabala, I. Villarreal Sarria, D.-I. Stroe, M. Swierczynski, A. Warnecke, J.-M. Timmermans, S. Goutam, N. Omar and P. Rodriguez. "Technical Viability of Battery Second Life: A Study From the Ageing Perspective". In: *IEEE Transactions on Industry Applications* 54 (3), 2018, pp. 2703–2713.

[177] A. Regett and J. Bangoj. "Cost and Metal Savings through a Second-Life for Electric Vehicle Batteries". In: *ENERDAY 2019 - 13th International Conference on Energy Economics and Technology*. Dresden, 2019.

[178] A. Regett. "Using Dynamic Energy and Material Flow Analysis for Assessing the Potential of Circular Approaches to Reduce Resource Criticality (Presentation)". In: *12th Society and Materials International Conference (SAM)*. Metz, 2018.

[179] K. Richa, C. W. Babbitt, G. Gaustad and X. Wang. "A Future Perspective on Lithium-Ion Battery Waste Flows from Electric Vehicles". In: *Resources, Conservation and Recycling* 83, 2014, pp. 63–76.

[180] S. Ziemann, D. Ketzer, S. B. Young, M. Weil and W. R. Poganietz. "Increased Lifetime and Resource Efficiency in Electric Mobility - Linking Material Flow Analysis with System Dynamics". In: *4. Symposium Rohstoffeffizienz und Rohstoffinnovationen*. Stuttgart, 2017.

[181] P. Novinsky, S. Glöser, A. Kühn and R. Walz. "Modeling the Feedback of Battery Raw Material Shortages on the Technological Development of Lithium-Ion-Batteries and the Diffusion of Alternative Automotive Drives - A System Dynamics Approach". In: *32nd International Conference of the System Dynamics Society*. Delft, 2014.

[182] P. Stenzel, J. Linssen, M. Robinius and D. Stolten. "Trends of Stationary Battery Storage Systems in Germany – A Database Analysis (Presentation)". In: *Strommarkttreffen „Batterien: Kostenentwicklung, Technologien, Anwendungen"*. Berlin: Forschungszentrum Jülich, 2018.

[183] *Monitoringbericht 2017*. Bonn: Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen, 2017.

[184] J. Bangoj. *Rohstoff- und Kosteneinsparpotential von Second-Life-Anwendungen unter Berücksichtigung von Verdrängungseffekten auf stationären Batteriespeichermärkten (Master Thesis)*. München: Technische Universität München, Forschungsstelle für Energiewirtschaft, 2018.

[185] M. Müller, J. Reinhard, A. Ostermann, T. Estermann and S. Köppl. "Regionales Flexibilitätspotenzial dezentraler Anlagen - Modellierung und Bewertung des regionalen Flexibilitäts-Potenzials von dezentralen Flexibilitätstypen im Verteilnetz". In: *Zukünftige Stromnetze*. 2019.

[186] J. Figgener, D. Haberschusz, K.-P. Kairies, O. Wessels, B. Tepe and D. U. Sauer. *Wissenschaftliches Mess- und Evaluierungsprogramm Solarstromspeicher 2.0 - Speichermonitoring 2018*. Aachen: RWTH Aachen, 2018.

[187] E. Chiodo, D. Lauria, N. Andrenacci and G. Pede. “Probabilistic Battery Design Based upon Accelerated Life Tests”. In: *Intelligent Industrial Systems* 2 (3), 2016, pp. 243–252.

[188] *Marktübersicht Batteriespeicher*. Straubing: Centrales Agrar-Rohstoff Marketing- und Energie-Netzwerk, 2017.

[189] *Automotive Industry Portal MarkLines: Vehicle Sales Data*. 2018. URL: `www.marklines.com/en/vehicle_sales/search` (visited on 04/06/2018).

[190] *FZ10.1 Neuzulassungen von Personenkraftwagen nach Marken und Modellreihen im Dezember 2017*. Flensburg: Kraftfahrt-Bundesamt, 2018.

[191] G. E. Blomgren. “The Development and Future of Lithium Ion Batteries”. In: *Journal of The Electrochemical Society* 164 (1), 2017, A5019–A5025.

[192] *Residential PV Energy Storage Market Overview 2017*. Bonn: EuPD Research, 2018.

[193] *DOE Global Energy Storage Database*. Sandia National Laboratories. Albuquerque, Livermore, 2018.

[194] J. Laport. *Cobalt - Statistics & Facts*. 2018. URL: `www.statista.com/topics/2276/cobalt/` (visited on 09/28/2019).

[195] P. Ralon, M. Taylor, A. Ilas, H. Dias-Bone and K.-P. Kairies. *Electricity Storage and Renewables - Costs and Markets to 2030*. Abu Dhabi: International Renewable Energy Agency, 2017.

[196] T. Hettesheimer, A. Thielmann, C. Neef, K.-C. Möller, M. Wolter, V. Lorentz, M. Gepp and M. Wagner. *Entwicklungsperspektiven für Zellformate von Lithium-Ionen-Batterien in der Elektromobilität*. Pfinztal: Fraunhofer-Allianz Batterien, 2017.

[197] C. R. Stanridge and L. Corneal. *Remanufacturing, Repurposing and Recycling of Post-Vehicle-Application Lithium-Ion Batteries*. San Jose: Mineta National Transit Research Consortium, 2014.

[198] A. Kwade and G. Bärwaldt. *Abschlussbericht zum Verbundvorhaben Recycling von Lithium-Ionen-Batterien im Rahmen des FuE-Programms "Förderung von Forschung und Entwicklung im Bereich der Elektromobilität" - LithoRec*. Braunschweig: Technische Universität Braunschweig, 2012.

[199] L. Casals Canals, B. García Amante and M. Gonzáles Benítez. “A Cost Analysis of Electric Vehicle Batteries Second Life Businesses”. In: *18th International Congress on Project Management and Engineering*. Alcañiz, 2014, pp. 129–141.

[200] J. Neubauer, K. Smith, E. Wood and A. Pesaran. *Identifying and Overcoming Critical Barriers to Widespread Second Use of PEV Batteries*. Golden: National Renewable Energy Laboratory, 2015.

[201] P. Ralon, M. Taylor, A. Ilas, H. Dias-Bone and K.-P. Kairies. *Electricity Storage and Renewables: Costs and Markets to 2030 - Cost-of-Service Tool*. International Renewable Energy Agency. Abu Dhabi, 2017.

[202] M. Müller, L. Viernstein, C. N. Truong, A. Eiting, H. C. Hesse, R. Witzmann and A. Jossen. “Evaluation of Grid-Level Adaptability for Stationary Battery Energy Storage System Applications in Europe”. In: *Journal of Energy Storage* 9, 2017, pp. 1–11.

[203] P. Ekins, F. Kesicki and A. Z. P. Smith. *Marginal Abatement Cost Curves: A Call for Caution*. London: UCL Energy Institute, University College London, 2011.

[204] M. Buschle. *Implementation Potential of Circular Business Models for Electric Vehicle Batteries: Empirical Analysis of Barriers and Drivers from a Stakeholder Perspective (Master Thesis)*. München: Technische Universität München, Forschungsstelle für Energiewirtschaft, 2019.

[205] F. Ganser. *Methode zur Analyse von kreislaufwirtschaftlichen Geschäftsideen am Beispiel von Lithium-Ionen-Batterien aus Elektrofahrzeugen (Master Thesis)*. Mittweida, München: Hochschule Mittweida, Forschungsstelle für Energiewirtschaft, 2017.

[206] *regelleistung.net - Internetplattform zur Vergabe von Regelleistung*. 2019. URL: `www.regelleistung.net` (visited on 07/31/2019).

[207] T. Struck. *BMUB-Umweltinnovationsprogramm - Abschlussbericht zum Vorhaben Batteriekraftwerk zur Teilnahme am Primärregelleistungsmarkt*. Schwerin: WEMAG, 2016.

[208] *Market Data EPEX SPOT*. 2019. URL: `www.epexspot.com` (visited on 08/21/2019).

[209] M. Haller, D. Ritter, C. Loreck and F. C. Matthes. *EEG-Rechner (Version 3.4.26)*. Agora Energiewende, Öko-Institut. Berlin.

[210] T. Schwencke and C. Bantle. *BDEW-Strompreisanalyse Januar 2019 - Haushalte und Industrie*. Berlin: Bundesverband der Energie- und Wasserwirtschaft, 2019.

[211] P. Elsner and D. U. Sauer. *Energiespeicher - Technologiesteckbrief zur Analyse „Flexibilitätskonzepte für die Stromversorgung 2050“*. Aachen: Deutsche Akademie der Technikwissenschaften, 2015.

[212] U. Bürger. *Protokoll zum Besuch des Second-Life-Batteriesystems von Smart Power (Interview by M. Buschle und A. Regett)*. 2019.

[213] A. Regett, M. Buschle and M. Stuchtey. “Der Weg zu zirkulären Geschäftsmodellen für Elektrofahrzeugbatterien”. In: *Energiewirtschaftliche Tagesfragen* 69 (9), 2019, pp. 66–70.

[214] G. Bressanelli, F. Adrodegari, M. Perona and N. Saccani. “Exploring How Usage-Focused Business Models Enable Circular Economy through Digital Technologies”. In: *Sustainability* 10 (3), 2018, p. 639.

[215] S. Bobba, A. Podias, F. Di Persio, M. Messagie, P. Tecchio, M. A. Cusenza, U. Eynard, F. Mathieux and A. Pfrang. “Sustainability Assessment of Second Life Application of Automotive Batteries (SASLAB)”. In: JRC Technical Reports. Petten: European Commission, 2018.

[216] N. Jiao and S. Evans. "Business Models for Sustainability: The Case of Second-Life Electric Vehicle Batteries". In: *Procedia CIRP* 40, 2016, pp. 250–255.

[217] S. Bräuer. "They Not Only Live Once - towards Product-Service Systems for Repurposed Electric Vehicle Batteries". In: *Multikonferenz Wirtschaftsinformatik (MKWI)*. Ilmenau, 2016.

[218] R. Vanner, M. Bicket, M. Hestin, A. Tan, S. Guilcher, S. Withana, P. ten Brink, P. Razzini, E. van Dijl, E. Watkins and E. Hudson. *Scoping Study to Identify Potential Circular Economy Actions, Priority Sectors, Material Flows and Value Chains*. Luxembourg: European Commission, 2014.

[219] *Commission Staff Working Document on the Evaluation of the Directive 2006/66/EC on Batteries and Accumulators and Waste Batteries and Accumulators and Repealing Directive 91/157/EEC*. Brussels: European Commission, 2019.

[220] C. Moedas and K. Vella. *The Joint Declaration of Intent for the Innovation Deal on "From E-Mobility to Recycling: The Virtuous Loop of the Electric Vehicle"*. Brussels: European Commission, 2018.

[221] *The Environmental Footprint Pilots*. 2019. URL: www.ec.europa.eu/environment/eussd/smgp/ef_pilots.htm (visited on 10/09/2019).

[222] S. Pichlmaier, A. Regett and S. Kigle. "Dynamisation of Life Cycle Assessment Through the Integration of Energy System Modelling to Assess Alternative Fuels". In: *Progress in Life Cycle Assessment 2018*. Sustainable Production, Life Cycle Engineering and Management. Cham: Springer, 2019, pp. 75–86.

[223] B. Held et al. *A Vision for a Sustainable Battery Value Chain in 2030 - Unlocking the Full Potential to Power Sustainable Development and Climate Change Mitigation*. Cologny: Global Battery Allicance, World Economic Forum, 2019.

Publications of the Author

A. Regett, U. Wagner, W. Mauch and J. Bangoj. “Environmental Impact of Electric Vehicles: Potential of the Circular Economy?” In: *Der Antrieb von Morgen 2019*. Wiesbaden: Springer Vieweg, 2019, pp. 121–140.

A. Regett and J. Bangoj. “Cost and Metal Savings through a Second-Life for Electric Vehicle Batteries”. In: *ENERDAY 2019 - 13th International Conference on Energy Economics and Technology*. Dresden, 2019.

A. Regett, M. Buschle and M. Stuchtey. “Der Weg zu zirkulären Geschäftsmodellen für Elektrofahrzeugbatterien”. In: *Energiewirtschaftliche Tagesfragen* 69 (9), 2019, pp. 66–70.

F. Böing and A. Regett. “Hourly CO_2 Emission Factors and Marginal Costs of Energy Carriers in Future Multi-Energy Systems”. In: *Energies* 12, 2019, p. 2260.

S. Fattler and A. Regett. “Environmental Impact of Electric Vehicles: Influence of Intelligent Charging Strategies (Submitted)”. In: *Grid Integration of Electric Mobility - 4. Internationale ATZ-Fachtagung*. Mannheim, 2019.

S. Pichlmaier, A. Regett and A. Guminski. “Development of Application-Related Emissions in the Course of the German Energy Transition”. In: *11. Internationale Energiewirtschaftstagung (IEWT)*. Wien, 2019.

S. Pichlmaier, A. Regett and S. Kigle. “Dynamisation of Life Cycle Assessment Through the Integration of Energy System Modelling to Assess Alternative Fuels”. In: *Progress in Life Cycle Assessment 2018*. Sustainable Production, Life Cycle Engineering and Management. Cham: Springer, 2019, pp. 75–86.

J. Conrad, A. Regett, S. Fattler and F. Jetter. “Von statischen CO_2-Verminderungskosten zur dynamischen Bewertung von Klimaschutzmaßnahmen”. In: *Energiewirtschaftliche Tagesfragen* 69 (10), 2019, pp. 47–52.

J. Conrad, S. Fattler, A. Regett, F. Böing, A. Guminski, S. Greif, T. Hübner, F. Jetter, T. Kern, B. Kleinertz, A. Murmann, A. Ostermann, C. Pellinger, S. Pichlmaier, T. Schmid and S. von Roon. *Dynamis – Dynamische und intersektorale Maßnahmenbewertung zur kosteneffizienten Dekarbonisierung des Energiesystems – Abschlussbericht*. München: Forschungsstelle für Energiewirtschaft, 2019.

F. Böing, A. Regett, C. Kranner, C. Pellinger, S. Fattler and J. Conrad. *Das Merit-Order-Dilemma der Emissionen - Eine Diskussionsgrundlage zur klimapolitischen Debatte (Working Paper)*. München: Forschungsstelle für Energiewirtschaft, 2019.

B. Kleinertz, A. Guminski, A. Regett, A. Kessler, D. Gamze, J. Conrad, S. Fattler, S. Pichlmaier, E. Rouyrre and S. von Roon. “Kosteneffizienz von fossilen und erneuerbaren Gasen zur CO_2-Verminderung im Energiesystem”. In: *Zeitschrift für Energiewirtschaft* 43 (1), 2019, pp. 51–68.

B. Kleinertz, A. Guminski, A. Regett and J. Bangoj. “Coping with Drawbacks of Conventional CO_2 Abatement Curves - A Case Study on Fossil and Renewable Gases (Poster)”. In: *11. Internationale Energiewirtschaftstagung (IEWT)*. Wien, 2019.

A. Regett, F. Böing, J. Conrad, S. Fattler and C. Kranner. “Emission Assessment of Electricity: Mix vs. Marginal Power Plant Method”. In: *15th International Conference on the European Energy Market (EEM)*. Lodz, 2018.

A. Regett, C. Kranner, S. Fischhaber and F. Böing. “Using Energy System Modelling Results for Assessing the Emission Effect of Vehicle-to-Grid for Peak Shaving”. In: *Progress in Life Cycle Assessment*. Sustainable Production, Life Cycle Engineering and Management. Cham: Springer, 2018, pp. 115–123.

A. Regett, W. Mauch and U. Wagner. *Klimabilanz von Elektrofahrzeugen - Ein Plädoyer für mehr Sachlichkeit*. München: Forschungsstelle für Energiewirtschaft, 2018.

A. Regett. “Using Dynamic Energy and Material Flow Analysis for Assessing the Potential of Circular Approaches to Reduce Resource Criticality (Presentation)”. In: *12th Society and Materials International Conference (SAM)*. Metz, 2018.

A. Regett and S. Fischhaber. “Reduction of Critical Resource Consumption through Second Life Applications of Lithium Ion Traction Batteries”. In: *10. Internationale Energiewirtschaftstagung (IEWT)*. Wien, 2017.

A. Regett, S. Fischhaber and C. Kranner. “Environmental Saving Potential of Circular Approaches for Traction Batteries (Poster)”. In: *NTNU Sustainability Science Conference*. Trondheim, 2017.

M. Rasch, A. Regett, S. Pichlmaier, J. Conrad, A. Guminski, E. Rouyrre, C. Orthofer and T. Zipperle. “Eine anwendungsorientierte Emissionsbilanz - Kosteneffiziente und sektorenübergreifende Dekarbonisierung des Energiesystems”. In: *BWK* 69 (3), 2017, pp. 38–42.

J. Conrad, S. Greif, A. Regett and B. Kleinertz. “Evolution und Vergleich der CO_2-Bewertungsmethoden in Wärmepumpen (Presentation)”. In: *3. Dialogplattform Power to Heat*. Berlin, 2017.

A. Regett, A. Zeiselmaier, K. Wachinger and C. Heller. *Merit Ordner Netz-Ausbau 2030 - Teilbericht 1: Szenario-Analyse*. München: Forschungsstelle für Energiewirtschaft, 2017.

D. Goldner and A. Regett. “Circular Approaches for Permanent Magnets from Wind Turbines (Poster)”. In: *8th International Conference on Life Cycle Management (LCM)*. Luxembourg, 2017.

S. Fischhaber, A. Regett, S. Schuster and H. Hesse. *Second-Life-Konzepte für Lithium-Ionen-Batterien aus Elektrofahrzeugen - Analyse von Nachnutzungsanwendungen, ökonomischen und ökologischen Potenzialen - Ergebnispapier 18*. Frankfurt am Main: Begleit- und Wirkungsforschung Schaufenster Elektromobilität, 2016.

A. Regett and N. Köppel. “Die zirkuläre Energiewirtschaft - Potenziale der Kreislaufwirtschaft für die Windkraft”. In: *Energiewirtschaftliche Tagesfragen* 66 (7), 2016, pp. 39–42.

A. Regett, C. Heller, T. Mayer and J. Wind. “Einfluss des Strom- und Wasserstoff-Produktionsmixes auf die Well-to-Wheels-Bilanz elektrisch angetriebener Fahrzeuge”. In: *Energiewirtschaftliche Tagesfragen* 65 (12), 2015, pp. 83–86.

A. Regett and C. Heller. “Relevanz zeitlich aufgelöster Emissionsfaktoren für die Bewertung tages- und jahreszeitlich schwankender Verbraucher”. In: *Energiewirtschaftliche Tagesfragen* 65 (7), 2015, pp. 46–50.

A. Regett and C. Heller. “Emissions- und Primärenergiefaktoren im Stundentakt - Berücksichtigung von energiewirtschaftlichen Entwicklungen in der Ökobilanzierung”. In: *BWK* 67 (3), 2015, pp. 55–56.

Theses Supervised by the Author

M. Gunkel. *Entwicklung und Evaluierung einer Methodik zur Bewertung von Recyclingverfahren auf die Treibhausgasemissionen von Dünnschicht-Photovoltaik-Modulen unter besonderer Beachtung des Einsatzes kritischer Rohstoffe (Master Thesis)*. Magdeburg, München: Universtität Magdeburg, Forschungsstelle für Energiewirtschaft, 2019.

M. Buschle. *Implementation Potential of Circular Business Models for Electric Vehicle Batteries: Empirical Analysis of Barriers and Drivers from a Stakeholder Perspective (Master Thesis)*. München: Technische Universität München, Forschungsstelle für Energiewirtschaft, 2019.

J. Bangoj. *Rohstoff- und Kosteneinsparpotential von Second-Life-Anwendungen unter Berücksichtigung von Verdrängungseffekten auf stationären Batteriespeichermärkten (Master Thesis)*. München: Technische Universität München, Forschungsstelle für Energiewirtschaft, 2018.

C. Kranner. *Emissionsbewertung von industriellem Spitzenlastmanagement durch Traktionsbatterien in Elektrofahrzeugen unter Berücksichtigung des Merit-Order-Effekts (Master Thesis)*. München: Technische Universität München, Forschungsstelle für Energiewirtschaft, 2018.

F. Ganser. *Methode zur Analyse von kreislaufwirtschaftlichen Geschäftsideen am Beispiel von Lithium-Ionen-Batterien aus Elektrofahrzeugen (Master Thesis)*. Mittweida, München: Hochschule Mittweida, Forschungsstelle für Energiewirtschaft, 2017.

C. Töpfer. *Dynamic Material Flow Analysis of Lithium and Cobalt in the Context of a Second Life Concept for Electric Vehicle Batteries (Master Thesis)*. Cottbus-Senftenberg, München: Brandenburgische Technische Universität, Forschungsstelle für Energiewirtschaft, 2017.

D. Goldner. *Neodym-Einsparpotenziale durch Ansätze der Kreislaufwirtschaft für Permanentmagneten aus Windenergieanlagen (Master Thesis)*. München: Technische Universität München, Forschungsstelle für Energiewirtschaft, 2016.

C. Tardt. *Ökologische Bewertung von Second-Life Konzepten für Lithium-Ionen-Batterien aus elektrischen Fahrzeugen (Bachelor Thesis)*. Augsburg, München: Hochschule Augsburg, Forschungsstelle für Energiewirtschaft, 2016.

N. Köppel. *Identifikation von Potenzialen der Kreislaufwirtschaft zur Senkung der Rohstoffkritikalität permanenterregter Windenergieanlagen (Bachelor Thesis)*. München: Technische Universität München, Forschungsstelle für Energiewirtschaft, 2016.

C. Taylor. *Development of LCA Methodology for Incorporating Energy Market Developments into the Life Cycle-Based Assessment of Load Flexibilisation - A Case Study on Power-to-Chemistry (Master Thesis)*. München: Technische Universität München, Forschungsstelle für Energiewirtschaft, 2014.