Energieforschungsprogramm

Publizierbarer Endbericht

Programmsteuerung:
Klima- und Energiefonds

Programmabwicklung:
Österreichische Forschungsförderungsgesellschaft mbH (FFG)

Endbericht
erstellt am
21/12/2023

BetterBatteries

Machbarkeitsstudie für Second-Life-Batteriespeicher zur Erhöhung der Energieeffizienz und Netzstabilität

Feasibility study for second-life battery storages to increase energy efficiency and grid stability

Projektnummer: FO999896661

Ausschreibung	8. Ausschreibung Energieforschungsprogramm
Projektstart	01/11/2022
Projektende	31/10/2023
Gesamtprojektdauer (in Monaten)	12 Monate
ProjektnehmerIn (Institution)	Virtual Vehicle Research GmbH
AnsprechpartnerIn	Alois Steiner
Postadresse	Inffeldgasse 21a, 8010 Graz
Telefon	+43 (316) 873 - 9025
Fax	+43 (316) 873 - 9002
E-mail	alois.steiner@v2c2.at
Website	www.v2c2.at

BetterBatteries

Machbarkeitsstudie für Second-Life-Batteriespeicher zur Erhöhung der Energieeffizienz und Netzstabilität

Feasibility study for second-life battery storages to increase energy efficiency and grid stability

AutorInnen:
Alois Steiner (Virtual Vehicle)
Franz Pichler (Virtual Vehicle)
Jelena Rubesa-Zrim (Virtual Vehicle)
Lucas Winder (Virtual Vehicle)
Nuria Gonzalez Garcia (betteries AMPS)
Sophia Bauknecht (betteries AMPS)
Alexander Pommer (Grazer Energieagentur)
Maria Schweighart (Grazer Energieagentur)

Table of contents

1 Introduction

Batteries are of crucial importance for the optimal integration of renewable energies into the power grid. Specifically, decentralized energy storage systems - i.e., small energy storage systems - are very attractive for both grid operators and consumers: on the one hand, they are a very competitive solution for improving the coverage of the own energy demand by end users, and on the other hand, they can also help stabilize the power grid. A rapid expansion of these energy storage systems is crucial to meet the flexibility needs of a decarbonized power system. Especially given the planned energy transition in Europe, innovative storage and control concepts as well as the simultaneous strong expansion of renewable energies are essential to guarantee a stable energy supply and to reduce CO_2 and pollutant emissions.

While the demand for batteries for distributed energy storage is increasing, the electromobility sector will account for the largest share of the battery market. According to estimates for 2030, this sector will account for most of the battery demand, drawing about 85% of the total demand (see **Figure 1**).

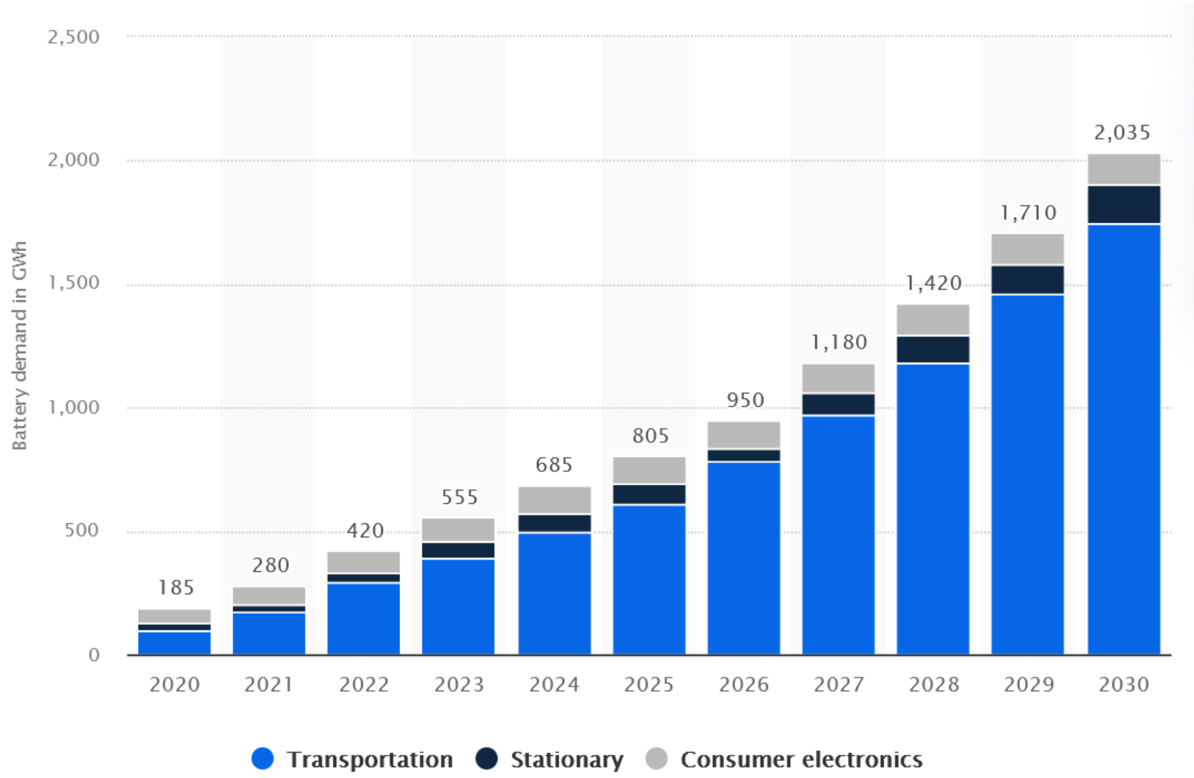


Figure 1: Global battery demand forecast [1]

Competing sectors in the sourcing of battery technology raise the question of whether the availability of raw materials can meet demand. The EU has set itself the goal of creating a competitive, sustainable, and circular battery value chain in Europe by 2030. In this context, second-life batteries are expected to play a crucial role.

Figure *2* shows the value chain for the repurpose of batteries for stationary storage applications [2].

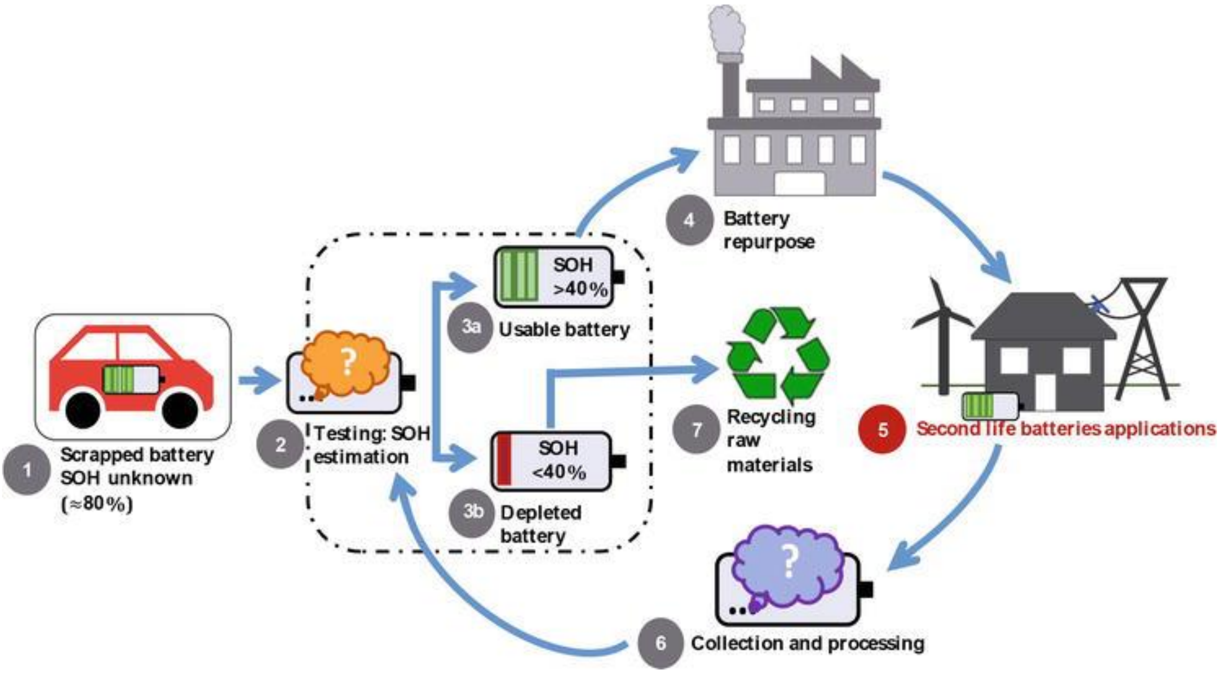


Figure 2: Value chain for the reuse of batteries [2]

Electric vehicle batteries will be phased out after about 10 years, at which point they will no longer be able to meet the stringent requirements for continuous charge/discharge cycles and range, even if these batteries still have about 70-80% of their original capacity. According to an IEA scenario "EV30@30" global EV sales are expected to reach 44 million e-vehicles per year by 2030. The supply of second-life batteries could thus exceed 200 gigawatt hours per year by 2030 [3].

The repurpose (I.e. using those batteries for a different use case from the 1st-life one) of these discarded EV batteries can bring benefits to the stationary energy storage market in applications that have lower demands. Second-life batteries offer a great opportunity for the energy sector to accelerate the integration of renewable energy into the grid while reducing the costs at the same time

However, the following problems are currently still preventing the wider market introduction of second-life batteries:
- Low volumes of 2nd-life batteries available, as only the very first EV that were on the roads by 2012-2015 are reaching now their end-of-life
- Lack of measurement data/field data of second-life batteries
- Lack of standard procedures enabling a profitable remanufacture of the battery car pack
- Lack of evidences on SOH degradation during 2nd-life (I.e. later stages of degradation)
- Current aging models focus on the early stages of degradation (i.e., first life)

- Challenge to understand second-life behavior without access to first-life data
- From a computational point of view, solving an electrochemical model that considers different mechanisms and the interactions between them is very complex - machine learning can generate significant advantages here

1.1 Main focus of the project

In this exploratory project, a technical, commercial, as well as financial feasibility study was conducted to establish the basis for using second-life batteries for specific stationary storage applications. For this purpose, a concept for a design tool for second-life battery storage was developed to select suitable battery cells or battery modules. The suitability depends on the aging mechanisms of the respective cells. Therefore, approaches for modeling cell aging for different battery types and battery materials were investigated and selected in this project. Further, with the help of system simulations, a defined use case for fast charging stations with a limited grid connection capacity was investigated. In parallel to the described modeling and simulation activities, approaches for a life cycle analysis (LCA) and total cost of ownership (TCO) considerations were carried out.

1.2 Relation to the work program

The project BetterBatteries contributes to the following points of the program:
- the targeted (further) development of technologies, components, and plants as well as their system integration
- the preservation and expansion of Austria as an industrial and business location by reducing the energy and CO_2 intensity of our actions
- Program goal 1:
Grand Challenges: Energy research at the center of major societal challenges

1.3 Content of this project report

This project report describes in Chapter 2 the results and conclusions of the BetterBatteries project with the following subchapters:

- 2.1 Literature study and selection of modeling approaches for cell aging
- 2.2 Concept for a design tool for second-life battery storages
- 2.3 Selection and simulation of use cases for second-life battery storages
- 2.4 Approaches for LCA and TCO for second-life battery storage systems

Afterwards, in Chapter 3, an outlook on further activities as well as recommendations will be given.

2 Results and conclusions

Currently, second-life car batteries are preferably used for larger applications in the industrial sector (storage capacity in the MWh range) for grid stabilization, peak shaving, or as energy storage for the improved use of renewable energies. By oversizing or redundant modules, the drop in efficiency of second-life batteries or the failure of a cell or module does not pose a problem. The challenge, however, is to optimize the system to minimize this oversizing – and thus reduce costs – as well as to achieve a balance between the installed capacity and the expected aging.

For the best possible dimensioning of battery storages in general, it is also necessary to simulate the use case based on historical data (energy consumption, energy generation, load profiles). This requires automatic or semi-automatic planning tools for various applications (PV self-consumption optimization, peak load capping, provision of balancing energy, possibly also in combination), which are based either on individual load profiles or – if not available – standard load profiles scaled to the total annual consumption.

<u>In this project, two important aspects of second-life batteries are considered:</u>

1. Understanding aging beyond SOH = 70% (I.e. having lost 30% of the initial capacity)- something that has not been the focus of many research projects so far - is crucial to understand the degradation mechanisms at this stage and operating the batteries according to their requirements.

2. Implementing data-driven pre-qualification of battery modules. While access to first-life data is the best strategy to classify these modules, new physics-based or data-driven tools can provide answers to understand the key parameters at the end of the first life- and determine the second-life. This can drastically reduce the need for expensive and time-consuming battery characterization testing, which in turn is critical to the economics of SLBs.

In the following sub-chapters, the main results of the BetterBatteries project are described in detail.

2.1 Literature study and selection of modeling approaches for cell aging

During the project execution, an extensive literature research was carried out to identify the following **four crucial aspects** to define a **concept for a battery design tool**:

2.1.1 Existing battery design tools

The existing, publicly available, battery design tools were examined and classified as a function of the criteria considered relevant in line with the project objectives. Those criteria include the following parameters (**Table 1**):

- **Battery models** available to simulate the battery performance, which includes equivalent circuit models – to simulate the response of the battery to an applied current, thermal model – to reproduce the different heat transfer processes within the system, and aging model – to simulate the loss of capacity during the battery lifetime.
- **Application level**, which includes the different system levels that the tool considers. From cell to module or pack level, each software (SW) enables different system-level modeling.
- **Cost** is an important factor to be considered.
- **Flexibility** refers to the level of modification/tailoring enabled by the tool.

Name	Description	URL	Solves	Application Level	Cost
Ansys	battery simulation gets the results you need from electrochemistry to electrode, cell, module, pack and system and the coupling of different physics	https://www.ansys.com/en-gb/applications/battery	electrochemical, electrical, thermal, mechanical, safety, control	Chemistry, Cell, Module, Pack	$$$
BatPac	A Spreadsheet Tool to Design a Lithium Ion Battery and Estimate Its Production Cost	https://www.anl.gov/cse/batpac-model-software	electrical, financial	Pack	Free
BEST	software environment for the physics-based three-dimensional simulation of lithium-ion batteries	https://www.itwm.fraunhofer.de/en/departments/sms/products-services/best-battery-electrochemistry-simulation-tool.html	electrochemical	Chemistry	?
CAEBAT	NREL has developed software tools to help battery designers, developers, and manufacturers create affordable, high-performance lithium-ion (Li-ion) batteries for next-generation electric-drive vehicles (EDVs).	https://www.nrel.gov/transportation/caebat-modeling-design.html	electrical, thermal, electrochemical, safety	Cell, Module, Pack	?
cideMOD	solves DFN physicochemical equations by Finite Element methods using FEniCS library. It enables doing physics-based battery simulations with a wide variety of use cases, from different drive cycles to characterization techniques.	https://github.com/cidetec-energy-storage	electrochemical, electrical, thermal	Chemistry, Cell	Free

Comsol	The Battery Design Module is an add-on to the Multiphysics software that encompasses descriptions over a large range of scales, from the detailed structures in the battery's porous electrode to the battery pack scale including thermal management systems.	https://www.comsol.com/battery-design-module	electrical, thermal, electrochemical	Chemistry, Cell, Module	$$$
DandeLiion	an ultra-fast solver for electrochemical models of planar lithium-ion cells and thermal-electrochemical models of three-dimensional composite pouch cells. It solves models of the form first described by Doyle, Fuller, and Newman	https://www.dandeliion.com/	electrochemical, electrical, thermal	Chemistry, Cell, Module	Free
GT-AutoLion	used by cell designers and OEMs to predict performance, degradation, and safety for any Lithium-ion cell. It predictively models the electrochemical processes within Lithium-ion cells using a fast and reliable, electrochemical, physics-based approach	https://www.gtisoft.com/gt-autolion/	electrochemical, thermal, electrical, safety	Chemistry, Cell, Pack	?
Mathworks SimScape Battery	create digital twins, run virtual tests of battery pack architectures, design battery management systems, and evaluate battery system behavior across normal and fault conditions.	https://uk.mathworks.com/products/simscape-battery.html	electrical, thermal, control	Cell, Module, Pack	$$
MPET	simulations of batteries with porous electrodes using porous electrode theory, which is a volume-averaged, multiscale approach to capture the coupled behavior of electrolyte and active material within electrodes	https://pypi.org/project/mpet/	electrochemical	Chemistry	Free
MSMD	The expandable, modular, and flexible architecture connects the physics of battery charge/discharge processes, thermal control, safety, and reliability in a computationally efficient manner.	https://www.nrel.gov/transportation/msmd.html	electrochemical, electrical, thermal, safety, control	Chemistry, Cell	?
PyBaMM	solves physics-based electrochemical DAE models by using state-of-the-art automatic differentiation and numerical solvers.	https://www.pybamm.org/	electrical, thermal, electrochemical, control	Cell, Chemistry	Free
Simcenter STAR-CCM+	a multiphysics computational fluid dynamics (CFD) software for the simulation of products operating under real-world conditions	https://www.plm.automation.siemens.com/global/en/products/simcenter/STAR-CCM.html	electrical, thermal, mechanical, electrochemical	Chemistry, Cell, Module, Pack	$$$

Table 1: Analysis of Battery Modeling tools available in the market [5]

After the analyzation of the design tools listed in Table 1 on the basis of the features listed above, it can be **concluded** that most of them do not incorporate an aging model for the batteries. If they do, they only consider the very early stages of the aging curve (i.e., SOH > 80%). In addition, a tool enabling the design of a battery based on used cells could not be found. A big difficulty in this analysis was that most of those tools – especially the commercial ones – are designed as black boxes, offering very reduced information to the user on the specific models incorporated, especially concerning the parametrization process. In line with these difficulties, it can be also concluded that tailoring existing tools to incorporate new features aligned with the needs is not an option.

2.1.2 Existing battery datasets

Having a good set of data is key to develop a battery model that optimally reproduces battery behaviour. As gathering data is not only time-demanding but expensive, using existing datasets is an opportunity to accelerate the development and reduce costs. To this end, a detailed bibliographic search on existing battery aging databases was done. The used dataset literature is listed in Chapter 5, i.e., [6-24]. The objective is to understand the availability of data from the literature to optimally design our data-gathering strategy and cover the existing gaps. The available databases were analyzed following these criteria:

- Cell type, including form (cylindrical, pouch, etc.), size (in capacity [Ah]), and chemistry.
- Testing conditions, which include aging tests (charge/discharge), the influence of temperature, and SOC.
- Data recorded: raw data that has been recorded in a time-series manner, e.g., current, voltage, cell temperature, etc.
- Information on battery status such as internal resistance, nominal capacity, etc.
- Number of cells tested per experimental setup.
- Publication date.
- Available file format, which is crucial to understanding how to feed the data in any battery aging model platform.
- License agreement, which describes the way to share, modify, and use a database, e.g., ODbl (Open Database license), CC (Creative Commons license).

The analysis is summarized in **Table 2**.

Repository	Comment
Mendeley	Contains many datasets from many sources all include literature.
Zenodo	Several Li-ion datasets can be found, not as many as Mendeley.
BatteryArchive	Contains datasets from six sources. The datasets are very large
Dryad	Repository very alike to Mendeley, not as large.
4TUReaserchData	Datasets referenced in other repositories.
Gonçalo dos Reis et al.	A paper with many references and sources for Li-ion battery datasets.

Table 2: Comparison of available Li-ion battery dataset sources

The **conclusion** is that most of the aging data available does not include the later degradation stages (i.e., SOH < 70%). There are however some specific datasets focusing on the knee point (i.e., the so-called “end-of-life"). A big challenge is the lack of open data on battery cells used in electric vehicles. This is a huge barrier when it comes to training or parametrizing any developed battery aging model as most of the data required would need to be generated on our own. The additional challenge linked to using EV batteries is the difficulties in generating cell data. While manufacturers provide cell data, there is not cell data available when it comes to lower SOH due to commercial agreements banning the disassembly of battery modules. This turns into a big challenge when it comes to parametrizing an electrochemical model that aims at reproducing cell behaviour.

2.1.3 Battery aging mechanisms

The number of electrochemical and physical processes occurring inside a battery cell is huge. The challenge arises not only from identifying them but especially from determining when they play a role and how they influence each other. While at the early stages of battery degradation (i.e., 1st life) only one or two mechanisms are relevant (Solid Electrolyte Interface (SEI) formation and Li plating [25]), at later stages more mechanisms must be included to accurately reproduce battery aging. The multitude of possible interactions between degradation mechanisms creates a maze of possible paths for a Li-ion battery, see **Figures 4 and 5.**

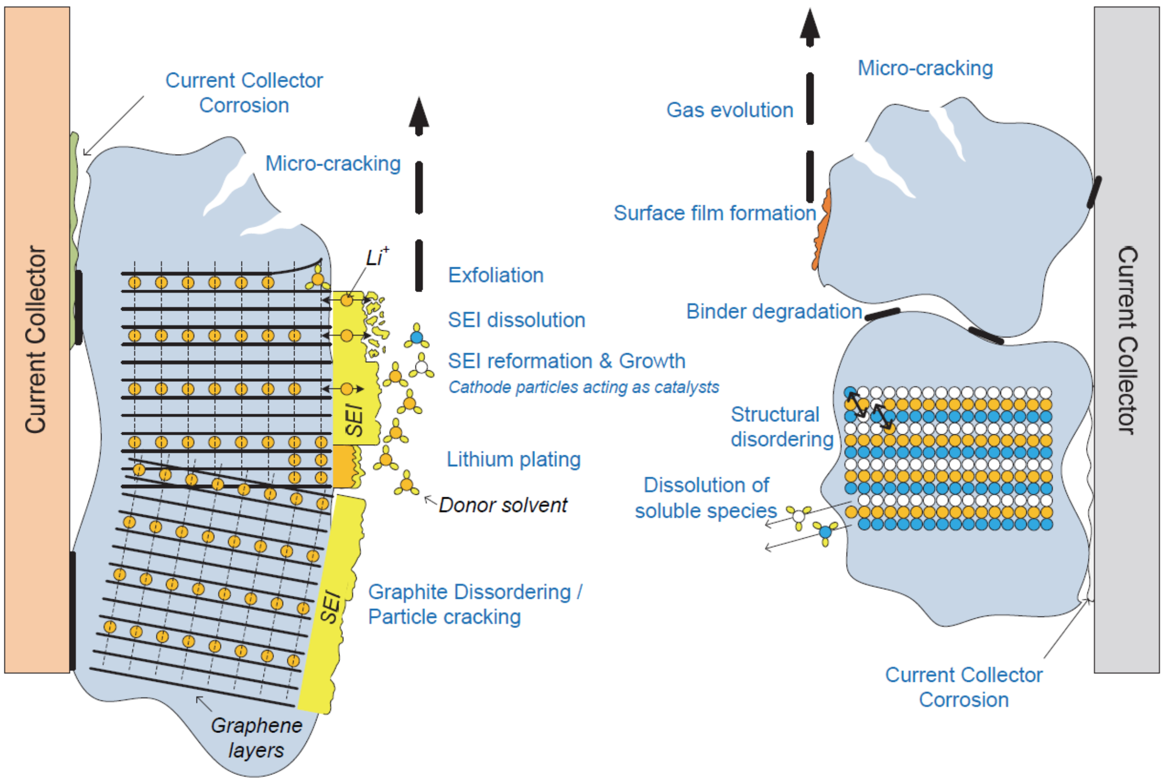


Figure 4: Degradation mechanisms occurring in Li-ion batteries [25]

After a detailed analysis of the multitude of electrochemical processes occurring inside battery cells that affect their state-of-health, it can be concluded that to accurately model second-life aging a wider range of degradation mechanisms beyond SEI formation and Li-plating must be considered. In addition, interdependence between those must also be analyzed. This poses a huge challenge to the modeling task, as the computational requirements – as well as data availability – are a relevant challenge to be analyzed in more detail.

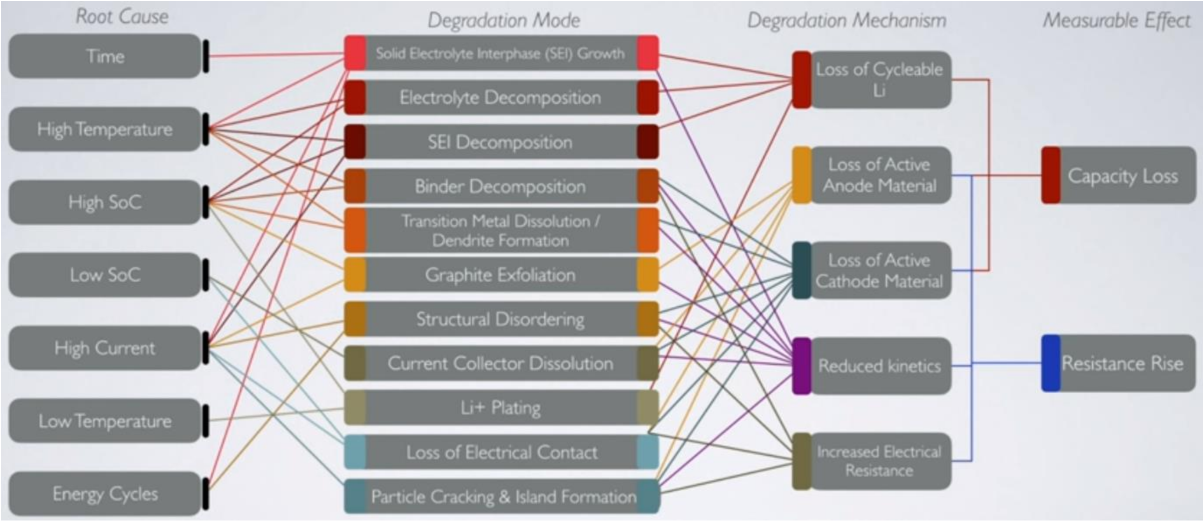
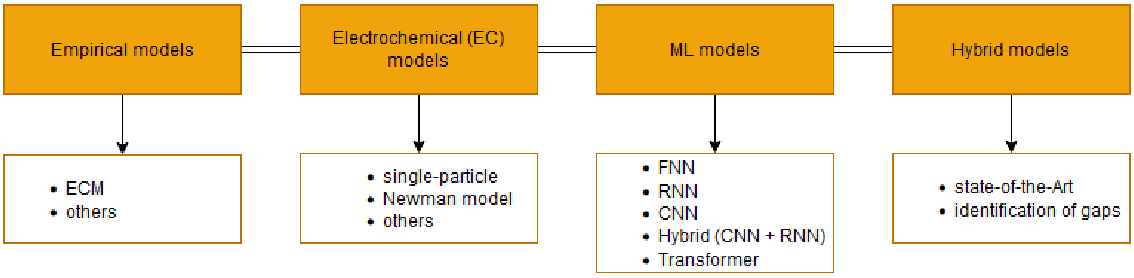


Figure 5: Degradation mechanisms occurring in Li-ion batteries [26]

2.1.4 Battery aging models

There is a wide range of available model types that reproduce the behavior of batteries with varying degrees of accuracy. **Figure 6** shows a diagram of the most common battery models used both in research as well as industrial fields.

Figure 6: Most common battery models in the literature



- Commercial BMS and monitoring tools for big battery systems rely on ***empirical models***, and more specifically, on equivalent circuit models (ECM).
- ***Electrochemical (EC) models*** are widely used in research works due to their high accuracy and ability to reproduce different aging mechanisms with their physical meaning. However, due to the high computational costs and data needs, they are not used in industrial applications.
- ***Data-driven (ML and DL) models*** have been widely investigated to increase the accuracy of battery models, although those models are "**data-hungry"**. Feed-forward Neural Networks (FNN) are very simple networks, but they are often used as a baseline for comparison. In **Table 3** the neural network architectures with respect to their types are listed.
- **Hybrid models.** A new research field, at the edge between EC models and machine learning (ML) is arising, and it is expected to enable moving the EC models "out of the lab".

Type	Neural Network
RNN	e.g., LSTM, GRU
CNN	e.g., ResNet, Inception
Hybrid (CNN + RNN)	e.g., ConvLSTM, ResNetLSTM
Transformer	e.g., Informer

Table 3: Neural network types and architectures

Thus, there is a clear gap between models used in research projects and simple equivalent circuit models embedded in commercial BMS. In addition, there are various ways to classify battery aging models, but overall, they can be classified as:

- **Physics-based models**
- **Data-driven models**
- **Hybrid models**

Benefits and drawbacks of each of the model classes are collected [27, 28, 29] and presented in **Figure 8**.

Model/physics-based	Data-driven methods	Hybrid
• **Electrochemical** (reactions, diffusion, conc. changes in electrode/electrolyte…) 1. Doyle-Fuller-Newman (DFN) precise Comp. Complexity →MOR 2. Single particle model (SPM) Fast Accurate only below 1C • **Equivalent circuit (RC)** Fast Electical circuits Missing **hysteresis** dynamics Accurate only below 1C	• **AI** (CNN, RNN, Particle swarm optimization) Learing from measurement data Extract Input-output relationship Fast and not complex Train requires large amounts of high-quality data Poorly interpreted black-box models Lack generalizability Risk producing physically unreasonable or incorrect prediction Even satisfactory training accuracy is often not accurate enough in test Problem of NN parameter identification o E.g, PSO to optimize initial weights • Filtering • Statistical	• Combination of different (same or diff. Kinds) methods Most research on lab data (2) Single-cell level Models are complex Require high par. accuracy 1. Use NN to **learn relationships** that are not physically meaningful 2. Use NN **to correct** the learning of model-based method

Figure 8. Benefits and drawbacks of the battery aging classes

The class “hybrid” is highly promising and involves the merging of physics-based models with ML approaches and is a new research field that must be explored.

2.1.5 Conclusions

In the field of battery design tools, it becomes evident that most existing tools do not incorporate a comprehensive aging model for batteries. In the few cases where such models are present, they tend to focus exclusively on the early phases of aging. Unfortunately, the available design tools are often built like **black boxes**. Therefore, they lack the required insights on the conditions and assumptions used in their methodology. Modifications or extensions of these existing battery design tools are thereby impractical.

In the case of existing databases, a similar pattern emerges. While some datasets exist with a specific focus on the "knee point" data for battery cells, databases commonly lack information about the later stages of battery degradation and fail to provide data on second-life batteries. Up to now, there is almost **no data available for batteries used in electric vehicles (EVs)**.

First-life battery aging models often incorporate surface film formation mechanisms like SEI (Solid Electrolyte Interface) formation and Li-plating. However, a wider range of degradation mechanisms, such as mechanical changes (particle cracking, gas formation), bulk material changes (structural disordering), and parasitic reactions (binder degradation, localized corrosion) must be included to accurately model second-life aging. Additionally, it is crucial to analyze the interdependencies between these aging mechanisms for a holistic understanding. However, the incorporation of all these degradation mechanisms would lead to very complex and computationally-expensive aging models. A discrepancy towards commercially available models is thereby formed. To bridge this gap, physics-based models merged with Machine Learning (ML) approaches should be explored.

2.2 Concept for a design tool for second-life battery storages

As a result of this detailed analysis as well as thanks to the work carried out in other WPs, a first draft for the design tool - shown in **Figure 9** - was prepared.

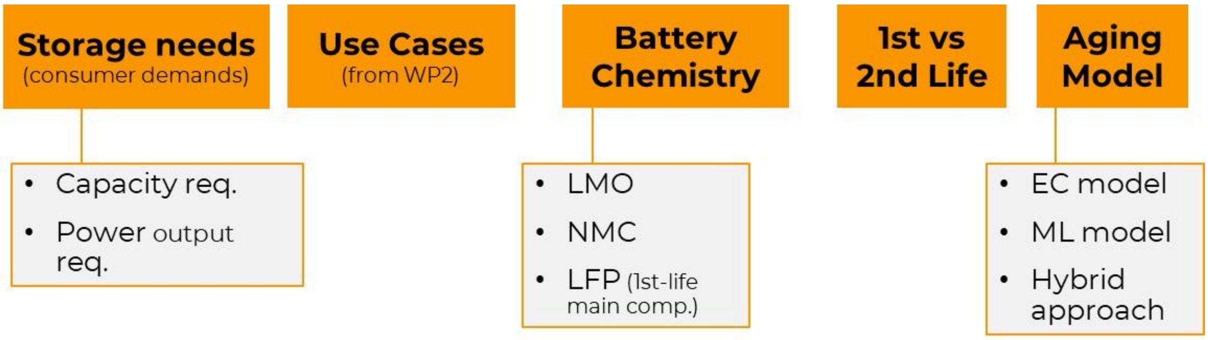


Figure 9: Diagram of the proposed battery design tool

Details related to the different parameters are listed in the following:

1. **Storage needs.** The design tool should include a first stage in which the user can provide the following details:
    - Expected capacity requirements, in Ah / kWh
    - Required power output, in kW
2. **Use cases.** The following use cases have been selected after the analysis carried out in WP2:

- Disaster relief – temporary installations of mobile batteries for off-grid power supply incl. response to natural disasters (i.e., earthquakes, …) etc.
- PV Storage – for self-consumption optimization
- EV charging stations **–** to provide fast charging capabilities in the context of weak grids

3. **Battery Chemistry.** Considering the current EV market, NMC and LFP are expected to be the dominant chemistries in the second-life battery market. Also LMO will be included as the battery chemistry that was used in the first electric vehicles in the market.

4. **1st vs 2nd life**. The tool must consider the most important aging effects of second-life batteries. It is relevant to highlight here the difficulties in finding second-life battery data in the literature. Most of the data does not reflect the later stage of aging.

5. **Aging model.** Depending on the purpose of the analysis, the end user may be interested in a detailed electrochemical simulation, a black-box one purely data-driven, or a combination of both.

In addition, the design tool will contain economic aspects enabling the end user to compare different storage options:

1. **Expected lifetime:** during operation, temperature and current are the most crucial parameters determining a battery's lifetime. In idle mode (i.e., when the energy is not withdrawn from the battery) SoC and storage temperature are the parameters playing a relevant role in battery lifetime.

2. **CAPEX:** initial investment linked to the battery acquisition. Here different prices must be considered by the simulator depending on the battery chemistry (LFP vs NMC) and whether it is a new or a second-life battery. Also, the need for oversizing will play a role in the initial design – different options can be considered in which the C-rate (i.e., the "speed" at which a battery is charged/discharged) plays a central role.

3. **OPEX:** maintenance costs must be also part of the simulation, as they strongly depend on the original battery design. While a smaller battery can reduce CAPEX, this can turn into higher OPEX due to faster aging.

The analysis carried out has identified OPEX (Operational costs) as the most relevant factor determining the price per kWh of storage for longer operating periods. To this end, a reliable aging model will provide crucial data to assess the expected lifetime of the batteries under different scenarios.

2.3 Selection and simulation of use cases for second-life battery storages

In the BetterBatteries project, potential on- and off-grid applications were collected through literature review and joint brainstorming sessions. These were later split into several application scenarios and end-user groups. The elaborated use cases are shown in the matrix depicted in **Figure 3**.

		End-user-group				
		Companies: industry (permanent)	Companies: construction sites (temporary)	real estate applications (e.g. shopping centers, multi-family-houses; medium-to-large-houses)	E-charging-provider	fire brigades and similar organisations (e.g. "Technisches Hilfswerk")
On-grid	Peak-Shaving	X	X (particularily in case of weak grids)	X	X (particularily in case of weak grids)	-
	Photovoltaics (self-consumption optimization)	X	-	X	X	-
	CHP	X	-	X	-	-
Off-grid	mobile primary power, e.g. desaster relief, festivals	-	X	-	X	X
	microgrid (in combi with PV, wind, biogas	-	X	X	-	-
E-mobility applications (weak grid)	EV charging stations for fast charging + weak grid or limited capacity or stability issues	X	-	X	X	-

Preferred use-cases for further analysis
Priority use-cases / end-user-groups for Betteries

Figure 3: Matrix of various battery systems with 4 preferred use cases for further analysis

Finally, the following four use cases were chosen to focus on:

- On-grid:
  - Peak-shaving for companies (construction sites - temporary)
  - Photovoltaics for real estate applications
- Weak grid/Off-grid:
  - Mobile primary power for fire brigades and similar organizations
  - Weak grid e-mobility applications for e-charging providers

For each of the selected four use cases, a value proposition was carried out to summarize convincing arguments as to why someone should choose a second-life battery storage. **Figure 4** shows an example for the value proposition for the use case "EV fast charging stations for fast charging and weak grid". On the right side, it shows the gains, pains, and the job, which has to be done and on the left side the gain creators and pain relievers of the product or service are described. In total, there were a lot of pros and cons for each of the use cases.

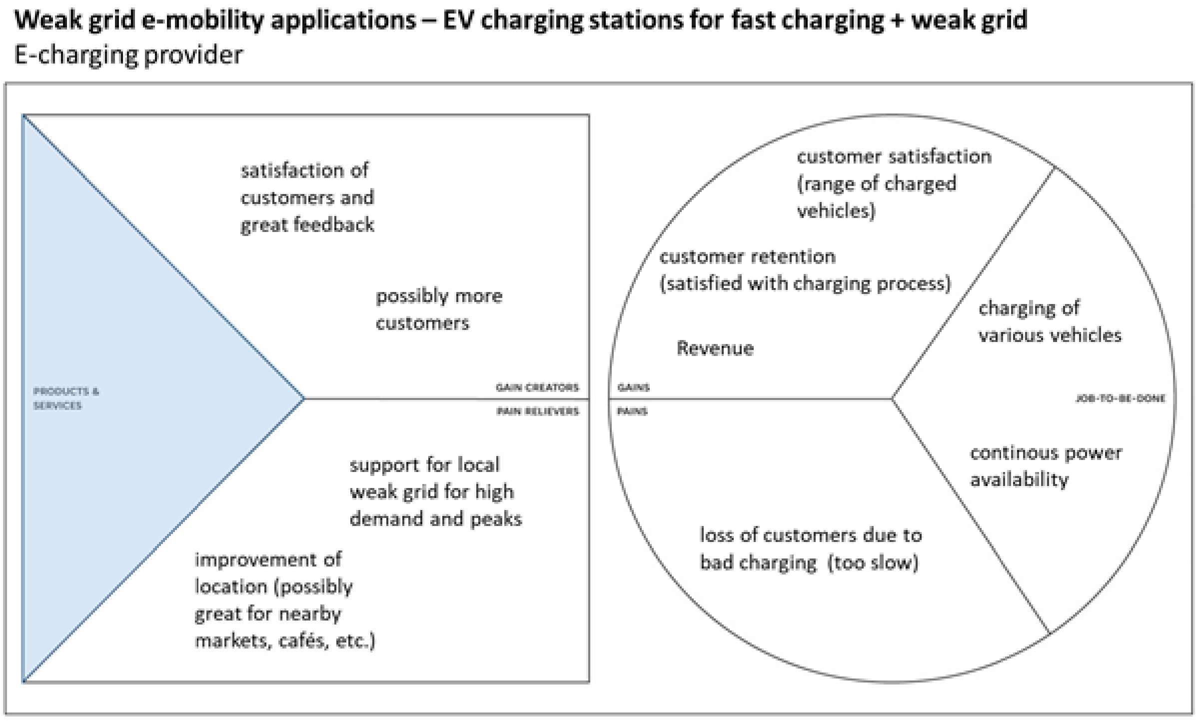


Figure 4: Use case 4 – E-charging provider (weak grid)

This use case "EV fast charging stations for fast charging and weak grid" was also chosen for a deeper investigation by means of simulations based on the decision matrix explained previously. **Figure 5** depicts a scheme of the selected use case that was investigated in simulation.

It is a weak grid application with the intention to enable the installation of fast charging points, where the grid power is insufficient for the fast charging needs. Due to the fact that the charging points are not occupied all the time and thus strongly depending on the user behavior, the average power needed is significantly lower than the maximum power which is required for fast charging. Thus, the battery storage acts as a buffer to cover the power needs during peak hours.

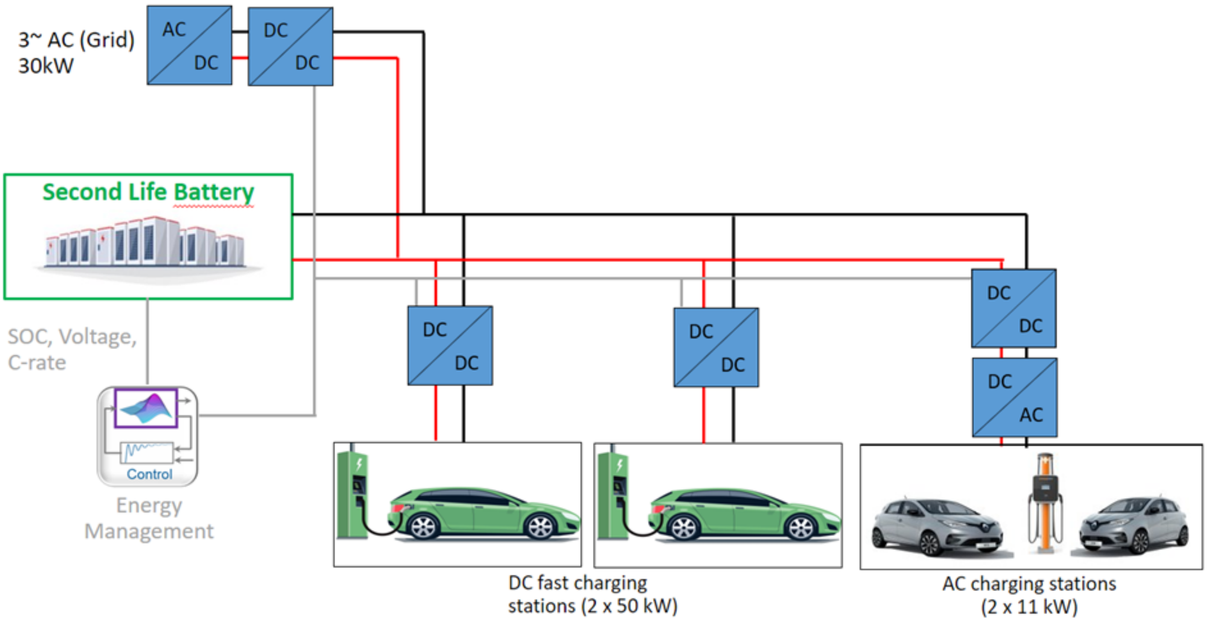


Figure 5: Schematic of selected use case "fast charging station for weak grid"

A second life battery storage is connected to the grid as well as to two DC fast charging points and two AC charging points with 50 kW and 11 kW peak power each, respectively. The maximum power provided from the grid is 30 kW. Based on the maximum power requirement of 122 kW from the charging points and a C-rate limitation of 0.5 C, the capacity of the battery storage was defined with 240 kWh with the intention of a less demanding second life for the battery in terms of C-rates compared to the first life during the operation in a vehicle. This general setup leads to a power of 120 kW that can be provided from the battery storage when neglecting energy losses.

A simulation model that includes the grid as well as the battery pack and the charging stations was built up in Matlab Simscape using the Simscape Electrical and Simscape Battery toolboxes (see **Figure 6**). Although the model worked properly, two issues had to be faced. First, the simulation speed was not faster than real time. Given that one objective of the project is to investigate the aging mechanism of second-life batteries and thus years of operation need to be simulated, the simulation speed needs to be increased dramatically. Second, Matlab Simscape was continuously writing simulation data to the RAM storage, which caused a memory overrun after a simulation time of less than a day. As one of the reasons for this issue the buck converter was identified. The fast switching operations of the controller lead to rapid changes in the system variables and make small time steps necessary. Another reason is the grid model itself with oscillations in the grid frequency. To address this issue, a simplification of the model seems to be inevitable. Since the focus of the project lies on the behavior of the second life battery, a simplification of the power electronics (AC/DC and DC/DC converters) is suggested for the follow-up activities. Nevertheless, it has to be ensured that all factors which influence the aging of the battery are considered.

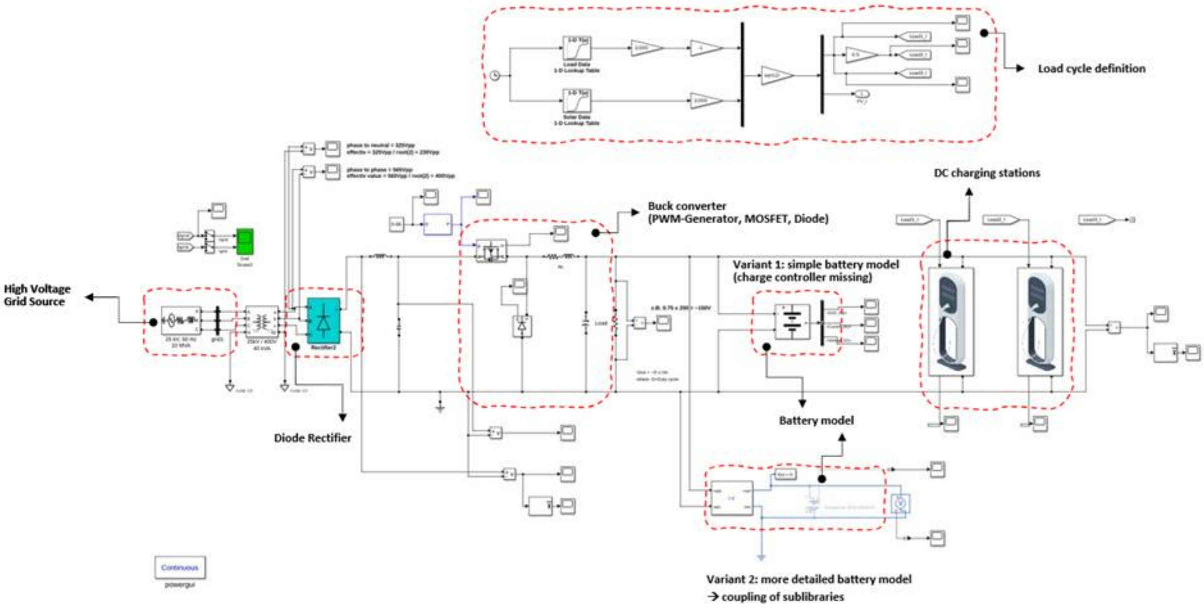


Figure 6: Matlab Simscape model

2.4 Approaches for LCA and TCO for second-life battery storage systems

This chapter shortly describes the conducted work related to approaches for life cycle analysis (LCA) as well as total cost of ownership (TCO) for second-life battery storage systems.

2.4.1 Life cycle analysis

A life cycle analysis refers to a structured investigation of the potential environmental impact and energy balance of a product over its entire life cycle. Before the analysis begins, the system boundaries need to be defined, whereby different boundaries are useful depending on the product and the objective of the analysis.

The life cycle analysis includes all environmental impacts during the production, use phase, and disposal of the product as well as the associated upstream and downstream processes (e.g., the production of raw materials, auxiliary materials, and operating materials). Environmental impacts include all relevant resource extractions from the environment (e.g., ores, crude oil) as well as emissions into the environment (e.g., waste, carbon dioxide emissions). **Figure 7** shows the life cycle of battery systems with the four additional pathways that are necessary for an efficient circular economy approach [4]. In the BetterBatteries project, simple approaches for each of these different stages of the lifecycle have been collected and documented.

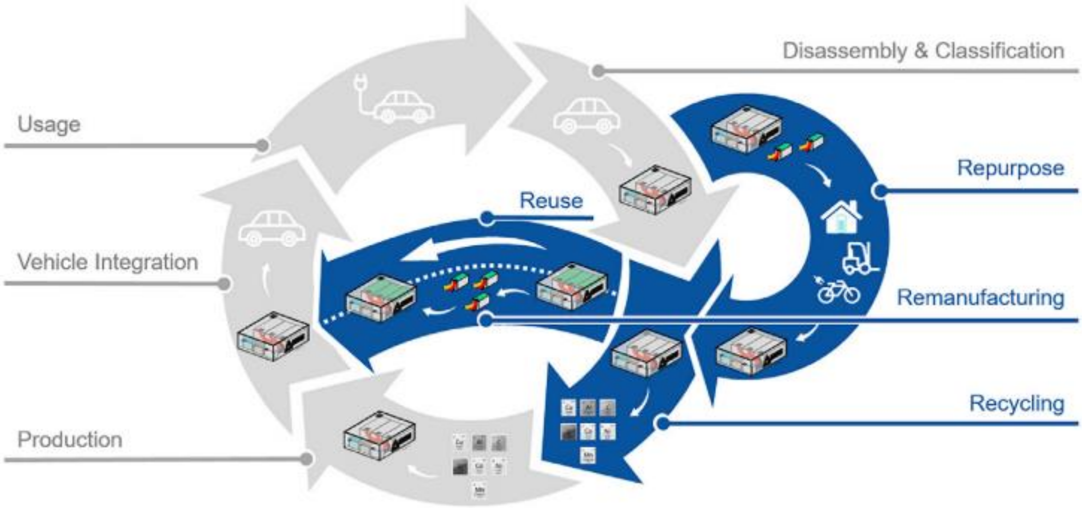


Figure 7: Life cycle of battery systems [4]

Related to environmental aspects, the following approaches for the calculation of the CO_2-emissions have been considered as most relevant:

a) **Cradle to gate:** It refers to the assessment of the environmental impacts of a product from the moment of its production until the moment it leaves the factory gate. To differentiate between new and second-life batteries, it is important to take into account the GHG emissions embedded in a battery cell, mostly linked to the manufacturing process.

b) **Gate to grave**: It refers to the distribution, storage, use, and disposal or recycling stages in this case, the use case will determine the CO_2 savings. Transportation is a crucial factor to be considered and minimized.

For the follow-up activities, it is planned to establish a CO_2 calculator for these scenarios.

2.4.2 TCO for first and second life batteries

In the following an exemplary total cost of ownership calculation for first and second life batteries has been conducted. Therefore, research has been done to determine figures for Capital Expenditures (CapEx) as well as Operational Expenditures (OpEx).

CapEx for a first-life battery system:

Current market prices of first-life battery storages in the range of 240 kWh were determined by doing research and obtaining quotes. Based on that, a best-case scenario of 900 €/kWh and a worst-case scenario of 950 €/kWh for the CapEx of first-life battery-storages was assumed. Research showed that lithium-ion battery modules normally last between 15 and 20 years.

CapEx for a second-life battery system:

To calculate the capital expenditures of a second-life battery storage current market prices of used EV batteries were taken and costs for repurposing quoted in studies were added. The calculated selling price includes an estimated profit margin of 10 to 20 %. According to literature the lifetime of a second-life battery module was estimated at 6 to 8 years.

Martinez-Laserna et al. (2018) states that costs for used battery modules make up for 56 % of the total costs of a second-life battery (see **Figure 8**). As battery prices have decreased since then, the numbers from this study were used as best case. As a worst-case scenario, it was assumed that the battery costs make up for 40 % of the total costs, which makes the complete battery storage more expensive. Based on that, a best-case scenario of 419 €/kWh and a worst-case scenario of 802 €/kWh for the CapEx of second-life battery-storages was assumed.

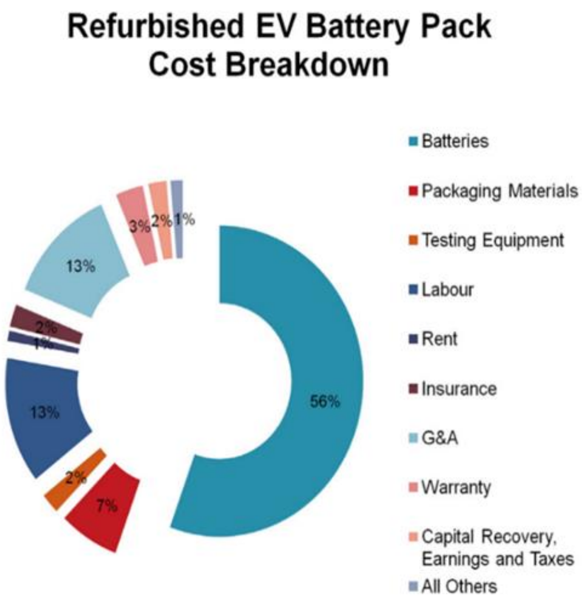


Figure 8: Costs involved in the refurbishment of EV batteries (Martinez-Laserna et al. (2018))

OpEx for first and second life batteries:

As a second-life battery consists basically of new components except the pre-aged battery modules the additional costs are the same for first and second-life batteries except the costs for module exchange. According to conducted research an inverter with a nominal power output of 100 kW (typically used in storages with comparable sizes to the storage in the use-case) costs about 6.500 € (incl. VAT) and lasts approximately 10 to 15 years. So, costs of 24 €/kWh-battery storage to 27 €/kWh-battery storage were used for the calculation. Maintenance costs are assumably 1% of the initial CapEx (5 €/kWh to 10 €/kWh). For the module replacement costs of 330 €/kWh to 520 €/kWh were used in the TCO calculation. **Table 4** summarizes the assumptions for operational expenditures for first and second life batteries.

OpEx (Operational Expenditures)				
	First life batteries		Second life batteries	
	Best case	Worst case	Best case	Worst case
Interval for replacement of modules	Every 20 years	Every 15 years	Every 8 years	Every 6 years
Costs per module [€/kWh]	330	520	248	332
Interval for inverter replacement	Every 15 years	Every 10 years	Every 15 years	Every 10 years
Costs per Inverter [€/kWh]	24	27	24	27
Maintenance costs [€ per kWh per year]	5,0	10,0	5,0	10,0

Table 4: Assumptions for operational expenditures for first and second life batteries

Based on the assumptions above, the total cost of ownership was calculated for an exemplary best and worst case scenario for first and second life batteries (see **Figure 9**).

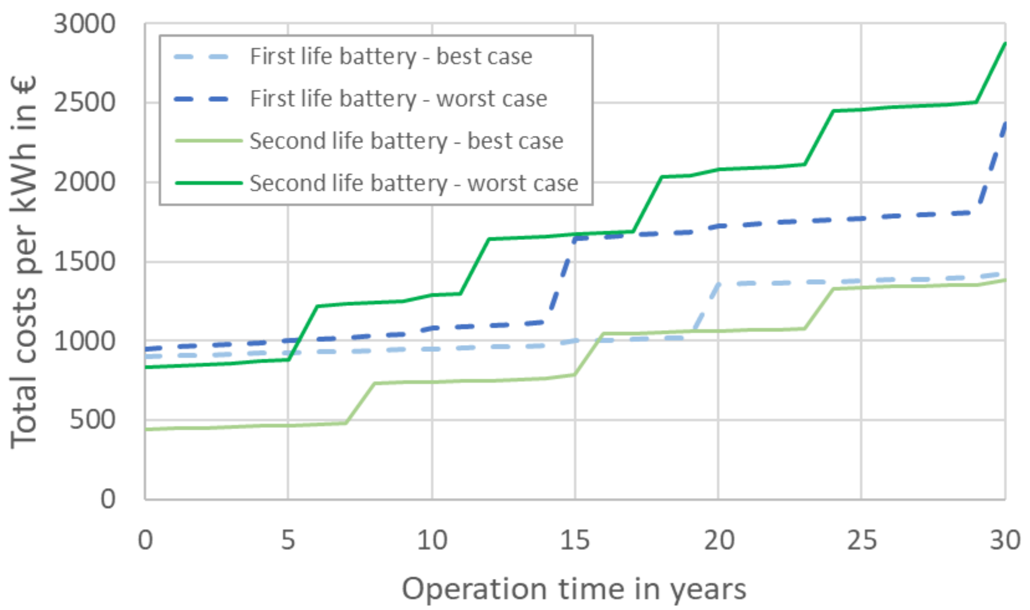


Figure 9: Exemplary best- and worst case scenarios for TCO for first and second life batteries

Depending on the actual scenario (best- and worst-case scenario for first and second-life batteries), both – first and second life batteries – can be the better option. In conclusion, the aim should be to minimize the operational expenditures (OpEx) for second-life batteries. By doing so, they can emerge as the more favourable option in terms of Total Cost of Ownership (TCO). With the implementation of the EU battery regulation in 2025 costs for identifying the SOH will be reduced or almost disappear. Hence, repurposing costs could be less than estimated for this calculation.

3 Outlook and recommendations

In this feasibility study several elements for the modelling and optimization of second life batteries have been investigated. For the targeted follow-up activities the following topics need to be addressed and the following recommendations can be given:

- In order to accurately model second-life ageing, a wider range of degradation mechanisms, such as mechanical changes (particle cracking, gas formation), bulk material changes (structural disordering), and parasitic reactions (binder degradation, localized corrosion) must be considered. However, the incorporation of all these degradation mechanisms would lead to very complex and computationally expensive aging models with low chances to be used for commercial purposes To bridge this gap, it is recommended to explore physics-based models in combination with Machine Learning (ML) approaches.

- The essential key features for the design tool of second-life batteries were identified. While some of them could be easily modeled, the bottleneck is linked to the accuracy of the aging model. Most of the efforts should be dedicated to develop an aging model for batteries that optimally balances accuracy and computational costs.

- For the simulation of use cases containing power electronics (AC/DC and DC/DC converters) and second-life batteries including their ageing behavior, simplified models for the power electronics (e.g. based on efficiencies but not considering pulsing effects of buck converters) are required in order to enable the simulation of longer time-periods.

- Related to LCA and environmental aspects, the approaches “cradle to gate” and “gate to grave” have been considered as most relevant for the calculation of the CO2-emissions. For the follow-up activities, it is planned to establish a CO_2 calculator for these scenarios.

4 References

[1] „www.statista.com," [Online]. https://www.statista.com/statistics/1103218/global-battery-demand-forecast/. [accessed on 30 10 2023]

[2] S. Montoya-Bedoya, L. A. Sabogal-Moncada, E. Garcia-Tamayo, H. V. Martínez-Tejada. A Circular Economy of Electrochemical Energy Storage Systems: Critical Review of SOH/RUL Estimation Methods for Second-Life Batteries. (2020)

[3] „www.mckinsey.com," [Online]. https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/second-life-ev-batteries-the-newest-value-pool-in-energy-storage. [accessed on 30 10 2023]

[4] Martin F. Börner, Moritz H. Frieges, Benedikt Späth, Kathrin Spütz, Heiner H. Heimes, Dirk Uwe Sauer, Weihan Li, Challenges of second-life concepts for retired electric vehicle batteries, Cell Reports Physical Science, Volume 3, Issue 10, 2022, 101095, ISSN 2666-3864, https://doi.org/10.1016/j.xcrp.2022.101095

[5] www.batterydesign.net, [Online]. https://www.batterydesign.net/modelling-software/

[6] Burzyński, Damian; Kasprzyk, Leszek (2021), "NMC cell 2600 mAh cyclic aging data", Mendeley Data, V1, doi: 10.17632/k6v83s2xdm.1

[7] Diao, Weiping (2019), "Data for: Accelerated Cycle Life Testing and Capacity Degradation Modeling of LiCoO2-graphite Cells", Mendeley Data, V1, doi: 10.17632/c35zbmn7j8.1

[8] zhang, shuzhi (2020), "Data for: A data-driven coulomb counting method for state of charge calibration and estimation of lithium-ion battery", Mendeley Data, V1, doi: 10.17632/c5dxwn6w92.1

[9] Gun, Defne; Perez, Hector; Moura, Scott (2015), Fast Charging Tests, Dryad, Dataset, doi: 10.6078/D1MS3X

[10] Trad, K. (2021), "Lifecycle ageing tests on commercial 18650 Li ion cell @ 25°C and 45°C", 4TU.ResearchData, V1, doi: 10.4121/13739296.V1

[11] Govindarajan, J. (2021), "Lifecycle ageing tests on commercial 18650 Li ion cell @ 10°C and 0°C", 4TU.ResearchData, V1, doi: 10.4121/14377295.V1

[12] Birkl, C. (2017). Oxford Battery Degradation Dataset 1. University of Oxford

[13] Severson et al. (2019), "Data-driven prediction of battery cycle life before capacity degradation", Nature Energy volume 4, pages 383–391 , Toyota Research Institute

[14] Attia, P.M., Grover, A., Jin, N. et al.(2020), " Closed-loop optimization of fast-charging protocols for batteries with machine learning", Nature 578, 397–402, Toyota Research Institute, doi: 10.1038/s41586-020-1994-5

[15] Buchicchio, Emanuele; De Angelis, Alessio; Santoni, Francesco; Carbone, Paolo (2022), "[OLD] Data For: Dataset on broadband Electrochemical Impedance Spectroscopy of Lithium-Ion Batteries for Different Values of the State of Charge", Mendeley Data, V3, doi: 10.17632/ch3sydbbrg.3

[16] Chen Fei, (2022), "Lithium-ion battery data set", IEEE Dataport, doi: 10.21227/fh1g-8k11.

[17] Paw, Yew Chai (2022). Lithium-Polymer Battery Storage Self-Discharge Dataset. Singapore Institute of Technology, doi : 10.25447/sit.21391377.v1

[18] Daniel Juarez-Robles et al 2020 J. Electrochem. Soc. 167 160510, "Degradation-Safety Analytics in Lithium-Ion Calls: Part I. Aging under Charge/Discharge Cycling", Underwriters Laboratories Inc. - Purdue University, BatteryArchive, doi : 10.1149/1945-7111/abc8c0

[19] Daniel Juarez-Robles et al 2021 J. Electrochem. Soc. 168 110501, "Degradation-Safety Analytics in Lithium-Ion Calls: Part III. Aging and Safety of Pouch Format Cells", Underwriters Laboratories Inc. - Purdue University, BatteryArchive, doi : 10.1149/1945-7111/ac30af

[20] Peyman Mohtat et al 2021 J. Electrochem. Soc. 168 100520, "Reversible and Irreversible Expansion of Lithium-Ion Batteries Under a Wide Range of Stress Factors", University if Michigan, BatteryArchive, doi : 10.1149/1945-7111/ac2d3e

[21] Andrew Weng, Peyman Mohtat, Peter M. Attia, Valentin Sulzer, Suhak Lee, Greg Less, Anna Stefanopoulou (2021), "Predicting the impact of formation protocols on battery lifetime immediately after manufacturing", Joule, Volume 5, Issue 11, Pages 2971-2992, ISSN 2542-4351, doi : 10.1016/j.joule.2021.09.015.

[22] Devie, Arnaud, George Baure, and Matthieu Dubarry. 2018. "Intrinsic Variability in the Degradation of a Batch of Commercial 18650 Lithium-Ion Cells" Energies 11, no. 5: 1031. doi : 10.3390/en11051031

[23] Yuliya Preger et al 2020 J. Electrochem. Soc. 167 120532, “Degradation of Comercial Lithium-Ion Cells as a Function of Chemistry and Cycling Conditions”, doi : 10.1149/1945-7111/abae37

[24] Gonçalo dos Reis, Calum Strange, Mohit Yadav, Shawn Li,(2021) ,“Lithium-ion battery data and where to find it”, Energy and AI,Volume 5, 100081, ISSN 2666-5468, doi : 10.1016/j.egyai.2021.100081.

[25] J. Groot, State of health estimation of Li-ion batteries cycle life test methods, Thesis for the Division of Electric Power Engineering, Department of Energy and Environment, Chalmers University of Technology, 2012, Available from: *https://www.researchgate.net/publication/272170200_The_Value_of_Battery_Diagnostics_and_Prognostics#fullTextFileContent [accessed Oct 12, 2023])*

[26] Battery Degradation Scientifically Explained - EV Battery Tech Explained, YouTube, 17. Mai 2019 Available from Battery Degradation Scientifically Explained - EV Battery Tech Explained - YouTube [accessed Oct 12 2023]) https://www.youtube.com/watch?v=XLnBg25JoHg

[27] Integrating physics-based modeling with machine learning for lithium-ion batteries (2023, Applied Energy, link)

[28] Machine learning-based state of health prediction for battery systems in real-world electric vehicles (2023, Journal of Energy Storage, link)

[29] Tamilselvi, S.; Gunasundari, S.; Karuppiah, N.; Razak RK, A.; Madhusudan, S.; Nagarajan, V.M.; Sathish, T.; Shamim, M.Z.M.; Saleel, C.A.; Afzal, A. A Review on Battery Modelling Techniques. Sustainability 2021, 13, 10042. https://doi.org/10.3390/su131810042

[30] E. Martinez-Laserna, I. Gandiaga, E. Sarasketa-Zabala, J. Badeda, D.-I. Stroe, M. Swierczynski, A. Goikoetxea, Battery second life: Hype, hope or reality? A critical review of the state of the art, Renewable and Sustainable Energy Reviews, Volume 93, 2018, Pages 701-718, ISSN 1364-0321, https://doi.org/10.1016/j.rser.2018.04.035

5 Contact

Projektleiter:

Dr. Alois Steiner
e-mail: alois.steiner@v2c2.at
Tel: +43 (316) 873 - 9025

Institut/Unternehmen:

Virtual Vehicle Research GmbH
Inffeldgasse 21/A/I
8010 Graz
Tel: +43 (316) 873 - 9001
Fax: +43 (316) 873 - 9002
www.v2c2.at

Auflistung der weiteren Projekt- bzw. KooperationspartnerInnen Name / Institut oder Unternehmen:

- betteries AMPS GmbH
- Grazer Energieagentur