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A Decision Support System for End-of-Life Management of Electric Vehicle Batteries: A Framework Addressing Disassembly Complexities

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Abstract

The increasing adoption of electric vehicles (EVs) necessitates efficient and sustainable end-of-life (EoL) management of electric vehicle batteries (EVBs). To maximize the value recovered from disposed batteries, an efficient disassembly process is fundamental, but this process is known to be complex. The purpose of this research is to address the complexities of the disassembly process for reconditioning EVBs by identifying key challenges and factors, through unstructured interviews with industry experts. This study identifies critical bottlenecks, operator skill requirements, and the variability in battery design and condition. Furthermore, this research explores the potential of a decision support system (DSS) by proposing a framework able to manage the complexities identified. This study aims to enhance the efficiency of the disassembly process, thereby supporting sustainable practices in EVB remanufacturing and reconditioning, ultimately contributing to reduced environmental impact and improved resource recovery.

Keywords: Electric vehicle battery; decision support system; simulation; End of Life; reconditioning

1. Introduction

The urgent need to mitigate climate change and reduce greenhouse gas emissions has focused on the transition to electrification in the transport sector (*Paris Agreement on Climate Change*, 2024). In 2020 it was estimated that this sector contributes significantly to global CO2 emissions, accounting for about 24% of the total (*Road Transport*, 2020). In this context, electric vehicles (EVs) emerge as a promising solution. Despite zero emissions during use, electric vehicle batteries (EVBs) have a significant environmental impact in the production phase, mainly due to intensive resource extraction. This has led to the need for efficient and sustainable methods to manage the end-of-life (EoL) phase of EVBs.

In a circular economy scenario, at the end of its useful life, an EVB can follow different paths, which depend on the severity of the product status after use. In the case of EVB, well-known strategies are recycling, remanufacturing, or repurposing. However, implementing strategies such as reconditioning and remanufacturing can significantly extend the life of batteries and reduce the need for intensive production of new batteries (Glöser-Chahoud et al., 2021). To implement all those strategies, the EVB needs to be disassembled, partially or completely. The correct disassembly strategy is the prerequisite of an efficient EoL strategy (Glöser-Chahoud et al., 2021). However, it is a complex procedure that involves various technical, operational, and environmental considerations. Efficient disassembly not only facilitates EoL strategies but also ensures that valuable materials are recovered and hazardous substances are managed appropriately. In particular, the reconditioning process focuses on returning a used product to a satisfactory working condition that may be inferior to the original specification. Generally, the resultant product has a warranty that is less than that of a newly manufactured equivalent (Matsumoto & Ijomah, 2013).

Despite its importance, the disassembly process for EVBs is inherently complex. This complexity arises from several factors, including the variability in the disassembly process linked to the intricate assembly of battery packs. The complexity lies in the battery itself. Each battery pack differs in state of health (SoH), making the disassembly process unpredictable and dependent on the state of the specific battery. Addressing these challenges requires an analysis of the disassembly process and the development of strategies to manage these variability aspects effectively to optimize operations and enhance sustainability outcomes.

This paper aims to identify and analyze the key problems affecting the disassembly process for reconditioning EVB. Furthermore, a framework for a simulation-based decision support system (DSS) to manage these identified problems is proposed.

The paper is organized as follows: in Section 2 the literature review is presented, Section 3 presents the materials and methods of the study, while Section 4 provides the results and discusses them. Finally, section 5 concludes the work.

2. State of the art

The anticipated increase in disassembly volumes highlights the inadequacy of relying solely on manual labor and current processes. Researchers took a broader perspective by evaluating the repurposing of EV batteries for grid-scale energy storage (Al-Alawi et al., 2022). However, it mainly focuses on the second-life application (Olsson et al., 2018). Different studies focused on remanufacturing processes and how they can be an economically viable approach (Foster et al., 2014), also from an environmental perspective (Govindan, 2022). Another area of application study is how to employ EV batteries in less-demanding applications, known as the repurposing of batteries (Hantanasirisakul & Sawangphruk, 2023). However, the reconditioning processes are less represented in the literature, but the differences among circular economy strategies revolve around the level and the accuracy of disassembly required (Baazouzi et al., 2021).

The reconditioning process requires a partial disassembly, which is gaining more interest (Al-Alawi et al., 2022) and the definition of models that address the optimization of the disassembly of target modules needs further study (Gentilini et al., 2020). This approach increases the complexity of the process by introducing variability aspects related to the returning product, for example, quality assessment, which is one of the major sources of uncertainty in disassembly systems for post-consumer product processes (Bentaha et al., 2019). Notably, one study by Klohs et al. (2023) has mapped the variabilities linked to a complete disassembly to investigate the feasibility of an automated process. Currently, many researchers are focusing on robotic disassembly to improve the efficiency of the process (Glöser-Chahoud et al., 2021), but, also in this area, they are focusing on complete disassembly.

Different variability aspects are often treated as independent problems. The biggest area of research regards the development of models that can predict battery behavior by leveraging the electrical properties of a battery (Yang et al., 2018) or data-driven methods (Wu et al., 2023). To optimize the performance and extend the lifespan of batteries, accurately determining the State of Health (SoH) emerges as a critical task. However, studies that aim to optimize SoH estimation jointly with process optimization are lacking.

It emerges that this process has too many variabilities, making the development of an automated disassembly less feasible (Klohs et al., 2023). Human labor remains highly valuable in this context, primarily due to the accuracy and adaptability that humans can provide, so, the need is to empower operators with a DSS to improve the efficiency of the process (Klör et al., 2018).

The use of DSS in the disassembly process has been investigated for the optimization of the disassembly process (Addocuhe et al., 2009) or to improve the safety of the process (Gentilini et al., 2020), as well as managing the bottlenecks (McConville et al., 2023) and the variability of the End-of-Life product quality (Colledani & Battaïa, 2016). Also, to optimize the potential for component reuse, it is necessary to augment the implicit knowledge of employees by implementing data-driven DSS (Mügge et al., 2024).

3. Materials and Methods

This study employs a qualitative research approach to gain a detailed understanding of the challenges and factors affecting the disassembly process for reconditioning EVB (Figure 1). The approach includes unstructured interviews with industry experts and detailed process analysis to identify, classify, and analyze all the complexities that are relevant in the disassembly process for reconditioning. The final aim was to define the architecture of a DSS able to manage them.

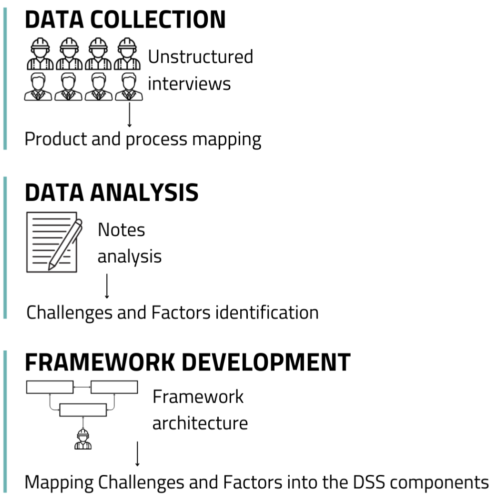

Figure 1. Methodology steps.

3.1. Data collection

To collect information on the complexities influencing the disassembly process, unstructured interviews with 4 operators of an EVB assembly/disassembly line and 4 managers of an automotive company were carried out. These interviews were conducted in 2024 during a company visit and multiple online meetings, during which, detailed annotations were made to capture all the information shared. The aim of these interviews was to:

- understand how an EVB is structured and the differences among the different packs.
- map the reconditioning process, understanding how the activities are characterized and the associated complexities.
- understand practically how the current system is being operated and how they are dealing with complexities.

3.1.1. Product complexity

EVBs are complex systems composed of multiple interconnected components designed to store and deliver electrical energy efficiently. A typical EVB consists of several modules, each containing multiple lithium-ion cells. These cells are organized in series and parallel configurations to achieve the desired voltage and capacity. The battery pack is encased in a robust housing that provides structural integrity and protection from environmental factors.

Each battery pack is equipped with a Battery Management System (BMS), which monitors and controls the performance of the cells. The BMS ensures the safety, reliability, and longevity of the battery by managing parameters such as state of charge (SOC), state of health (SOH), temperature, and voltage balance among cells. Additionally, the BMS facilitates diagnostic assessments, crucial for determining the suitability of the battery for reconditioning or other EoL strategies. The modular design of the battery pack allows for the replacement of individual modules or cells, which is a key aspect of the reconditioning process. However, the variability in design, assembly, and usage history introduces significant complexity in the disassembly and reconditioning processes.

3.1.2. Process complexity

The first step of the reconditioning process (Figure 2) is a diagnostic assessment to verify the safety of handling the battery pack. After that, the data coming from the Battery Management System (BMS) are analyzed to understand if a reconditioning process is suitable and which modules need to be replaced.

Subsequently, the battery pack is disassembled to access the target modules identified which require replacement, followed by a general inspection and repair of the battery. Before assembling the new modules into the battery pack, they need to be balanced to harmonize their state of charge (SOC) with that of the pack, ensuring uniformity in performance.

Reassembly follows and the battery undergoes a series of quality and functional tests. The aim here is to estimate the new value for the SoH of the battery pack. Upon successful completion of these tests, the upper case is bonded, and the unit is set aside to undergo polymerization.

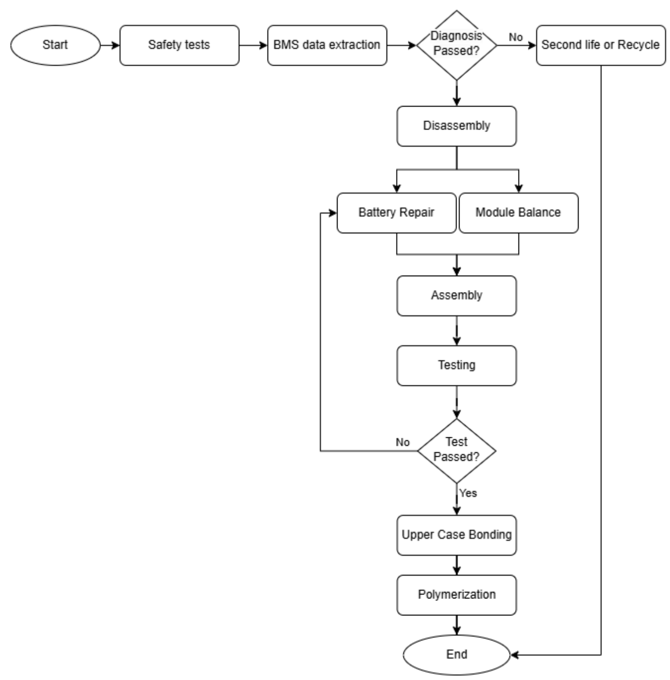

Figure 2. Reconditioning process flowchart.

3.2. Data analysis

This stage of the research was aimed at identifying all the aspects that influence the disassembly process. As the first step, all annotations taken during the interview were carefully transcribed. This transcription process involved reviewing the notes multiple times to ensure completeness and accuracy.

The next step involved coding the transcribed data. All the problems highlighted by the interviewees were analyzed to identify recurring concepts and themes. Practically, this means that it was possible to collect similar problems into concepts, which in turn were classified into two themes. Through the identification of two themes, it was possible to explain the complexity of the disassembly process. It depends on:

- *Process-related challenges*: which include the inherent difficulties associated with the disassembly process itself.
- *Product-related factors*: the complexities introduced by the product and its structure.

To ensure the reliability of the identified themes, the coded data and resultant themes were reviewed by two independent researchers and the interviewee. A detailed description of the identified factors is provided in the Results section.

3.3. Framework development

After having identified the two themes mentioned in the previous section, this step was aimed at the definition of a framework for a DSS to help the operator with decision-making activities. Usually, a DSS has some key components (Figure 3):

- a database, which includes information from internal sources (information collected in a transaction process system) and external sources (newspapers and online databases). It collects and utilizes the implicit knowledge of experienced operators. This information ensures that accurate and up-to-date information is available for analysis and decision-making.
- a model, in which the DSS can manage different models that can be used for decision-making.
- a user interface, which includes tools that help the end-user of a DSS to navigate through the system.

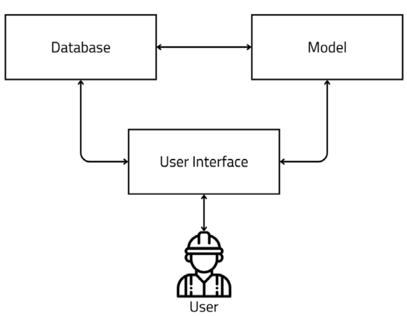

Figure 3. Decision Support System general architecture, adapted from (Sprague, 1980).

The framework development process involved mapping the problems identified during the data analysis phase into specific components of the DSS. Each component was designed to address distinct challenges and factors revealed through the interviews and process analysis.

4. Results and Discussion

The results comprise the identification of the complexities related both to the product and the process and the development of the Framework for a simulation-based DSS able to manage these complexities.

4.1. Process analysis

The disassembly process for EVBs presents a range of inherent challenges and factors that can vary significantly between different batteries. These challenges and factors, detailed in Table 1, are crucial to understanding the complexities of the disassembly process and informing the development of effective solutions.

4.1.1. Challenges

EVBs are intricate products composed of multiple assembly and subassembly components, including cells, modules, and packs. Each of these components serves distinct roles, such as thermal management and electrical functionality, which adds layers of complexity to the disassembly process. This structural complexity necessitates precise methods to avoid damaging valuable components during disassembly. A major challenge in this process is dealing with the robust adhesive used to bond the upper and lower parts of the battery case. Specialized screws and tools are necessary to prevent damage during separation, and the unique geometry of each battery case requires tailored methodologies for separation.

In the reconditioning process, it is crucial to access the specified module that needs replacement implying the careful disassembly of all the components to access the module. However, during this process, some components may be inadvertently damaged. The same consideration needs to be applied to the reassembly; after the replacement process, reassembly must ensure that all components meet stringent quality standards. This step requires careful handling and precision to maintain the functionality and safety of the reconditioned battery.

During disassembly, operators may encounter anomalies in the internal status of the battery that are not currently mapped. These anomalies are typically addressed based on the operator's experience, introducing variability and potential inconsistencies in the process. As the volume of returned EVBs increases, relying solely on highly experienced operators becomes impractical. The variability in operator skills can lead to inconsistencies, impacting both the efficiency and safety of the disassembly process.

Testing is the most time-intensive activity within the reconditioning process and serves as a critical stage where bottlenecks occur. Accurate testing typically involves cycling the battery from full charge to complete discharge in a controlled environment maintained at 25 degrees Celsius, simulating standard operating conditions. These tests are essential for ensuring battery safety and functionality but can significantly slow down the overall process.

4.1.2. Factors

As already explained, each EVB model introduces structural variability, which significantly impacts the disassembly process. The different shapes, sizes, and configurations require specific tools and methodologies for disassembly, making standardization challenging. Going deeper into the geometry, the position of modules within the battery pack varies across different models. This variability affects the ease of accessing and replacing modules, as some designs may necessitate the removal of multiple components to reach the target module. The smallest level of an EVB is represented by cells. They can be composed of various types of cells (e.g., lithium-ion, nickel-metal hydride), each with distinct chemical properties. This aspect influences the estimation of SOH because not all methodologies are suitable for all chemistries. This is related to the internal reactions and aging mechanisms that happen in the cell.

The quality of data available from the Battery Management System (BMS) can vary based on how the battery was used and maintained. Poor data quality can lead to inaccurate assessment and decision-making during the disassembly and reconditioning process.

Batteries returned for reconditioning may have physical damage that impacts their disassembly. They may complicate the process, requiring further intervention, thus leading to longer processing times. Similarly, internal damage that is not immediately visible or detectable poses significant challenges. Such damage can only be identified during the disassembly process, relying heavily on the operator's expertise to diagnose and address the issues effectively.

Table 1. Challenges and factors identified.

Code	Concept	Problem
C1	Bottleneck	Time-intensive final testing
C2	SOH estimation	Initial analysis to select target modules
		Accuracy in final estimation
C3	Physical difficulties	Variability in the saws to separate the case’s adhesive bonding according to the models
		Risk of damaging components
		Variability in the disassembly steps to access the target modules
		Presence of multiple components with different functions
		Quality standards in reassembly
C4	Operator skills	Understanding BMS data
		Reliance on operator experience to identify unmapped anomalies
		Variability in operators' skills
F1	Model Variability	Pack geometry and structure
		Module position
		Cell chemistry and type
F2	Usage history	Data quality
		Physical damage is identifiable only after opening the pack
		Not accessible internal damage

4.2. Preliminary design

To address the challenges and factors identified, it is possible to build the architecture of the simulation-based DSS (Figure 5).

The design of the DSS is based on the distinction between challenges and factors. Challenges represent recurring issues inherent to the disassembly process, while factors are variable parameters that differ with each battery processed. This differentiation is essential in structuring the DSS to handle both process modeling and dynamic input management effectively.

4.2.1. Database

The database component of the DSS needs to manage the factors identified. To address the model variability (F1), this database catalogs the detailed characteristics of each battery model, including pack volume, structural configuration, module positioning, cell chemistry, and nominal performance values, such as voltage and capacity. The database contained all the characterizing elements of the battery pack, module, and cell, creating a battery’s identification card for each model the company is reconditioning. This solution allows easier management of the inputs for the simulation model and ensures that the DSS can accommodate the heterogeneity of battery models effectively, enhancing the system's adaptability and precision.

Furthermore, the database addresses the variability in usage history (F2) by using statistical distributions that can model the probability of various issues occurring to be used in the model to have more accurate simulations. Currently, these anomalies are undocumented, operators will be required to record these anomalies in real-time to compute and update the statistical distribution. By integrating this empirical knowledge into the DSS, the system will improve its predictive accuracy and decision-making capabilities, allowing for proactive management of potential disassembly challenges.

4.2.2. Model

Given the difference between process and product, two models will be needed to manage the variabilities of both elements and need to be interoperable (Figure 4).

First of all, the battery is an electrical component and, as such, it can be modeled through an electrical model designed to simulate its behavior and performance. This model is influenced by the cell chemistry and the aging mechanisms that are triggered by the use and aging (F1). This model has two functions in two stages of the disassembly process. Initially, it aids operators in analyzing data from the BMS, facilitating accurate analysis of the parameters. This initial analysis supports informed decisions regarding modules that require a replacement. At the final stage, the electrical model is employed to evaluate the SOH of the reconditioned battery, ensuring compliance with operational standards and reducing the final testing time. By implementing the electrical model, the DSS effectively addresses the bottleneck challenge (C1) in the final SOH testing phase and enhances the precision of module selection and estimation (C2).

The process simulation model offers a comprehensive representation of the entire disassembly workflow. This model is constructed based on extensive process mapping conducted during field visits to relevant facilities. It simulates each step of the disassembly process, enabling the identification and optimization of process inefficiencies. The model's adaptability allows it to address challenges related to physical difficulties (C3), such as tool selection and handling procedures, thereby improving overall process safety and efficiency.

By addressing these challenges, it is possible to build a generalized model. However, the biggest variability of the process is linked with the product, it is important to consider that there is variability both in the model (F1) and in the status (F2) of the battery that needs to be reconditioned. For these reasons, the simulation model should be able to address the inputs dynamically, ensuring robustness and flexibility in operational execution. Based on this assumption, upon the arrival of a battery, its specific attributes will be input into the model, allowing the simulation models to generate a tailored disassembly process based on the information in the database.

Software

To develop the simulation-based DSS, two software tools were selected: MATLAB for the electrical simulation model and AnyLogic for the process simulation model. Both software applications were chosen for their robustness, flexibility, and ability to handle the specific requirements of the project.

MATLAB is utilized for the electrical simulation model due to its advanced mathematical capabilities and comprehensive toolboxes designed for modeling and simulating electrical systems. It is employed to analyze BMS data and estimate SOH values, both for selecting target modules, based on the optimal SOH achievable and then help the process to estimate the final SOH after reconditioning.

AnyLogic is selected for the process simulation model due to its powerful features in simulating complex processes and workflows. It provides a comprehensive representation of the entire disassembly workflow, built from extensive process mapping conducted during field visits to relevant facilities. Furthermore, it allows to build the battery database and model them through objects, enabling dynamic adaptation to the variability in both the battery model and its status.

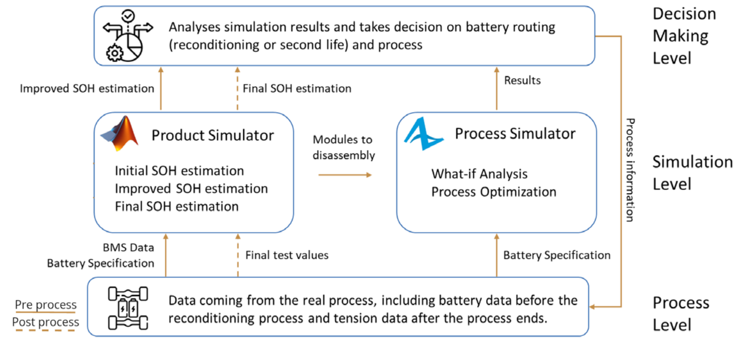

Figure 4. Interaction between the two simulation models in the DSS architecture.

4.2.3. *User Interface*

The user interface component of the DSS is engineered to facilitate seamless interaction between operators and the system.

Through this interface, the operator will manage the input data. In particular, the operator will interact with both models. The electrical model receives input from the BMS data and outputs the SOH estimation and the information on the target modules. Instead, for the process model, the operator inputs the information on the battery data, such as model and actual performance, receiving in output all the information to enable the decision-making.

By addressing operator skill variability (C4), the user interface will enhance consistency and reliability in the disassembly process. This interface will provide operators with clear, actionable information and decision-making tools. This component will undergo a separate, detailed design phase to determine the specific user requirements and interface features that will optimize operator performance.

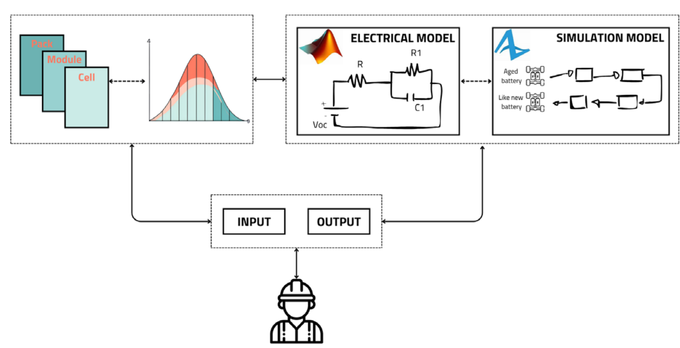

Figure 5. Architecture for the Decision Support System.

5. Conclusions

The study addresses the complexities of the disassembly process for reconditioning EVBs. Through unstructured interviews with industry experts, key challenges such as bottlenecks, operator skill variability, and diversity in battery design and condition were identified. To tackle these challenges, a framework for a DSS was proposed aimed at optimizing the disassembly process. The electrical model within the DSS aids in the accurate determination of the SoH of batteries, while the process simulation model helps streamline the entire disassembly workflow. By integrating these elements, the DSS provides actionable insights and enhances decision-making, ultimately contributing to more efficient and sustainable practices in EVB remanufacturing and reconditioning.

While this study offers significant insights, it is important to acknowledge certain limitations. The primary limitation is the reliance on unstructured interviews, which, while providing deep insights, may introduce subjectivity and limit the generalizability of the findings. The data collected from 4 operators and 4 managers from a single company may not represent the broader industry perspective. The proposed DSS framework, while comprehensive, requires further validation through real-world implementation and testing to ensure its efficacy across different scenarios and battery types.

Future research should focus on expanding the scope of data collection to include a broader range of industry stakeholders involved in more EoL processes. Future work should also explore the integration of advanced technologies, such as machine learning, to further enhance the efficiency and scalability of the disassembly process. In particular, to accurately predict battery behavior and optimize the State of Health (SoH) estimation. These advancements will contribute to more sustainable and efficient end-of-life management of EVBs, ultimately supporting the broader goals of environmental conservation and resource recovery.

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