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To shred or to disassemble – A techno-economic assessment of automated disassembly vs. shredding in lithium-ion battery module recycling

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A R T I C L E I N F O

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A B S T R A C T

The global adoption of electric vehicles (EVs) is driving a surge in the use of lithium-ion batteries (LIBs), creating an urgent need for sophisticated recycling techniques to recover valuable materials and manage waste. Particularly, automating the laborintensive disassembly process is critical for scaling up recycling efforts. This study provides a techno-economic evaluation of a robotic line for disassembling EV LIB modules, exploring whether it's more profitable to extend automation to the cell level. Three different EV modules are examined, and several scenarios are proposed, showing that investments in robotic disassembly could be financially sound, particularly with the anticipated rise in end-of-life EV LIBs. The key to profitability lies in disassembling to the cell level, which enables the recovery of more valuable materials and reduces downstream processing requirements. This research offers practical guidelines for automating the disassembly process in line with future waste management demands.

1. Introduction

As we navigate the climate crisis and move towards increased use of Lithium-Ion Batteries (LIBs) in transportation, which still encompassed 28 % of global greenhouse gas emissions in 2021 (US EPA, 2023), it is critical to develop efficient and economically viable recycling solutions. LIB recycling primarily involves pyrometallurgy, hydrometallurgy, or a combination of both, with most EV batteries currently being manually disassembled to module level before shredding (Brückner et al., 2020; Chen et al., 2019; Harper et al., 2019; Or et al., 2020; Sommerville et al., 2020; Velázquez-Martínez et al., 2019; Wei et al., 2023; Zhao et al., 2021). This manual process, often due to diverse product variants and low waste stream volumes, poses challenges for automation (Harper et al., 2019; Thompson et al., 2020). Robotic disassembly, powered by recent advancements in artificial intelligence (Meng et al., 2022), offers a promising direction (Choux et al., 2021; Li et al., 2018; Marshall et al., 2020; Marturi et al., 2018; Poschmann et al., 2021) especially in enhancing safety (Glöser-Chahoud et al., 2021), efficiency, and economic viability of the initial steps in the recycling process (Wei et al., 2023). A crucial aspect in the existing literature pertains to whether automated disassembly should halt at the module or cell level prior to recycling (Alfaro-Algaba and Ramirez, 2020; Thompson et al., 2021). Indeed, the level of disassembly impacts the purity of waste streams, with disassembled cells re- ported to produce higher purity waste streams than shredded modules (Thompson et al., 2021). However, its necessity from a recycling standpoint remains undetermined (Lander et al., 2023). Even if automated disassembly at cell level, which would enable direct recycling, is not expected in the near future, as automation from pack to module level is prioritised and has yet to be proven on an industrial scale, while these technical challenges are being addressed (Harper et al., 2019; Meng et al., 2022), the economic feasibility of such innovations should nevertheless be examined, as it could be the most critical barrier (Wrålsen et al., 2021).

This can be achieved through a Techno-Economic Analysis (TEA), a framework combining technical and economic factors to evaluate a project's feasibility, viability, and potential outcomes (Kuppens et al., 2015; Zimmermann et al., 2020). However, conducting TEAs presents its challenges, given the absence of a standardized method- ology, leading to variations among studies and complicating comparisons (Giacomella, 2021; Zimmermann et al., 2020). For TEAs to effectively evaluate economic feasibility, they need a detailed breakdown into parameters such as cost estimation, market conditions, and profitability, tailored to each specific case. In the context of EV LIB recycling, this is often presented as cost per kWh disassembled or per kg of cells recycled (Lander et al.,

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2021; Thompson et al., 2021). Furthermore, it is essential to specify system boundaries, as they play a critical role in identifying input and output flows, uncovering potential flaws, and determining the analysis's scope (Zimmermann et al., 2020).

Therefore, to shape future strategies for LIB recycling, the main objective of this study is to perform a well-structured TEA of automated disassembly from module to cell level, exploring the economic viability of a robotic mod- ule disassembly line. The present work will exclusively focus on automated disassembly from module level to cell level and will consider recycling, the ultimate fate of all EoL EV LIBs, rather than reuse or repurposing.

After presenting the methods used for the assessment, the research will compare three commercially EV battery modules that are representative for a large variety of both module design and cell chemistry, considering three different recycling scenarios, and conclude on the economic viability of a robotic module disassembly line.

2. Material and methods

2.1. Overview and sampling of battery types

The main focus of this study is on robotic module disassembly and the mechanical processing side of LIB recycling. Hence, initial steps such as transportation, discharge and disassembly to module level, and final steps such as hydrometallurgical processing (e.g. leaching) are out of the scope of this study. To assess the economic viability of an automated EV LIB disassembly process from module to cell level, the following steps will be performed:

1. Modelling a robotic module disassembly line to estimate the costs of such a disassembly line and the potential annual throughput of EV battery modules.
2. Identifying under what circumstances cost savings or revenue gains could be obtained by processing cells instead of modules.
3. Estimating the potential cost savings or revenue gains from the identi- fied circumstances for the purpose of calculating the net present value (NPV) of the robotic module disassembly line.

To establish requirements for the robotic operations and to ensure a repre- sentative study, we opted to conduct a disassembly analysis of three different yet common battery modules used in the following car model: the Volkswa- gen E-Golf 2019 (NMC111), the Hyundai Ioniq 2. Gen 2019 (NMC622), and the Mitsubishi Outlander PHEV 2017 (LCO). These three battery modules represent a breadth of battery architectures and chemistries from three con- siderable car manufacturers, with Volkswagen E-golf reaching a shared third place for the most sold EV in Europe in 2019 (Hall et al., 2020). The Hyundai Ioniq reached a considerable 6.5 % market share in the global EV market in 2019, ranking fifth in the world (Yoon, 2022). Lastly, the Mitsubishi Outlander was the number one sold PHEV in Europe in 2017, responsible for 13 % of a total 150,000 PHEV units sold inside the European market (Demandt, 2018). Equally important, the modules differ in terms of cathode chemistry, a factor that greatly influences recycling revenue.

All cost calculations were done in $[1] using a currency conversion factor of 10.0 (NOK to $) from early 2023.

2.2. Methodology for modeling robotic module disassembly

To model a robotic disassembly line, a teardown analysis for each battery module was conducted. Modules were manually disassembled in the univer- sity lab, detailing the process from module to cell. A connection diagram was created for each module, showing component links. Essential tools for each disassembly step were noted. All components were weighed and tagged, assuming they could generate revenue when sold. It should be noted that the components of the module are those that constitute the module, with the exclusion of the battery cells.

This information informed the robotic disassembly line model, enabling the selection of suitable robotic manipulators, tooling, and other hardware. This was done in collaboration with a well-known robot supplier.

2.2.1. Cost estimation

Cost data were collected for all required components for the robotic mod- ule disassembly line. Both the investment (capital) and the operating costs were estimated.

The capital cost of an asset is given by (Bjørnenak, 2019):

$$\text{Capitalcost} = \text{depreciation} + \text{cost of capital} \tag{1}$$

A nominal annuity depreciation model was used (i.e. a linear capital cost during the assets' economic lifetime). The discount rate reflects the owners' expected return on capital invested, often adjusted for risks (e.g. inflation). The capital cost was calculated by Eq. (2)

$$C_c = C_i \cdot \frac{r_d(1+r_d)^n}{(1+r_d)^n - 1} \tag{2}$$

Where:

C_c = Capital cost [$]
C_i = Investment cost [$]
r_d = Discount rate [%]
n = Service lifetime [years]

Investment cost, C_i, is the sum of all hardware costs, including robots, tooling, and other hardware (e.g. vision system). All other costs are included in the operating costs. We used a discount rate of 12 %. For all equipment, we assumed a service lifetime of six (6) years and a residual value of zero (0).

Operating costs include costs of software licenses, cost of electric power, and maintenance costs. Operating costs were calculated by using Eq. (3):

$$C_o = \left(\sum_{i=1}^{n} P_i \cdot t_i\right) \cdot C_e + C_m + C_s \tag{3}$$

Where:

C_o = Operating costs [$]
i = Index for each equipment from 1 to n
P_i = Power consumption of hardware i [kWh]
t_i = Working time of equipment i [h]
C_e = Cost of electricity for industrial uses [$/kWh]
C_m = Cost of maintenance of equipment [$]
C_s = Cost of required software licences [$]

The variable electricity cost for a ten-year average, as well as fixed and variable net expenses, were used to determine the cost of electricity C_e. We further assumed robotic operating hours per year to be 8700.[2]

The investment costs, maintenance costs, software costs and other costs related to the robotic cell are collected from various suppliers in Norway. The data was collected by requesting a quote on the required equipment.

The total annual costs of the robotic disassembly line are then given by Eq. (4).

$$C_a = C_c + C_o \tag{4}$$

Where:

C_a = Annual costs

[1] Costs are adjusted by a yearly inflation factor of 4% to the reference year 2023.

[2] Generally, robots can work 24 hours a day, 7 days a week. However, some maintenance downtime is assumed

2.2.2. Capacity estimation

The annual throughput of EV modules in the disassembly line was esti- mated by assessing robot cycle time for each operation and module. Robotic cycle times were calculated in collaboration with university lab engineers us- ing three-point estimation. The sum of all steps was determined in two ways: total disassembly time and total robotic operation time. Some operations can be concurrent, so the total disassembly time reflects potential annual throughput, while total robotic operation time impacts electrical power cost (e.g., as input to parameter t_i in Eq. (3)).

A variant of the three-point estimation, the successive principle, was used to calculate the expected duration of the disassembly process (Lichtenberg and Partners, n.d.). The expected disassembly time for each activity is obtained by Eq. (5):

$$E = \frac{o + 0.42m + p}{2.42} \tag{5}$$

Where:

E = Expected value
m = most likely estimate
o = Optimistic estimate
p = Pessimistic estimate

The standard deviation for each disassembly activity is obtained by Eq. (6):

$$\sigma = \frac{p - o}{2.53} \tag{6}$$

Where:

σ = Standard deviation

The total expected disassembly time for one module is obtained by Eq. (7), while the sum of all standard deviations is obtained by Eq. (8):

$$E_{total} = E\left(\sum X_i\right) = \sum E(X_i) \tag{7}$$

Where:

E_{total} = Expected duration of disassembly process
X_i = Expected activity duration

$$\sigma_{total} = \sqrt{\sum_{i=1}^{n} \sigma^2(X_i)} \tag{8}$$

Where:

σ_{total} = Sum standard deviation of disassembly process
σ^2 = Variance

The expected value E in Eq. (5) is often denoted P50 (percentile 50 in the Erlang distribution). To increase the certainty of the estimate, P90 can be used (90 % chance of reaching the given value). Calculation of percentile 90 (P90) is expressed in Eq. (9) and was used to calculate the robot cycle times after obtaining the expected value.

$$F^{\{-1\}}(0.9) = E_{total} + \sigma_{total} \cdot \varphi^{-1}(0.9) \tag{9}$$

The potential annual throughput for the different battery modules was derived by Eq. (10):

$$Q = \frac{8,700}{F^{-1}(0.9)} \tag{10}$$

Where:

Q = Annual throughput

2.3. Methodology for modelling the recycling process

This section outlines the methodology for estimating revenue gains or cost savings in recycling. Calculations rely on LithoRec's mechanical processing, a well-documented process with all needed data (Kwade and Diekmann, 2017). Revenue per kg cell recycled was sourced from the public EverBatt model (Dai et al., 2019), an Excel-based tool for analyzing EV LIB manufacturing and recycling stages. Notably, EverBatt focuses on cell recycling, not modules. Though LithoRec and EverBatt are rooted in different hydrometallurgical processes, the LithoRec process can be successfully modeled in the EverBatt model by adjusting the recycling rate and the recovered battery materials.

2.3.1. Estimating recovery rates and material values

The mechanical processing steps of LithoRec are modeled for two capac- ity classes: 1200 and 6000 tons/year. Investment cost for the smaller is 2106,223 $ and operating costs are 385,664 $. For the larger, the costs are 4020,857 $ and 668,069 $, respectively [24].

Recovered materials and their unit prices are summarized in Table 1. The unit prices were obtained from the EverBatt model (Dai et al., 2019), which uses macros to keep material unit pricing up to date with market prices. The LithoRec process achieves an 80 % recycling rate for EV batteries, excluding graphite (Kwade and Diekmann, 2017). Nevertheless, this study adjusts mechanical separation recycling rates for each material, considering existing commercial processes, as referenced in (Dai et al., 2019). When disassembling battery modules and processing cells, components like plastic caps, aluminum plates, and screws are separated and sent for specialized recycling, where they can be recovered at nearly a 100 % rate due to their unmixed state.

The cell material composition of the three different battery chemistries included in this study is presented in Appendix A based on data obtained from the EverBatt model.

2.3.2. Calculating revenues and cost savings

It is assumed that processing of battery cells instead of battery modules will under no circumstances increase the recycling cost related to mechanical- or hydrometallurgical processing.

Potential revenue gains or cost savings were identified and economically evaluated in both capacity classes for the different battery chemistries. All recovered module components are sold to a third-party. The revenue from module components was calculated using Eq. (11):

$$R_m = \sum_{z=1}^{n} \frac{M_{mz}}{Mtot_{mz}} \cdot V_{mz} \tag{11}$$

Where:

R_m = Revenue from module materials [$] z = Index for each material from 1 to z M_{mz} = Mass of module material z [kg]
$Mtot_{mz}$ = Total mass of module material [kg]
V_{mz} = Value of module material z [$]

The profitability of the investments in a robotic disassembly line can then be assessed using the NPV formula (a positive value indicating a favorable investment):

$$NPV = -C_i + \sum_{t=1}^{n} \frac{CF_t}{(1+i)^t} \tag{12}$$

C_i reflects the initial investments into the robotic module disassembly line. CF_t is the cash flow in each period t. The cash flow is composed of operation costs related to the disassembly line (C_o) and potential revenues or cost savings obtained by processing cells instead of

Table 1
Unit prices and recovery rates of recovered battery materials.

Materials	Unit prices [$/kg]	Recovery rate [%]
Aluminium	1.45	90%
Plastics	0.10	50%
Copper	5.43	90%
Nickel	13.00	80%
Steel	0.28	90%
Cobalt	52.00	80%
Manganese	3.00	80%
Lithium carbonate	7.90	90%

modules, *i* is the discount rate.

3. Results

This section presents results on (1) the cost of the robotic module disas- sembly line in addition to the potential annual throughput of EV modules and (2) potential recycling revenues and the NPV of the robotic module disassembly line given different circumstances.

3.1. Robotic module disassembly

This section presents the costs of the robotic module disassembly line and the potential annual throughput of EV modules. First, the complete teardown analysis for each module is reviewed.

3.1.1. Module specifications

The 2019 Volkswagen E-Golf battery module, with dimensions 350 × 150 × 107 mm, 10,896 g mass, and 1.6 kWh capacity, is visualised in Fig. 1 and is hereafter referred to as "Volkswagen". It comprises 12 cells (f) (145 × 25 × 90 mm, 797 g, and 0.134 kWh each), a plastic cover (a) (100 g, plastic), a CMC unit (b) (180 g, plastic), compressive plates (c) (888 g, steel), 8 cell bridges

(d) (aluminium), and 2 side module junctions (82 g each, aluminium). Fig. 1 outlines the interconnections among its parts.

- The 2019 Hyundai Ioniq 2. Gen battery module, hereafter referred to as "Hyundai", consists of 40 cells, whereas the 2017 Mistubishi Outlander PHEV battery module, simply referred as "Mitsubishi" contains 16 cells. Similar results as for the Volkswagen module have been developed and can be found in Appendix B.

Finally, Table 2 summarizes the amount of materials recovered from the different modules.

3.1.2. Modelling the robotic module disassembly line

Based on the manual disassembly of the three different modules, a robotic module disassembly line can be modelled, focusing on economic implications rather than technical specifics. Despite the work realised by Schumacher and Jouaneh (Schumacher and Jouaneh, 2013), automatic removal of snap-fit covers is still currently an inefficient process not capable of module disassembly at an industrial scale.

Therefore, a semi-destructive disassembly approach is deemed most convenient: snap-fit connections are broken by a milling tool which is also used for destroying welds and bridges between cell connectors, whereas dismantling screws can be done by milling or unscrewing, depending on their condition. To minimize tool change time loss, three robots, each with a specific tool (a milling tool, a spindle tool (e.g.

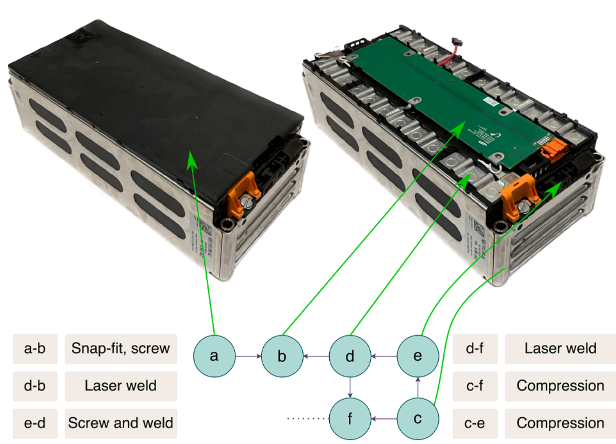

Fig. 1. Battery module and connection diagram, Volkswagen. For example, the plastic cover (a) is connected to the CMC unit (b) by snap-fit and screw.

Table 2
Amount of recovered materials from the different modules.

	Volkswagen (Wt%)	Hyundai (Wt%)	Mitsubishi (Wt%)
Aluminum [g]	164 (1.5%)	2,564 (5.8%)	0 (0.0%)
Plastic [g]	280 (2.6%)	3,915 (8.9%)	1,106 (4.3%)
Steel [g]	888 (8.1%)	2,753 (6.3%)	2,036 (8.0%)

screwdriver), and a gripper tool) will equip the disassembly workstation, together with a rotary table and a fixture system for holding the battery module, a conveyor belt for transportation, and a vision system for component detection. All hardware, including robots and OnRobot tools, are assumed to have a uniform service life of 6 years, or 50,000 operating hours, leading to adjustments in investment costs for specific tools. The required components for the disassembly line, their function, the specific hardware used, and associated costs are listed in Appendix C.

3.1.3. Robotic cycle times

Based on the robotic disassembly steps for each battery module type, the three-point estimates for each individual robotic operation, which are calcu- lated by using Eqs. (5) through (10), are available in the Supplementary Information spreadsheets. The resulting total operation- and disassembly times for each module are presented in Table 3, together with the potential annual throughput for each module, calculated in accordance with Eq. (10). The operation time is further used as input to calculate the annual cost of electric power for each robot, also outlined in Supplementary Information.

As an example, for the Volkswagen, 405,878 disassembled modules correlates to a total weight of 4442 tons of modules and 3882 tons of cells. Using table 2, the disassembled module components yield 40.59 tons of aluminum, 113.65 tons of plastic and 360.42 tons of steel.

Fig. 2 displays the cumulative distribution function of the probability distribution of disassembly time for the different modules. For Volkswagen, the probability that disassembly time is less than or equal to 77 s is 90 %. Similarly, for Hyundai and Mitsubishi, the disassembly time at 90 % probability is 594 s and 254 s, respectively.

3.1.4. Annual cost for automated disassembly and revenue

From the costs and cycle data previously presented and using Eq. (2), the capital cost of all equipment was calculated. Further, annual operating costs were calculated by Eq. (3): 1) considering that the IRB 6660 will be used at average 1.0 kWh, and the GoFa and Swifty at 0.5 kWh each, electricity costs amount for $1000 to $2000, depending on the type of mod- ule being disassembled due to distinctive robotic operating time, 2) license annual costs (RobotStudio and D:PLOY software) amount for $8568, and 3) annual maintenance cost for each robot, IRBP A, and Conveyor belt being rated at $800, the total annual maintenance costs amounts for $4000. Annual costs were estimated by Eq. (4). Using this information, alongside the annual module throughput and module capacities, the cost per disassem- bled module and cost per kWh disassembled were determined. These results, along with previous findings, are combined and presented in the consolidated table 4.

The LithoRec process was modelled in the EverBatt model for the pur- pose of obtaining the potential revenue per kilo cell recycled for the

Table 3
Potential annual throughput of an automated dismantling line for the three battery types.

	Volkswagen	Hyundai	Mitsubishi
Operation time [sec] (t_i)	142	803	300
Disassembly time [sec] ($F^{-1}(90)$)	77	594	254
Throughput [nr. of modules] (Q)	405,878	52,686	123,110
Throughput [nr. of cells]	4,870,536	2,107,440	1,969,760
Throughput modules [ton]	4,422	2,314	3,137
Throughput cells [ton]	3,882	1,829	2,750

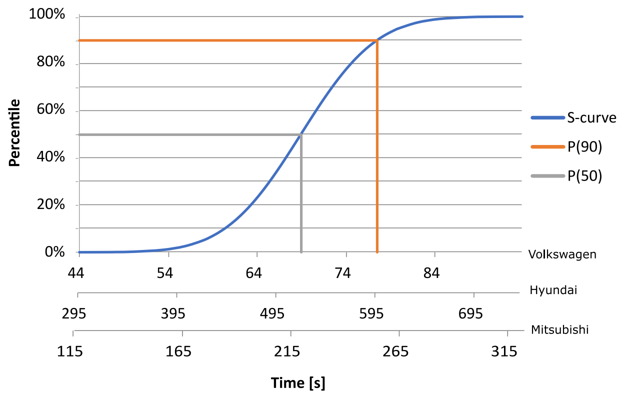

Fig. 2. Cumulative distribution function, disassembly times.

Table 4
Costs and potential revenue for automated disassembly.

		Volkswagen	Hyundai	Mitsubishi
Costs	**Capital cost (C_c)**	74,405	74,405	74,405
	Operating cost (C_o)	14,688	14,427	14,324
	Annual cost (C_a)	89,093	88,832	88,729
	Cost per module	0.22	1.69	0.721
	Cost per kWh	0.137	0.193	0.316
Revenue	**Potential revenue [$/kg cell]**	5.38	4.39	10.15
	Potential revenue [$/kg module components]	0.386	0.529	0.217

different battery modules with specific cathode chemistry. Furthermore, the potential revenue per kilo of disassembled module components was calculated using Eq. (11), using the data from Tables 1 and 2 as input parameters. The results are presented in Table 4.

3.2. Recycling process

To enable a meaningful assessment of the economic implications of auto- mated disassembly, three scenarios that impact recycling revenue are formu- lated: (1) improved capacity utilization, (2) cost reduction potential under current supply volumes, and (3) reduction of processing steps in recycling. All calculations were executed in the Supplementary Information spreadsheets.

3.2.1. Improved capacity utilization

Assuming that a recycler can acquire an increased number of battery modules, processing cells rather than modules could increase the volume of valuable materials like cobalt, nickel, and manganese, hence increasing the economic viability of recycling (Chen et al., 2019). Potential revenue gains for the small and large capacity mechanical processing steps of the LithoRec process are presented in scenarios 1a and 1b below.

Scenario 1a. The LithoRec's mechanical processing has a design capacity of 1200 tons/year. The Volkswagen's cell-to-module weight ratio is $(12 \times 0.797$ kg cell$)/10.896$ kg module $= 0.878$. Through this process, 1053.6 tons of cells and 146.4 tons of module components are recycled. Given the rev- enues per kg in Table 4, total revenue is $5.717 M.

Alternatively, when exclusively processing cells as shown in Fig. 3, 1,200 tons are recycled, boosting cell recycling by 146.4 tons. Module com- ponents are recovered with a 100 % rate before recycling. The total recycling revenue in this case is $6.521 M, an increase of $804,0 K. Using Eq. (12), the NPV for a robotic disassembly line is approximately $2.923 M. This scenario is also modeled for Hyundai and Mitsubishi, with results in Table 5.

Scenario 1b. LithoRec's large mechanical processing step has a 6000-ton yearly capacity. The robotic disassembly line processes 4422 tons of Volk- swagen battery modules, equaling 3882 tons of cells. Due to the line's ca- pacity constraints, both cells (3882 tons) and modules (2118 tons) undergo mechanical processing. Processing both instead of just modules augments cell recycling by 475 tons, as depicted in Fig. 4.

Scenario 1a.* Cell processing may yield further cost savings. LithoRec's process separates steel after module shredding and drying. However, since cells don't contain steel (Appendix A), module disassembly might negate this step, cutting costs if the magnetic separator is excluded in scenarios 1a. Consultations with a retailer provided a magnetic separator cost of $35,000, fitting the needed flow rate. As per EverBatt's estimates, it would demand three daily labor hours (Dai et al., 2019). Factoring in labor, 2 % maintenance, and electricity, annual operational savings amount to $23,800. Plus, initial plant investment might drop by $35,000, increasing the NPV of scenario 1a to $3.056 M for the Volkswagen module.

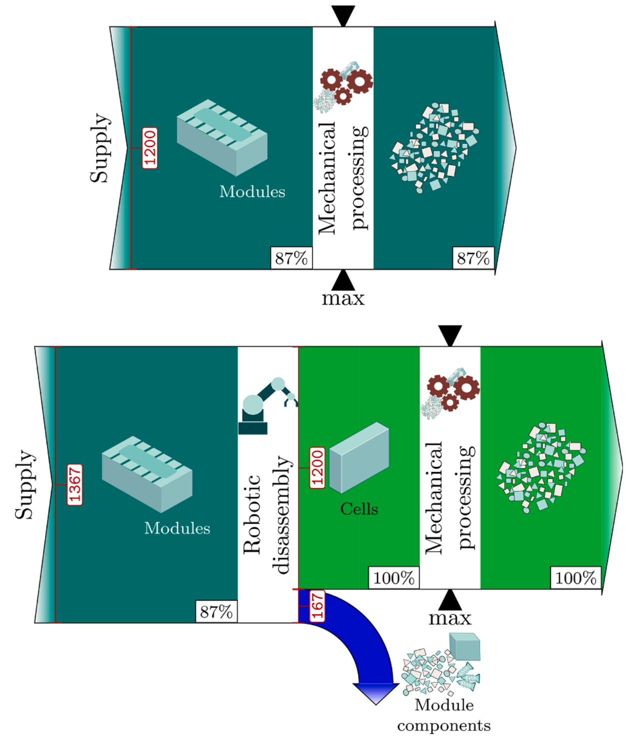

Fig. 3. a) Scenario without robotic disassembly, with 1200 tons maximum capacity. b) Scenario 1a showcasing the robotic module disassembly, processing 1367 tons of modules and extracting 167 tons of material, followed by the mechanical processing of 1200 tons of cells at maximum capacity. The percentages denote the relative density of cell materials at each stage of the process.

Table 5
Parameters for Scenarios with improved capacity utilization where $1.00M = $1,000,000.

Scenario		Volkswagen	Hyundai	Mitsubishi
1a	Revenue, processing modules	$5.717M	$4.280M	$10.705M
	Additional cells	146.4 [ton]	252 [ton]	147.6 [ton]
	Revenue, processing cells	$6.521M	$5.436M	$12.217M
	NPV	$2.923M	$4.371M	$5.833M
1b	Revenue, shredding modules	$28.583M	$21.398M	$53.524M
	Additional cells	475 [ton]	383 [ton]	339 [ton]
	Revenue, shredding cells/ modules	$31.183M	$23.162M	$56.986M
	Annual revenue gain	$2.600M	$1.764M	$3.462M
	NPV	$10.304M	$6.867M	$13.852M
1a*	Annual revenue gain	$0.828M	$1.180M	$1.536M
	NPV	$3.056M	$4.504M	$5.966M

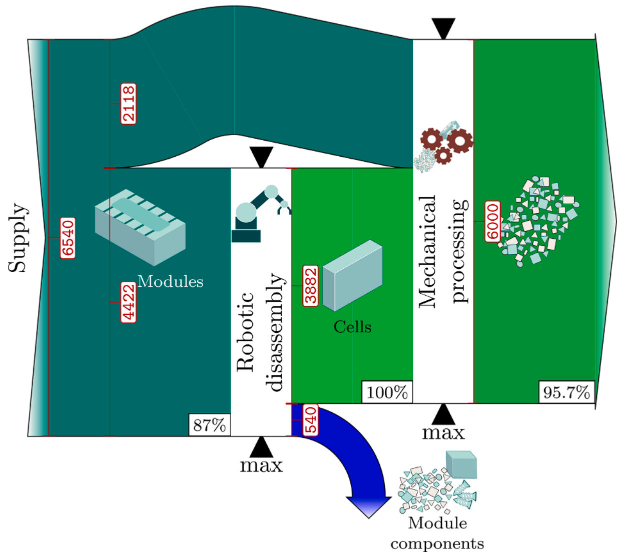

Fig. 4. Scenario 1b represents the automated disassembly process at full capacity, where both robotic disassembly and mechanical processing are at their limits, handling 4422 tons and 6000 tons respectively, with an excess of 2118 tons of modules directed to mechanical processing without prior disassembly.

Potential revenue gains and NPV for this scenario, including Hyundai and Mitsubishi modules, are shown in Table 5.

3.2.2. *Cost reduction potential under current supply volumes*

With an expected rise in EOL EV LIBs, the demand for large-scale recycling equipment increases. However, the current supply of spent LIBs remains limited (Statista, 2023). This hints at a supply bottleneck of EoL LIBs until waste volumes grow, potentially hindering recyclers from achieving the projected revenue in scenarios 1a and 1b. Yet, by processing cells over modules, savings in operational costs might arise from less processed material.

Scenarios 2a and 2b differ from 1a and 1b: they don't augment recycled cell numbers but reduce the volume processed by eliminating module components pre-recycling. Since the cell count stays consistent and module components are reclaimed during robotic disassembly, revenues remain sta- ble. Conversely, operating expenses might decrease with reduced material volume. Cost savings for LithoRec's capacities are discussed in scenarios 2a and 2b.

Scenario 2a. Assuming a battery module supply limited to the mechanical process's small capacity (1200 tons), by processing Volkswagen cells instead of modules, the processed material reduces to 1054 tons, a 146-ton decrease, as shown in Fig. 5. If operating costs scale with

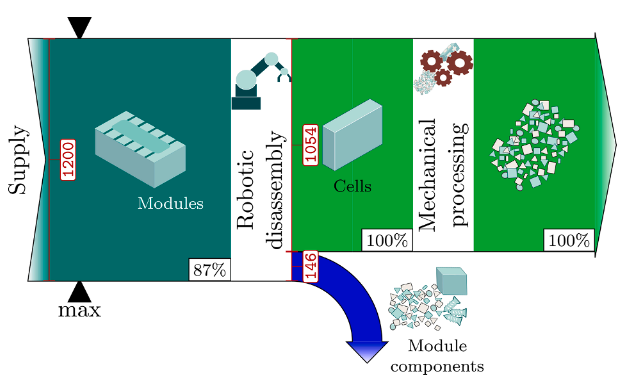

Fig. 5. Scenario 2a illustrates the constrained supply situation with a maximum input of 1200 tons of modules. Robotic disassembly enables the separation of 146 tons of non-cell material, reducing the load on mechanical processing to 1054 tons of cells.

Table 6
Parameters for Scenarios under current supply volumes. $1K = $1000.

Scenario		Volkswagen	Hyundai	Mitsubishi
2a	Decrease in processed material	147 [ton]	251 [ton]	148 [ton]
	Annual cost savings	$8.6K	$14.8K	$8.7K
	NPV	-$319K	-$250K	-$325K
2b	Decrease in processed material	540 [ton]	485 [ton]	387 [ton]
	Annual cost savings	$31.8K	$28.5K	$22.8K
	NPV	-$151K	-$128K	-$234K
2a*	Annual cost savings	$32.4K	$38.8K	$32.5K
	NPV	-$186K	-$117K	-$192K

throughput, this material reduction cuts costs, yielding annual savings of $8.6 K. This translates to a NPV of $−319 K for the robotic line. Hyundai and Mitsubishi outcomes are also presented in Table 6.

Scenario 2b. In a scenario similar to 2a, the large capacity class might hit a bottleneck where recycled cell quantities won't rise due to EoL EV LIBs' limited supply. Like scenario 1b, both cells and modules are processed within the constraints of the robotic disassembly line's capacity which controls the reductions in material and potential cost savings, as depicted in Fig. 6. Annually, 4422 tons of Volkswagen modules are disassembled to 3882 tons of cells, cutting 540 tons. Hence, the facility handles 5460 tons instead of 6000. If operating costs scale with throughput, annual savings amount to

$31.8 K. The NPV for the line is $−151 K. Hyundai and Mitsubishi results are also presented in Table 6.

Scenario 2a.* Mirroring scenario 1a*, scenario 2a* also benefits from a reduction in processing steps during the recycling process. Applying this logic to scenario 2a, the NPV is enhanced to -$186 K for the Volkswagen module.

Potential revenue gains and NPV for this scenario, including Hyundai and Mitsubishi modules, are shown in Table 6.

4. Discussion

4.1. *Improved capacity utilization*

Scenario 1a. Given the conditions set forth in scenario 1a, the data presented in Table 5 indicates a notable improvement in revenue generated through the processing of cells, as opposed to modules, across all three battery modules. All things considered, the NPV presents a positive outcome across the battery modules which indicates that investing in a disassembly line for robotic modules is deemed

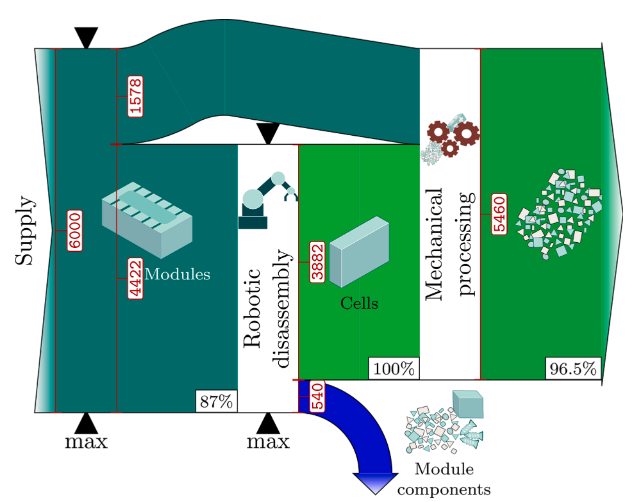

Fig. 6. Scenario 2b displays a supply limit of 6000 tons of modules, with robotic disassembly maxed at 4422 tons. This leads to 5460 tons, including unprocessed modules, entering mechanical processing, with 540 tons removed by disassembly.

economically viable. However, it is the extent of increase in revenue gain observed from cell processing that merits attention. Volkswagen's revenue increased by 14 %, Mitsubishi's by 14 %, and Hyundai's by a substantial 27 %. The higher percentage for Hyundai is primarily due to its lower cell to module weight ratio in comparison to the latter two modules. In other words, processing Hyundai modules as input to the mechanical process would result in a relatively low number of cells being processed initially. However, when pure cells are fed to the mechanical process, the Hyundai yields a significantly higher quantity of additional valuable cell material. Moreover, the robotic disassembly line modelled in this study has the capacity to process 3.24 times more tons of material than the mechanical process. In this scenario, the robotic disassembly line could be downscaled, or the remaining disassembled cells could be sold to a third-party. The same applies for the Hyundai and the Mitsubishi battery.

Scenario 1b. Regarding scenario 1b, the mechanical process has a capacity limit of 6000 tons of material, which the disassembly line is unable to match and therefore modules are added to reach the mechanical process capacity limit. In this scenario, the revenue gains for Volkswagen, Mitsubishi, and Hyundai are 9 %, 6 %, and 8 %, respectively. All battery modules experienced a percentage decrease in revenue gain compared to scenario 1a, with the most substantial decline observed in the case of Hyundai. That is logical explained by the fact that this scenario is not able to fully utilize the potential of processing pure cells in the mechanical process. However, the NPV of the robotic investment indicates, once again, a positive outcome for all battery modules.

Therefore, considering unlimited supply volumes, investing in a robotic module disassembly line is in fact economically viable.

4.2. Cost reduction potential under current supply volumes

The recycling industry is preparing for the anticipated increase of EoL EV LIBs in the future. However, as scenarios 2a and 2b reveal, the quantity of recyclable spent LIBs is currently limited. Thus, the question is whether such an investment is economically feasible at present times.

As indicated in Table 6, when the bottleneck equals the supply volumes, reducing the amount of materials processed results in lower operational costs for the mechanical process. Nevertheless, the investment cost of the disas- sembly line is prohibitively high, and the NPV alone is not favorable within the designated six-year investment time frame alone. Nonetheless, it does shed light on the potential cost savings that may be realized in the presence of an inadequate supply of EoL EV LIBs. Therefore, it should be taken into consideration solely by stakeholders who are seeking to proactively prepare for the impending supply stream.

4.3. Reduction of processing steps in recycling

Provided that the capacity of mechanical processing does not exceed the disassembly line (scenarios 1a and 2a), scenarios 1a* and 2a* explore the potential of reducing process steps in recycling. The findings suggest that cost savings could be obtained by removing the magnetic separator from the mechanical process, resulting in an annual cost savings of $23.8 K for all three battery modules, as well as a reduction in investment costs by $35 K. This scenario should be considered as an extension for additional cost savings in the other scenarios. It is worthy of consideration that if the disassembly line were proportionately expanded to align with the mechanical process, the magnetic separation stage would become entirely superfluous and dispensable for all subsequent recycling operations.

4.4. Other scenarios

Additional scenarios beyond those discussed could be relevant but have not been quantitatively presented due to constraints on data accessibility and collection. This study analyzes the recycling of EoL EV LIBs as opposed to reuse and repurpose options. Yet, disassembling modules to cell level may benefit these options. Harper et al. argue that if an LIB module cannot easily be reused, it must be recycled (Harper et al., 2019). This is often due to inhomogeneous cell aging, resulting in a situation where only a few out-of-condition cells are enough to render an entire module unsuitable for reuse (Zhao et al., 2021). Rather, if the modules are disassembled to cell level, usable cells can be repurposed or reused. This would require an accurate State of Health (SoH) assessment, needing time and money investment but offers environmental benefits and economic gains. Another key point is the potential for increased recycling efficiency and purity of output materials in the mechanical processing steps. Sommerville et al. argue for effective separation of battery components for cost-effective recycling (Sommerville et al., 2020). Processing cells instead of modules reduces non-targeted material, potentially enhancing output material purity and increasing recycling revenue. Another interesting scenario is to combine automated disassembly with direct recycling, which refers to the process of recovering the functional cathode without decomposing it into its substituent parts.

5. Conclusions

This study has shown that automated disassembly of EV LIBs from module to cell level prior to recycling could be economically viable given certain circumstances. The assessed EV modules include the Volkswagen E-Golf 2019, Hyundai Ioniq 2. Gen 2019 and the Mitsubishi Outlander 2017, which are common battery types and give a fair indication of the techno-economic viability of automated disassembly. Based on a detailed tear-down analysis of the battery modules, a robotic module disassembly line was modelled, and associated robotic disassembly times and costs were estimated. Further, using the mechanical processing steps of LithoRec as a reference recycling process, potential recycling revenues per kilo recycled cell was estimated in the EverBatt model. From this, potential scenarios that could increase recycling revenue or reduce recycling costs by mechanically processing cells instead of modules were established. Hence, this research study builds upon earlier techno-economic analyses of LIB disassembly techniques and recycling processes, providing a more comprehensive modelling of the costs and benefits of an automated disassembly process to the cell level.

The annual costs of the robotic module disassembly line were estimated at approximately $89,000, disassembling an annual amount of 405,878 Volkswa- gen modules, 52,686 Hyundai modules and 123,100 Mitsubishi modules. This translates to a disassembly cost per module of $0.22, $1.69 and $0.721, res- pectively. The potential annual revenue per kilo cell recycled was estimated at $5.38, $4.39 and $10.15.

The economic viability of the robotic module disassembly line is depen- dent on several factors. In general, the main findings indicate that processing of cells instead of modules could increase recycling revenue by 6 % to 27 % depending on processing capacity and type of module. As a consequence, the NPV of the robotic disassembly line was estimated to fall within the range of

$2.9 M to $14.8 M. This was based on the condition that the volume of cells recycled is increased while still operating within a given recycling capacity. Considering the anticipated increase in the number of EoL EV LIBs in the future, this scenario gains even more relevance. Conversely, process- ing cells instead of modules at current supply volumes does not result in a positive NPV. Finally, it should be noted that additional cost savings were identified by avoiding certain process steps when processing cells instead of modules, which was subject to the condition that the cells did not contain any steel.

Our study rests on the assumption that the dismantling line can adapt to new designs thanks to cutting-edge computer vision, enhanced robotic dexterity, and reinforcement learning, and will require minimal human intervention. We do realize that in practice, this may appear optimistic, particularly given the current stage of technological development. Yet, we believe it is important to conduct such forward-looking analyses to assess the potential profitability of innovative automated disassembly and standardisation.

In conclusion, it can be stated that automated disassembly of EV LIBs to cell level is economically viable, particularly when considering the projected increase of EoL EV LIBs. The main reason for this is the increased amount of valuable materials that can be recovered by subjecting the cells to the recycling process. In contrast, processing modules limits recycling capacity due to the additional recycling of less valuable module components.

Declaration of Generative AI and AI-assisted technologies in the writing pro- cess. During the preparation of this work the authors used ChatGPT by OpenAI in order to improve readability and language. After using this tool, the authors reviewed and edited the content as needed and take full respon- sibility for the content of the publication.

CRediT authorship contribution statement

Martin Choux: Conceptualization, Methodology, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Simon Waldemar Pripp:** Formal analysis, Investigation, Visualization, Writing – original draft. **Frode Kvalnes:** Formal analysis, Investigation, Visualization, Writing – original draft. **Magnus Hellström:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Martin Choux reports equipment, drugs, or supplies was provided by RHINOCEROS Funded by the European Union under Grant Agreement No 101069685

Data availability

No data was used for the research described in the article.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.resconrec.2024.107430.

Appendix A. Cell material composition

The cell material composition of the three different battery chemistries included in this study is presented in Table A1

Table A1
Cell material composition [wt%].

Materials	NMC111	NMC622	LCO
Cathode	38.8 %	36.0 %	35.3 %
Graphite	20.0 %	21.6 %	18.5 %
Carbon black	0.8 %	0.7 %	2.4 %
Binder: PVDF	0.8 %	0.7 %	2.4 %
Binder: anode	1.1 %	0.4 %	0.6 %
Copper	16.8 %	18.1 %	16.1 %
Aluminium	8.5 %	9.1 %	8.1 %
Electrolyte: LiPF6	1.7 %	1.7 %	2.2 %
Electrolyte: EC	4.6 %	4.6 %	6.0 %
Electrolyte: DMC	4.6 %	4.6 %	6.0 %
Plastic: PP	1.6 %	1.7 %	1.8 %
Plastic: PE	0.4 %	0.4 %	0.3 %
Plastic: PET	0.3 %	0.3 %	0.3 %
Steel	0.0 %	0.0 %	0.0 %

Appendix B. Module specifications

Appendix B.1. Hyundai Ioniq 2. Gen 2019 (Figs. B1 and B2, Tables B1 and B2)

Table B1
Dimensions and weight, Hyundai.

Level	Length [mm]	Width [mm]	Height [mm]	Weight [g]	Capacity [kWh]
Module	390	310	*235*	*43,922*	*8.72*
Cell	180	35	*170*	*868*	*0.218*

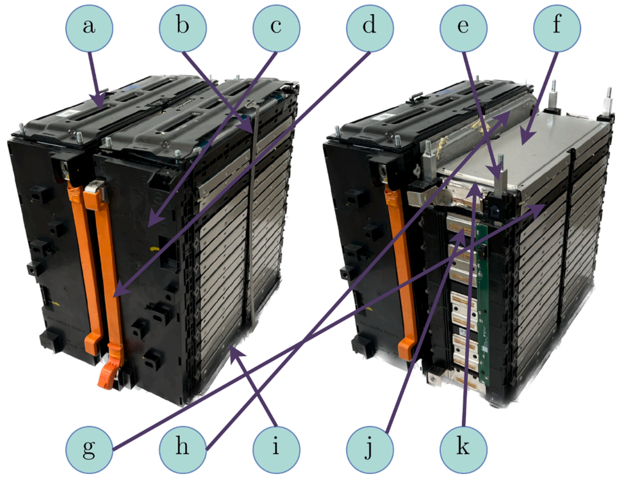

Fig. B. 1: Battery module, Hyundai.

Table B2
Main components, Hyundai.

Component	Tag	Qty.	Mass [g]	Sum mass [g]	Material
Top cover	a	2	372/99	744/198	Steel/Plastic
Top cover brace	b	4	35	140	Aluminium
Side cover	c	4	74	296	Plastic
Side cover brace	d	2	114	228	Steel
Module brace	e	8	88	704	Steel
Cell cover	f	40	40	1600	Aluminum
Cell frame	g	20	140	2800	Plastic
Cooling radiator	h	1	824	824	Aluminium
Module platform	i	1	1829/198	1829/198	Steel / Plastic
Cell bridge	j	4	NA	NA	Steel
Individual cell	k	40	868	34,720	–
Other components	–	–	248/423	248/423	Steel / Plastic

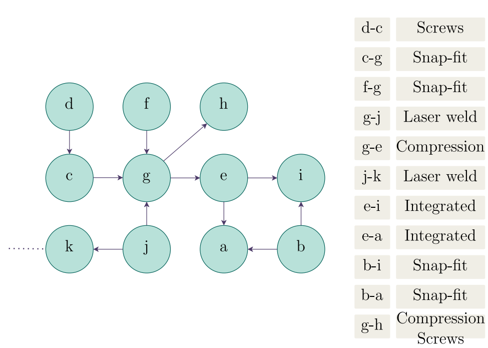

Fig. B2. Connection Diagram, Hyunda.

Appendix B.2. Mitsubishi Outlander PHEV 2017 (Figs. B2 and B3 Tables B3 and B4)

Table B3
Dimensions and weight, Mitsubishi.

Level	Length [mm]	Width [mm]	Height [mm]	Weight [g]	Capacity [kWh]
Module	625	185	*130*	*25,478*	*2.28*
Cell	180	35	*170*	*1396*	*0.134*

Fig. B3. Battery module, Mitsubishi.

Table B4
Main components, Mitsubishi.

Component	Tag	Qty.	Mass [g]	Sum mass [g]	Material
Top metal cover	a	1	1108	1108	Steel
Top plastic cover	b	2	98	196	Plastic
CMC unit	c	2	214	428	Plastic
Cell frame	d	2	241	482	Plastic
Bottom metal cover	e	1	733	733	Steel
Cell bridge	f	28	7	195	Steel
Individual cell	g	16	1396	22,336	–

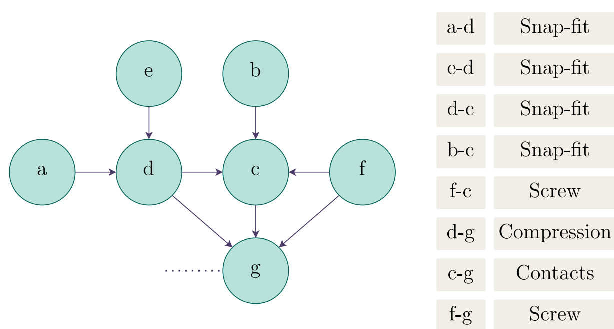

Fig. B4. Connection Diagram, Mitsubishi.

Appendix C. Required hardware for disassembly line

The required components for the disassembly line, their function, the specific hardware used, and associated costs are listed in Table C1

Table C1
Required hardware for disassembly line.

ID nr.	Description	Function	Hardware	Cost [$]
1	Rotary worktable	Manipulation	IRBP A Workpiece Positioner	19,00
2	Fixture system	Manipulation	Custom made	10,000
3	Vision system	Detection	Zivid One+	19,200
4	Machine guarding	Safety	Machine guarding	2411
5	Conveyor belt system	Transporta-tion	Conveyor belt	7800
6	Milling Robot with milling tool	Cutting operations	ABB IRB 6660	125,000
7	Unscrewing Robot	Unscrewing operations	ABB GoFa CRB 15,000	41,500
8	Spindle tool	Unscrewing operations	OnRobot Screw-driver	25,652
9	Grasping Robot	Pick and place operations	ABB Swifty CRB 1300	40,076
10	Finger gripper	Pick and place operations	OnRobot finger gripper	11,484
11	Vacuum gripper	Pick and place operations	OnRobot vacuum gripper	11,651
12	Setup and shipment			6422
Sum (C_i)				**325,197**

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