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End of Life Pathways for Battery Energy Storage Systems(BESS): Designing a Decision Support Tool for Optimal Route Selection

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Abstract

The global acceleration of electrification and renewable energy integration has placed lithium-ion batteries (LIBs) at the centre of sustainable energy systems. However, as large volumes of batteries from electric vehicles and stationary storage approach the end of their operational life, their end-of-life (EoL) management has become a critical technical, economic, and environmental challenge. The growing diversity of recycling and second-life options has made the decision of whether a battery should be reused, repurposed, or recycled increasingly complex, with limited standardised guidance to support such choices.

This thesis aims to address this gap by developing a transparent and adaptable decision-support framework for optimal EoL pathway selection for Battery Energy Storage Systems (BESS). A multi-criteria decision-making (MCDM) approach, based on the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), is applied in combination with fuzzy logic to handle uncertainty and variability in stakeholder perspectives. Key Performance Indicators (KPIs) influencing EoL decisions are identified from literature and grouped into three dimensions: technical (State of Health(SoH), Internal Resistance(IR)), economic (Refurbishment Cost, Scrap Value, Chemistry/Material Value), and environmental (CO_2 Savings, Hazard). Weights for each criterion are derived from three representative seed papers, reflecting technical, economic, and sustainability-oriented priorities to ensure a literature-grounded, replicable methodology.

The model is then demonstrated through a comparative analysis of four representative battery packs with industry demonstrated but hypothetical data. Results highlight how shifts in weighting priorities influence optimal decisions, showing that higher SoH and lower resistance favour reuse scenarios, while higher material value and hazard levels tilt the decision towards recycling. These findings underline the importance of context-sensitive decision frameworks and reveal how trade-offs between technical performance, cost efficiency, and environmental impact shape EoL outcomes.

Whilst this study provides a structured foundation for EoL decision-making, it represents an early-stage framework that relies solely on secondary data and literature-based weights. Future research should incorporate expert interviews, empirical datasets, and dynamic weighting schemes to capture real-world complexity. Ultimately, this thesis contributes a replicable, transparent, and evidence-based approach that can guide policymakers, manufacturers, and recyclers in advancing battery circularity and supporting the broader energy transition.

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Sincerely,
Sharada Priya Vijaya Kumar

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Acronyms

BESS	Battery Energy Storage System.
LIB	Lithium-Ion Battery.
EV	Electric Vehicle.
EoL	End of Life.
SoH	State of Health.
IR	Internal Resistance.
KPI	Key Performance Indicator.
CO_2	Carbon Dioxide.
GHG	Greenhouse Gas.
LCOE	Levelised Cost of Energy.
NPV	Net Present Value.
BMS	Battery Management System.
MCDM	Multi-Criteria Decision-Making.
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution.
TFN	Triangular Fuzzy Number.
AHP	Analytic Hierarchy Process.
LCA	Life Cycle Assessment.

NMC Nickel Manganese Cobalt Oxide.
NCA Nickel Cobalt Aluminium Oxide.

LFP Lithium Iron Phosphate.
$LiPF_6$ Lithium Hexafluorophosphate.

HF Hydrogen Fluoride.

NREL National Renewable Energy Laboratory.

EU European Union.

IEA International Energy Agency.
ICCT International Council on Clean Transportation.

OEM Original Equipment Manufacturer.

SLB Second-Life Battery.

ESS Energy Storage System.

BLAST Battery Lifetime Analysis and Simulation Tool.

LIBRA Lithium-Ion Battery Resource Assessment.

TRL Technology Readiness Level.

EPR Extended Producer Responsibility.

RUL Remaining Useful Life.
RE Renewable Energy.

USD United States Dollar.

MW Megawatt.
MWh Megawatt-hour.

Chapter 1

Introduction

1.1 Background and Motivation

Over the past decade, the global transition towards electrification and decarbonisation has accelerated the deployment of battery energy storage systems (BESS) across key sectors such as electric mobility, stationary energy storage, and consumer electronics. Lithium-ion batteries (LIBs), in particular, have emerged as the dominant storage technology due to their high energy density, declining costs, and technical maturity[1]. Their role is critical not only for enabling low-emission transport but also for stabilising renewable rich grids and supporting distributed energy systems.

According to global energy outlooks, battery demand is expected to rise exponentially from 184 GWh in 2018 to over 2,600 GWh by 2030, driven largely by electric mobility, with energy storage systems becoming an increasingly significant contributor (Figure 1.1). This growth, while enabling clean energy transitions, introduces an equally urgent and complex challenge: the sustainable management of batteries at the end of their useful life.

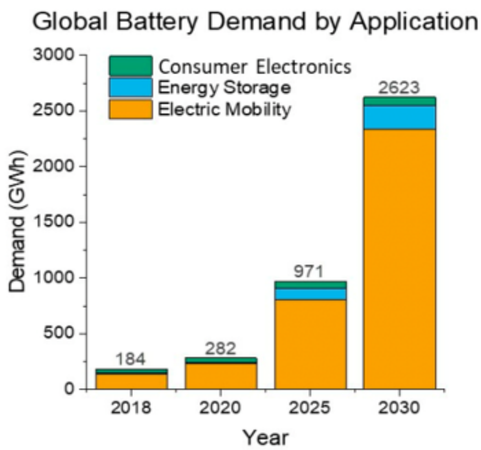

Figure 1.1: Global battery demand by application. Electric mobility dominates future growth, followed by stationary energy storage and consumer electronics. [2]

As battery systems deployed today reach retirement over the next two decades, the volume of end-of-life (EoL) batteries will surge. Electric vehicle (EV) batteries, in particular, typically retire once their State of Health (SoH) falls below 70-80%, often still retaining significant usable capacity. If repurposed effectively, these batteries can serve in less demanding applications such as residential or commercial storage, microgrids, or backup power systems. This repurposing, often referred to as second-life application, can delay recycling, reduce lifecycle emissions, and provide affordable storage solutions.

Projections suggest that by 2050, more than 11,000 GWh of cumulative battery capacity from retired EVs could become available globally for reuse (Figure 1.2). This represents a substantial latent resource comparable to building hundreds of gigawatt-scale storage plants, only if appropriate routing, diagnostic, and safety frameworks are in place.

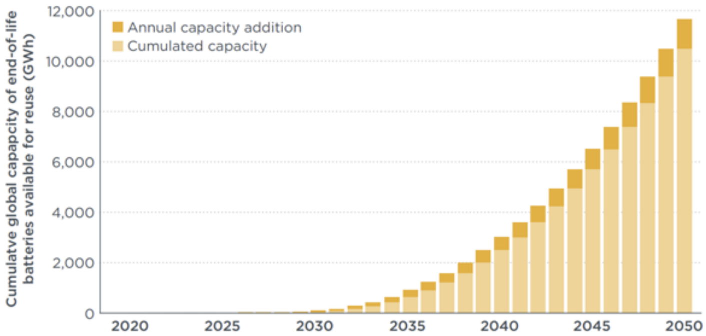

Figure 1.2: Projected cumulative global capacity of end-of-life EV batteries available for reuse. Reuse potential scales significantly from 2030 onward. [3]

However, the decision-making processes that determine whether a battery should be reused, recycled, or disposed of remain largely unstructured, inconsistent, and highly dependent on local conditions or stakeholder preferences. Recycling is often prioritised when material value recovery (especially cobalt, nickel, lithium) is high, while reuse is favoured when SoH and refurbishment economics align. Yet, there is no widely adopted framework that systematically integrates technical, economic, and environmental indicators into a replicable and data-driven EoL decision tool.

Existing tools and approaches either focus on single aspects such as, life cycle assessments (LCAs), financial returns, or SoH diagnostics. They lack adaptability across regions, chemistries, and application scales.This results in operational inefficiencies, misaligned policy incentives, and missed opportunities to maximise value from EoL batteries.

In this context, the need for a structured, transparent, and multi-dimensional decision-making framework is both timely and necessary. This thesis addresses that gap by developing a hybrid Multi-Criteria Decision-Making (MCDM) model, using fuzzy logic and TOPSIS ranking, that integrates literature-derived KPIs and stakeholder perspectives into a practical, adaptable decision-support tool for battery EoL routing.

1.1.1 Research Problem

The absence of a uniform decision-making framework creates inefficiencies and uncertainty for both industry and policymakers. For example, a battery with 75% State of Health (SoH) may still be valuable for secondary use in stationary storage, but only if the refurbishment costs are not really high and if there is demand for such applications. Conversely, a battery with lower SoH might be more suitable for immediate recycling, especially if the material value is high. These trade-offs are complex and context-dependent.

Existing literature has proposed various approaches to evaluating EoL options such as LIBRA, BLAST, Machine Learning(ML) based tools and MCDM models [4, 5, 6]. Despite these contributions, there remains a gap: no consensus exists on how to integrate these technical, economic, and environmental KPIs into a transparent, replicable, and adaptable framework. Industry actors may prioritise profitability, while policymakers emphasise environmental outcomes. Without harmonisation, EoL strategies risk being either suboptimal or inconsistent across regions.

1.1.2 Research Questions

This thesis is guided by the following research questions:

1. What are the different End of Life pathways for Battery Energy Storage Systems?

2. Which key performance indicators (KPIs) are most relevant for guiding decision-making in BESS end-of-life pathways?

3. How can a multi-criteria decision-making (MCDM) approach, specifically the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), be applied to integrate these KPIs into a robust framework?

4. What insights can be drawn from applying this framework to realistic battery scenarios, and how do different weighting profiles influence the results?

1.1.3 Objectives and Contributions

The primary objective of this thesis was to identify the main EoL pathways for BESS and understand how the decisions are made in the current scenario. In addition to this, after identifying a gap in the decision making process, a sub-objective was to try and develop and apply a transparent, literature-based decision-making framework for battery EoL pathways. To achieve this, the thesis pursues the following sub-objectives:

- Identify and categorise relevant KPIs across technical, economic, and environmental dimensions

- Review existing decision frameworks and extract their implied weighting priorities

- Develop a MCDM model that integrates KPIs into a comparative decision-making process
- Apply the model to synthetic yet realistic case scenarios, representing different battery chemistries, costs, and environmental profiles

The contributions of this thesis are threefold. First, it consolidates literature on battery end-of-life (EoL) pathways, including reuse, recycling, and disposal and condenses it into a structured framework for identifying and weighting key performance indicators (KPIs). Second, it adapts and applies a classical MCDM technique, TOPSIS, enhanced with fuzzy logic to the context of BESS EoL assessment. Finally, it delivers a replicable and adaptable decision-support tool that can assist diverse stakeholders, such as recyclers, policymakers, and energy system planners in navigating the complex trade-offs between technical viability, economic value, and environmental impact when routing batteries at the end of their useful life.

Chapter 2

Literature Review

2.1 Methodology

The literature review was conducted in a systematic and exploratory manner to identify both the current state of EoL pathways for lithium-ion batteries and the decision-support frameworks that guide the selection of the route at EoL.The flowchart (Figure A.1) in Appendix A visually summarises the literature review process from keyword search to KPI derivation.

The initial search was performed across two scientific databases: Scopus and Google Scholar, targeting peer-reviewed publications between 2015 and 2024. Additionally, whitepapers and reports from reputed institutions such as International Council on Clean Transportation(ICCT) [3] and United Nations Development Program(UNDP) [7] and policy insights from the EU Battery Regulation [8] were included to ground the review in current industrial and regulatory developments. The keywords used in various combinations include : "Battery second life", "Battery end of life", "Recycling", "Reuse", "Repurposing", "MCDM", "TOPSIS", "Decision support battery", and "Battery KPI selection".

Publications were then shortlisted on the basis of relevance to either describing EoL pathways, or applying decision-making models or MCDM techniques to battery assessment problems keeping in line with the objectives described in the Introduction. Additional articles were identified through backward citation tracing, where the papers referenced within key publications were retrieved for further review. Relevance was verified by reading the abstracts and key sections in detail.

The reviewed papers were grouped into the following categories:
1. EoL Landscape Studies: Outlining the general trends in reuse, repurposing, and recycling of LIBs (e.g. [1], [2])
2. Case-Based Applications: Discussing the suitability of specific battery types for second-life or recycling, often in techno-economic contexts ([9, 10, 11, 12])
3. Decision-Making Frameworks: Introducing MCDM methods such as Machine

Learning, AHP, TOPSIS for battery EoL decisions ([13, 14, 15, 16])

From the MCDM literature pool, three seed papers were selected for their methodological robustness, KPI reporting, and practical relevance. These seed papers were then qualitatively analysed to extract the relative importance assigned to key performance indicators (KPIs), such as state of health, internal resistance, refurbishing cost, scrap value, material value, CO_2 savings, and hazard index. This is described in detail further in Section 3.

2.2 Introduction

The transition towards renewable energy and electrified transport has made lithium-ion batteries (LIBs) one of the most critical technologies of this decade, underpinning efforts to decarbonise transport and power sectors alike [17] . They have been rapidly adopted in electric vehicles (EVs), portable electronics, and stationary storage systems. However, this widespread uptake has created a parallel challenge: the accelerating volume of batteries approaching their end of life (EoL) [18, 19, 7]. Efficient management of batteries' EoL is therefore essential to minimise raw-material extraction, reduce greenhouse-gas emissions, and support the principles of circular economy [20].

Several studies emphasise that an uncoordinated approach to EoL handling could offset the environmental benefits gained from electrification [17]. Recycling alone cannot close the resource loop without effective collection, classification and reuse strategies [21]. Patel et al. note that current industrial practices often rely on simple capacity thresholds (for example, 80% of nominal capacity [17]) to determine whether a battery is reusable or should be recycled, but these thresholds are rarely validated across chemistries or applications. Dunn et al. and Harper et al. further show that repurposing a battery before recycling typically reduces total life-cycle emissions and improves the overall material utility, provided that technical safety and state-of-health (SoH) criteria are met [22, 23].

Policy frameworks are starting to recognise the strategic importance of these secondary pathways. The European Union's Battery Regulation (2023/1542) establishes requirements for traceability through a digital battery passport, minimum recycling efficiencies and producer responsibility for collection [8]. Similar initiatives appear in national regulations in the United States and East Asia, but implementation and verification remain inconsistent [7]. Industry reports from the ICCT suggest that the lack of unified testing and certification procedures for retired batteries is a primary obstacle to large-scale adoption of second-life systems [3].

The academic discussion has therefore moved beyond material recovery towards decision frameworks that balance technical, economic and environmental factors. Several reviews identify a clear need for tools capable of supporting reuse and recycling choices at different scales, from pack-level diagnostics to regional policy planning [24]. The research reviewed collectively shows that end-of-life decisions are still largely manual, fragmented across actors and seldom based on transparent multi-criteria reasoning. Addressing this gap requires structured evaluation models that combine measurable indicators, such as SoH and internal resistance, with broader metrics including cost, carbon impact and resource recovery potential [25].

By effectively extending the lifespan of lithium-ion batteries through reuse and repurposing, the immediate need for recycling is reduced, lessening the environmental impact associated with recycling processes and reducing risks associated with large-scale battery disposal [26]. When a battery reaches its EoL for the original application, current options generally include direct disposal (pathway increasingly discouraged), recycling for resource recovery, reuse in alternative automotive contexts, or repurposing for second-life applications such as stationary energy storage, followed by eventual recycling [21].

Direct disposal presents serious environmental hazards due to toxic metals leaching into soil and water or releasing harmful emissions into air, hence the strict regulations globally on waste battery handling and treatment. Second life applications harness batteries no longer suited for automotive duty but still functional enough for lower-power demands which extends their economic and environmental value and additionally supports grid stability with applications ranging from residential to utility scale [20].

Despite these clear benefits, the lack of universal standards, unified testing protocols and differing national policies complicates widespread second-life adoption. Increasing coordination and clear policy direction, supported by improved diagnostic tools and transparent data exchange, are essential for unlocking the full potential of lithium-ion battery circularity.

2.3 End of Life Pathways for Li-ion batteries

End-of-life (EoL) management for lithium-ion batteries (LIBs) is fundamental to achieving sustainability within electrified transport and the broader energy sector [19]. As the population of retired batteries grows, EoL approaches fall into four main categories: reuse, second-life (repurposing), recycling, and, as a final step, disposal [17, 9].The main pathways are depicted in the figure 2.1. Each pathway offers distinct environmental, technical, and economic value depending on battery condition, chemistry, and the policy/regulatory environment.

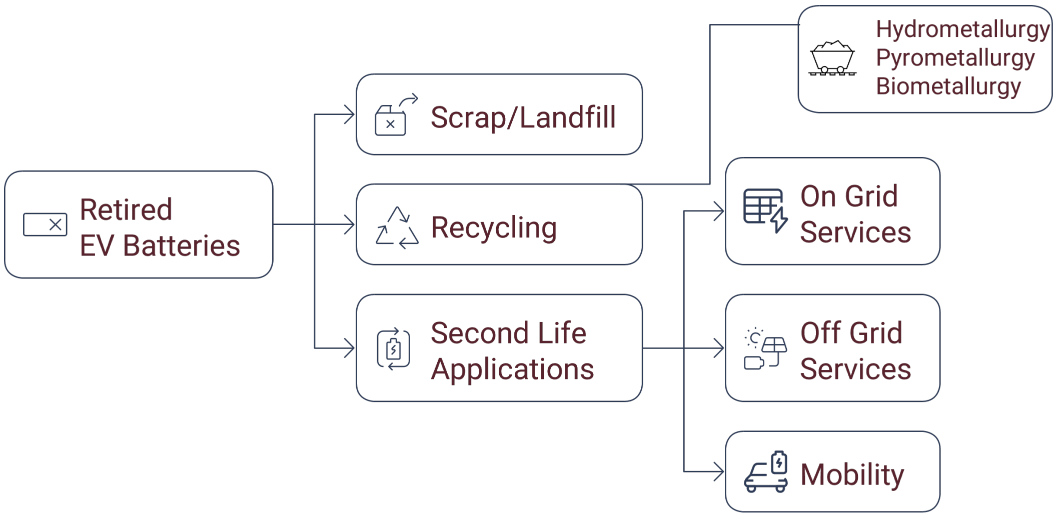

Figure 2.1: Flowchart of End-of-Life (EoL) pathways for Li-ion batteries

2.3.1 Reuse and Second Life Applications

Reuse refers to redeploying batteries that retain adequate technical performance, usually above 70-80% state of health (SoH), in their original roles or closely related functions with minimal processing. Second-life or repurposing goes further by adapting batteries retired from high-stress EV application environments for less demanding new uses, such as stationary storage, backup power, or microgrid applications[9].

To integrate retired EV batteries into various stationary or mobile applications, certain electrical and operational adjustments are necessary. M. Haram et al. note that typically, industrial energy storage systems operate within a voltage range of 800–1000 V, which is higher than that of EV systems [9]. The operational conditions of EV batteries differ substantially from those required for repurposed stationary systems, particularly in terms of voltage levels, temperature ranges, and thermal management strategies as detailed in table B.1 in Appendix B.

Figure 2.2 highlights that second-life battery (SLB) applications within energy storage systems (ESS) encompass a wide variety of use cases, ranging from grid-connected to off-grid and mobile applications. However, the degree of suitability for each application varies, depending on the technical and performance requirements of the batteries. M. Haram et al. also note that applications among on-grid applications, renewable farming, area and frequency regulation are more common whereas peak reduction and voltage/reactive power support are least common and sometimes considered infeasible. Similarly, among off-grid applications, microgrids and smart-grids are more frequently implemented, whereas power quality and reliability and spinning reserve are deemed infeasible. Most of the mobile applications are rarely or occasionally implemented, with EV charging station being the most common application [9].

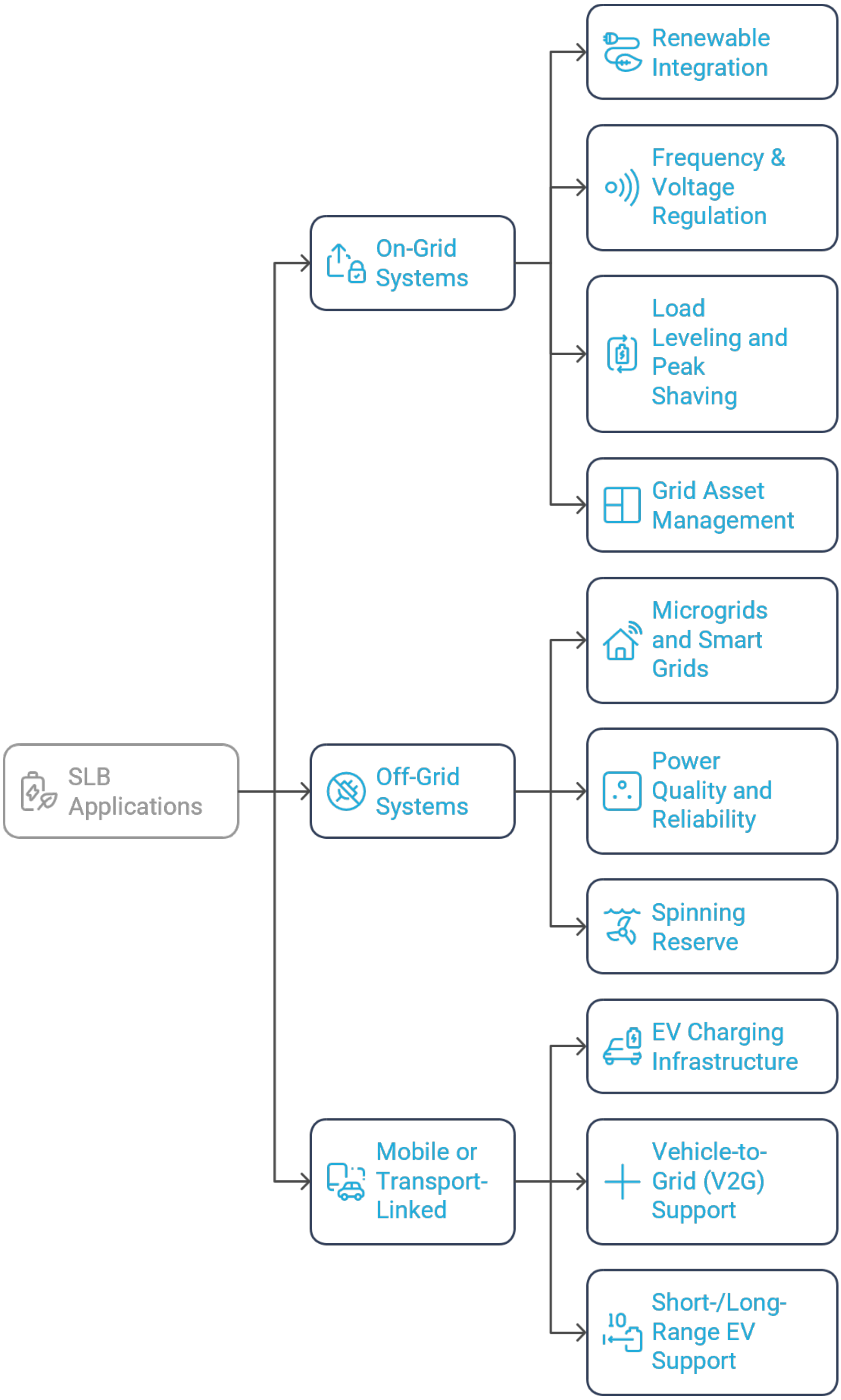

Figure 2.2: Typical second-life battery (SLB) ESS use cases across on-grid, off-grid, and mobile applications (adapted from [9]).

Applications and Benefits: Second-life batteries have demonstrated technical, economic and environmental benefits in applications ranging from domestic solar storage and grid services (peak-shaving, frequency regulation) to large-scale commercial or community resilience projects [9, 10]. For example, a study that modelled the reuse of SLBs in frequency containment reserves (FCRs) found the approach to be highly economically attractive, reporting internal rates of return (IRR) between 8 % and 21 % [27]. Similarly, a case study conducted by the American Council for an Energy-Efficient Economy (ACEEE) found that SLB systems can provide a more affordable energy storage option, expanding access to communities, particularly historically marginalized communities that face higher energy burdens, potentially reducing costs up to 60% [28].

Pilot projects provide evidence that second-life batteries can operate effectively in stationary systems for up to ten additional years, significantly extending the functional lifespan and reducing the carbon footprint of battery production. However, technical challenges remain around safety, performance uniformity, and SoH assessment [29]. Demonstration and pilot initiatives represent a crucial mechanism for understanding the practical implementation of second-life battery systems. They enable stakeholders to evaluate both technical feasibility and real-world operational logistics, spanning integration with renewables, regulatory compliance, and economic return. Patel et al. present an extensive catalogue of global pilot deployments expanded from Reinhardt et al.[30] and Zhu et al. [31]. Extending this, Table 2.1 below highlights major recently launched and planned projects that reflect the current evolution and global expansion of second-life battery applications.

Table 2.1: Recent and planned large-scale SLB (second-life battery) projects worldwide (adapted from multiple sources).

OEM / Lead	Partners / Provider	Cells/Packs	Power / Capacity	Year	Application	Country	Source
Connected Energy	Forsee Power, EDF	∼300 second-life EV packs	Multi-MW, grid utility	2025	Utility-scale BESS	UK/EU	[32]
Voltfang	Grid, C&I partners	Not disclosed, mixed chemistry	€250M+ factory, MW scale	2025-26	Grid, industrial, C&I	Germany/EU	[33]
General Motors(GM)	Redwood Materials	GM EV packs	Multi-MWh	2025+	Grid/utility storage	USA	[34]
Fraunhofer ISE	ADR, Rome Airport	Nissan LEAF	5 MW / 10 MWh	2025	Airport + PV hybrid	Italy	[35]
Lohum	MG Motor	LFP/NMC mixed, modular	kWh-MWh, off-grid	2025-27	Off-grid / backup	India	[36]
Redwood	Crusoe	Retired EVs	63 MWh	2025	Data centre / grid	USA	[37]
Battery2Life	EU, Horizon, OEMs	Multi-brand EV packs	MW, residential / grid	2025-26	Residential / grid	Greece,EU	[38]
BYD	Saudi Electricity Co.	Mixed BYD (car, bus)	12.5 GWh (multi-site)	2026-27	Grid modernisation	Saudi Arabia	[39]
Volkswagen, E.ON	Audi	VW e-Golf + retired packs	MW per site	2024-26+	Municipal grid / C&I	Germany, EU	[40]

2.3.2 Recycling

When LIBs are no longer suitable for reuse or re-purposing, recycling processes extract valuable raw materials and prevent environmental harm. Each major recycling route has distinct features. The major methods of recycling spent LIBs and the overview of the processes for each recycling is summarised visually in the Figure 2.3. While the first three methods are technically applied, bioloeaching is still in the experimental and laboratory stage [41].

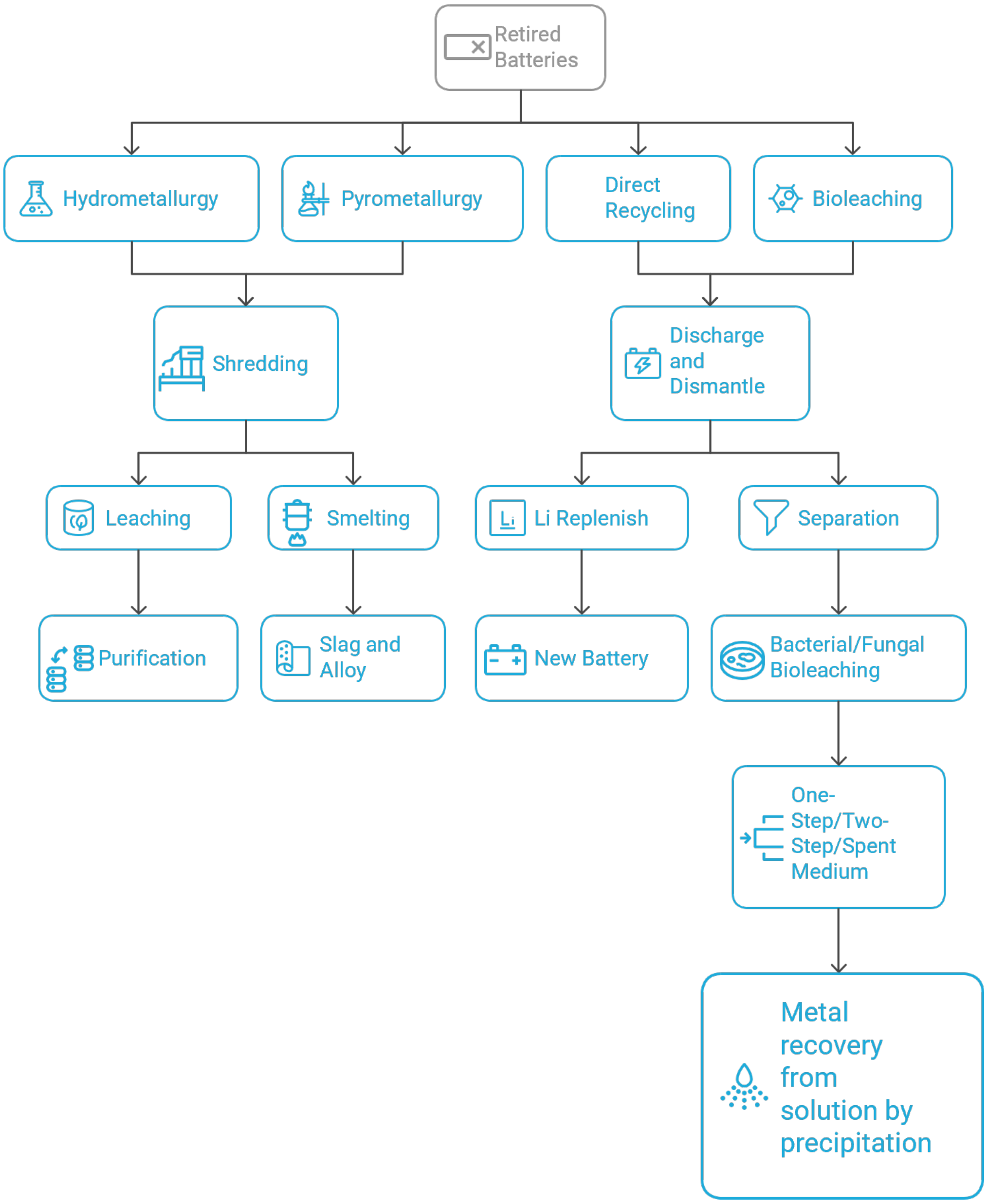

Figure 2.3: Recycling methods for spent LIBs (adapted from [42, 41]).

Pyrometallurgy is a mature industrial process that involves smelting battery cells at high temperatures to produce metal alloys containing cobalt, nickel, copper, and other usable materials. Lithium generally remains in the slag and requires secondary treatment [11, 12]. It is best suited to batteries with high cobalt/nickel content and is widely employed in Europe, North America, and East Asia. However, it is very energy-intensive, emits significant CO_2 and recovers lower amounts of lithium compared to other methods [12].

Hydrometallurgical recycling uses chemical leaching at low to moderate temperatures, often after mechanical treatment, to extract cobalt, nickel, manganese, lithium, and copper into solution. These metals are then precipitated as battery-grade compounds [19, 42]. Hydrometallurgy is less energy-intensive than pyrometallurgy and can achieve high recovery rates for most battery chemistries. Environmental challenges include wastewater management, solvent use, and reliance on pre-processing. Major players in China, the EU, and increasingly the US are scaling new hydrometallurgical plants for LIBs [11, 42].

Direct recycling aims to recover and refurbish cathode and anode materials as functional electrodes, avoiding full breakdown to elemental metals. Mechanical and physicochemical methods including mild chemical treatments, shredding, and sorting are used [43, 44]. This approach uses the lowest energy and consequently has the lowest carbon footprint [45] and can restore up to 90% of original cathode performance, but requires sophisticated sorting of cells by chemistry and state, limiting immediate scalability. Leading labs in the US, EU, and China have announced commercial-scale pilot lines for 2025-2026 [3].

Biometallurgy, often referred to as bioleaching or bio-hydro-metallurgy, is an emerging and environmentally benign technique that employs microorganisms such as bacteria (e.g., Acidithiobacillus ferrooxidans or A. thiooxidans) or fungi (e.g., Aspergillus niger or Gluconobacter oxydans) to selectively extract critical metals from processed cathode materials[46]. This process uses biolixiviants containing organic acids (such as gluconic acid) to dissolve metals like cobalt, nickel, lithium, and manganese[46]. The primary advantages of this approach include its status as the most environmentally friendly method, offering low operation cost and less energy intensive processing compared to pyrometallurgy and hydrometallurgy with respect to all e-wastes [47].

Experimental studies suggest bioleaching is economically feasible, with one techno-economic analysis projecting a potential 21% average profit margin for processing 10,000 tonnes of black mass annually and demonstrating a reduction in Global Warming Potential (GWP) by up to 8 times compared to certain conventional leaching methods[48]. Despite these clear benefits, industrial adoption of bioleaching is hindered because the process exhibits slower kinetics and is typically less efficient than conventional recycling pathways. The technology is still largely explored only at the laboratory or pilot scale, often possessing a low Technology Readiness Level, TRL>4. On the other hand, hydro and pyrometallurgical methods have a typical TRL value greater than 6.[41].

2.3.3 Disposal

Although prohibited under EU Regulation 2023/1542, which mandates that collected waste batteries shall not be disposed of or be the subject of an energy recovery operation [8], uncontrolled disposal remains common in regions lacking formal recycling infrastructure. Improper treatment or direct dumping of spent LIBs releases hazardous and toxic chemicals into the environment [49]. Landfilling or incineration can harm ecosystems and lead to the release of toxic components such as heavy metals that contaminate the soil and water.

Several studies warn that landfilling or incineration releases specific toxic compounds, including the toxic gases Hydrogen Fluoride (HF) and products resulting from the decomposition of Lithium Hexafluorophosphate ($LiPF_6$) [49, 50]. $LiPF_6$ is a common electrolyte salt which decomposes under certain conditions (including during degradation and abuse situations) to form HF. HF is of particular concern due to its toxicity and corrosive nature[50].

2.4 Decision Drivers: KPIs

The selection of an optimal end-of-life (EoL) pathway for lithium-ion batteries is shaped by a complex interplay of technical, economic, and environmental factors, alongside emerging regulatory and logistical considerations. Historically, decisions regarding reuse, repurposing, recycling, or disposal have often relied on simplistic heuristics, such as residual capacity thresholds or visual inspections. While these methods offer quick assessments, they frequently fail to capture underlying degradation mechanisms, chemistry-specific variations, or latent safety issues, increasing the risk of suboptimal, inconsistent, or even hazardous outcomes [17, 51].

Advancements in diagnostic tools have now enabled more robust and granular technical evaluations. These tools allow for the analysis of state-of-health (SoH), internal resistance, voltage response curves, and thermal behaviour which provides a stronger foundation for EoL decision-making across multiple use cases such as reuse, repurposing for second-life applications, or safe material recovery via recycling [13]

After going through mulptiple articles and research papers, it becomes clear that the factors influencing end-of-life decisions for lithium-ion batteries tend to fall into three main categories: technical, economic, and environmental. Most papers approach these topics from different angles, but these three themes consistently show up as the core pillars in EoL assessments. Grouping the KPIs this way helps to make sense of the trade-offs involved and creates a clearer foundation for comparing reuse, repurposing and recycling options. It also sets the stage for developing structured tools that can support decision-making in a more balanced and practical way.

Technical KPIs

Technical indicators are central to assessing whether a battery is fit for continued use, repurposing, or must be dismantled and recycled. They provide insight into the battery's remaining performance, safety profile, and degradation trends.

- State of Health (SoH): Representing the retained capacity as a percentage of the original, SoH is one of the most widely used indicators for EoL evaluation. Batteries with SoH above 70-80% are generally considered viable for second-life deployment, although thresholds vary depending on application and chemistry [17, 51].
- Internal Resistance(IR): A key metric for power capability and safety, internal resistance tends to increase with age. High internal resistance signifies advanced electrochemical degradation and reduced efficiency, rendering batteries less suitable for reuse or repurposing [51].
- Cycle Count & Voltage Response: The number of charge-discharge cycles, when analysed alongside voltage curve behaviour provides insight into electrochemical wear, ageing patterns and the battery's remaining operational life [17].
- Thermal Stability and Safety Metrics: Monitoring thermal performance, including heat generation under load, capacity fade, and self-discharge rates. This is vital to identifying potential safety risks, especially for batteries intended for second-life or grid-scale storage applications [13].

Economic KPIs

Economic considerations are equally pivotal in determining whether to invest in battery testing, refurbishing, and repurposing, or to opt for direct recycling. These indicators reflect the financial viability of each EoL pathway based on market conditions and technological costs.

- Net Present Value (NPV) / Internal Rate of Return (IRR): These financial metrics evaluate long-term returns from battery refurbishment or resale relative to upfront costs. When logistics, testing, and labour exceed potential revenue, recycling becomes the more pragmatic choice [19].
- Levelised Cost of Storage (LCOS): LCOE enables the comparison of the lifetime cost-effectiveness of repurposed battery systems against conventional energy storage solutions, factoring in performance degradation over time [10].
- Material Value Recovery: The recoverable value of metals such as nickel, cobalt, lithium, and copper is increasingly important given the volatility of raw material markets and the rise in global recycling capacity. This metric influences whether direct recycling offers greater returns than reuse [51].

Environmental KPIs

Environmental metrics assess the sustainability and ecological impact of each EoL pathway. They are becoming increasingly central due to tightening regulations and the global shift towards circular economy models.

- Lifecycle Greenhouse Gas (GHG) Emissions: Life Cycle Assessment (LCA) methods are used to compare GHG emissions associated with reuse, recycling, and disposal. Reuse generally offers the lowest emissions profile (nearly 25%) particularly when batteries are redeployed in stationary storage such as smartgrids [52].

- Resource Depletion and Circularity: This KPI tracks how well critical raw materials are preserved through reuse or recovered through recycling. It also encompasses broader resource intensity (e.g., water and energy use) and helps quantify the contribution of the EoL strategy to a circular battery value chain [53].

- Toxicity Potential: Poorly managed EoL batteries pose serious risks, ranging from soil and water contamination due to leachates, to fire hazards from thermal runaway. This KPI accounts for the likelihood and severity of such outcomes [13].

Recent studies have approached the evaluation of KPIs for lithium-ion battery EoL decisions through a variety of robust frameworks and case-based analyses. Systematic reviews, such as those by Patel et al. [17] and the National Renewable Energy Laboratory (NREL) [51] highlight that technical KPIs like SoH, internal resistance, and cycle count are most often quantified using laboratory diagnostics, historical operational data. More recently, machine learning models to predict second-life suitability with increasing accuracy.

In terms of economic KPIs, several techno-economic assessments adopt metrics such as levelised cost of storage (LCOS), internal rate of return, and material value recovery. For instance, a 2024 study by Jin et al. proposed integrating KPIs for battery degradation, efficiency, and cycling behaviour within broader financial models to optimise EoL choices and enhance profitability [54].

Environmental KPIs, on the other hand, are most frequently captured through life cycle assessment (LCA) methodology. Nordelöf et al. systematically reviewed EoL modelling in LCA studies, finding common indicators including lifecycle greenhouse gas emissions, resource depletion, toxicity, and circularity impact [55]. Several large-scale LCAs have also used energy payback time, carbon footprint, and recycling rates as decisive KPIs, especially when comparing direct recycling and pyrometallurgical routes [52].

Finally, multi-criteria decision analysis (MCDA) methods are commonly applied for holistic comparison. For example, Chakraborty et al. (2022) used a fuzzy group decision-making technique to simultaneously evaluate technical, economic, and environmental KPIs, confirming the value of MCDA for robust and transparent EoL strategy selection [6] . These diverse evaluation strategies demonstrate the ongoing trend towards data-driven and multi-faceted approaches in battery EoL management research.

2.5 Chemistry-Specific Suitability for Reuse and Recycling of Lithium-Ion Batteries

The selection of the most appropriate end-of-life (EoL) pathway for lithium-ion batteries is highly influenced by the underlying battery chemistry, as this determines key technical, safety, and economic characteristics in both secondary use and recycling scenarios [56, 17].

Lithium Iron Phosphate (LFP) Batteries

LFP batteries are widely regarded as optimal candidates for reuse and second-life applications. Their robust thermal stability, comparatively slow capacity fade, and excellent safety record make them attractive for stationary energy storage, grid support, and off-grid installations[13]. Even after intensive use in electric vehicles, LFP batteries tend to retain a high percentage of their rated capacity and do not suffer from rapid or unpredictable degradation, thereby prolonging their usable lifespan[17]. Furthermore, the absence of cobalt and nickel in their cathodes reduces both ethical and supply-chain risks, and makes eventual recycling logistically and environmentally less complex [57].

Lithium Nickel Manganese Cobalt Oxide (NMC) and Lithium Nickel Cobalt Aluminium Oxide (NCA) Batteries

NMC and NCA chemistries, which dominate the passenger EV market due to their high energy density, present different EoL considerations. On the one hand, their higher initial specific energy yields strong environmental benefits when repurposed for stationary storage. This attributes in displacing fossil-heavy grid peaking and buffering applications. However, both NMC and NCA exhibit more pronounced degradation, especially capacity and power fade under deep cycling. This results in a higher uncertainty for second-life deployments and a greater need for stringent screening and SoH assessment before reuse [13].

From a recycling perspective, NMC and NCA batteries are valuable feedstocks due to their high cobalt and nickel content, with enhanced economic returns from metal recovery [57]. Multiple life cycle assessment (LCA) studies indicate that direct cathode recycling for these chemistries offers the lowest environmental footprint, outperforming both hydrometallurgical and pyrometallurgical methods and sometimes surpassing the environmental benefit from second-life reuse. This is even more evident in cases when recycling becomes more efficient as the grid electricity decarbonises more. [17, 57].

Comparative Analysis

Recent comparative analyses and LCAs consistently support the relative long-term suitability of LFP chemistries for reuse, given their physical stability, safety, and longer cycle life, even if their inherent material value is lower [13]. By contrast, batteries rich in cobalt and nickel, especially advanced NMC/NCA types tend to be better candidates for direct, early recycling when their residual performance is uncertain but their metal recovery value remains high [3].

2.6 Tools for End-of-Life Decision-Making: From Deterministic Models to Data-Driven Approaches

A growing number of decision-support tools are available to guide battery managers, recyclers, and policymakers through the complexity of EoL choices for LIBs. These platforms increasingly enable systematic, data-driven evaluations of second-life, reuse, and recycling versus disposal.

- NREL B2U (Battery Second-Use) Calculator: This freely available model from the National Renewable Energy Laboratory (NREL) enables users to assess the comparative costs and benefits of reuse, repurposing, and recycling of electric vehicle (EV) batteries.By varying input parameters such as battery age, chemistry, remaining capacity, and market value, stakeholders can estimate the economic viability of second-life applications in real-world market conditions. The B2U calculator directly supports investment planning for grid storage and other stationary deployments [58].

- BLAST (Battery Lifetime Analysis and Simulation Tool): BLAST is a library of degradation models for commercial batteries, developed by NREL, which provides predictive simulation of battery life under a variety of user-defined profiles (including temperature, depth of discharge, and charge rates)[59]. Its algorithms are calibrated to both empirical laboratory data and semi-empirical models, enabling robust forecasting of battery behaviour and likely EoL timing in both mobile and stationary uses.

- LIBRA: The LIBRA resource assessment model is designed to provide dynamic, system-level insights into material flows, resource availability, and supply chain scenarios for lithium-ion batteries in diverse sectors, including EVs, consumer electronics, and grid storage [4]. LIBRA incorporates projections for battery deployment, chemistry transitions, policy factors, recycling yields, and market shifts, enabling users to evaluate infrastructure investment and material recovery strategies [4].

- Battery Failure Databank: Curated by NREL, NASA, and European research partners, the Battery Failure Databank assembles detailed results from hundreds of controlled abuse and failure tests, capturing thermal runaway, venting, and structural breach events in real cells [60]. Data in this repository underpins risk assessment for reuse and guides pack selection and dismantling protocols.For example, highlighting patterns that raise warning flags for cell re-qualification.
- Machine Learning(ML) Based Approaches: Recent advances have introduced ML powered prognostics, such as ML augmented cycle life prediction, remaining useful life (RUL) estimators, and auto-classifiers for EoL sorting [61]. These approaches integrate capacity trend features, internal resistance, and incremental capacity results to automate decisions or flag outliers for manual review. Subset selection by ML can dramatically cut physical testing costs and reduce false negatives in secondary use assessment [62].

Several other studies have systematically evaluated the choice between second-life (reuse) and direct recycling of LIBs using robust multi-criteria or comparative frameworks. Sun et al. (as reviewed in Patel et al. [17]) undertook simulation-based cost and market analysis, demonstrating that the case for reuse versus recycling depends strongly on battery chemistry, energy-value use cases, and recycling policy incentives. As industrial systems for recycling become more efficient or circularity-focused, the net advantage of extended second-life narrows [17].

Chakraborty et al. (2022) applied a multi-criteria group decision-making (MCGDM) approach to compare LIB recycling options, integrating technical, environmental, economic, and social criteria; although focused on recycling technology choice, the MCGDM roadmap is readily applicable to EoL routing (reuse vs recycling) when including relevant alternatives and KPIs [6]. Ölçer & Aktaş (2023, Turkish Journal of Engineering) compared leading recycling methods (pyrometallurgical, hydrometallurgical, direct) and evaluated them using multiple MCDM tools (e.g., ANP, TOPSIS), providing a reproducible blueprint for future work that could include reuse as an explicit alternative [16].

Patel et al. and Tao et al., also identify how recent LCA studies consistently integrate indicators like net greenhouse gas emissions, energy use, and resource depletion for comparing EoL routes, demonstrating that the relative environmental superiority is sensitive to local grid mixes, collection logistics, and product design [17, 63].

2.6.1 Comparison of Existing Tools

The main distinction between institutional and academic tools lies in their scope. Industrial tools are data-rich but narrowly focused, while academic frameworks are comprehensive but often theoretical. Combining these perspectives could enable practical decision support for real world stakeholders. Both show how empirical data can enhance multi-criteria evaluation.

However, a recurring issue is that most existing tools rely on assumptions suited to specific geographies or chemistries, limiting their transferability. Furthermore, few incorporate ML based SoH estimation or predictive reliability analysis, even though such data are increasingly available. Integrating these diagnostic inputs into an MCDM framework could improve objectivity and automation in EoL routing.

2.7 Research Gaps and Motivation for the Present Study

A critical evaluation of the recent literature reveals that decision-making for the EoL management of LIBs remains highly fragmented and inconsistent across research, industry, and policy domains. While both second-life applications and advanced recycling technologies are recognised as pivotal to battery circularity, there are few universally accepted, integrated decision support framework that equitably compares these pathways based on robust and context sensitive performance indicators.

Several industry and academic initiatives have produced valuable models for EoL evaluation, such as NREL's techno-economic assessment tools, scenario analyses, and life-cycle models. Nevertheless, these solutions often focus on a single dimension, such as battery degradation prediction, economic returns, or environmental impacts, without providing multi-dimensional, holistic guidance suitable for operational routing of batteries at EoL.

Similarly, while the academic community has introduced structured evaluation methods such as AHP, ANP, TOPSIS, and fuzzy MCDM analysis for recycling or technology selection[16, 6], most remain theoretical or case bound, and lack the adaptability needed for commercial or regional application.

2.7.1 Identified Gaps

Three key gaps are repeatedly highlighted in recent studies:

- Lack of Integrated Multi-Criteria Decision Tools: The majority of frameworks treat technical, economic, and environmental indicators in isolation. Technical studies focus on battery diagnostics and SoH, economic research on levelised cost or resale value, and environmental work on recycling emissions or critical mineral recovery. Very few academic papers synthesise these KPIs into a repeatable, transparent, and transferable framework [6].
- Limited Automation and Predictive Capacity: The application of machine learning and advanced analytics for SoH assessment and EoL screening is

progressing [64], but these technologies are rarely integrated with wider multi-criteria evaluation or stakeholder input. Thus, real-world EoL decisions remain heavily reliant on expert judgement, institutional inertia, and local practicalities as in [6].

- Insufficient Localisation and Sensitivity: Many published tools or models are generic and do not accommodate regional variations in energy mix, labour costs, regulatory settings, or battery chemistries. Context sensitive modelling can substantially shift optimal EoL pathways.

2.7.2 Motivation for the Present Study

In response to these gaps, this thesis seeks to design a hybrid multi-criteria decision-support tool that unifies technical, economic, and environmental dimensions in a single flexible framework. Building on the methodological precedents set by recent MCDM research [16][6], the proposed model will also incorporate uncertainty handling via fuzzy weighting and scenario analysis. Key quantitative KPIs, such as state of health and internal resistance will be used to make assessments and improve data-driven comparability.

Chapter 3

Methodology

The primary objective while building this model was to examine whether combining technical, economic and environmental factors can influence the final decision between the EoL pathways. To achieve the same, a multi-step approach that combines a fuzzy TOPSIS multi-criteria decision model with criteria identification and weighting based on a thorough review of relevant literature was adopted.

In order to ensure that the evaluation criteria is based on reputable research and industry reports, the important decision variables (i.e, KPIs) were first identified through a comprehensive review of research papers and publications addressing EoL routes for spent Li-ion and EV batteries (Detailed in Section 2.4). The KPIs were then divided into three domains: technical, economic, and environmental. The weighting of these KPIs was then guided by "seed" papers, which are three core studies that offer different perspectives on the relative importance of the three KPI domains (Montes et al., 2022 [15]; Seika & Kubli, 2024 [14]; Chakraborty & Saha, 2022 [6]). The qualitative importance of the chosen KPIs was inferred from these three papers. Rather than making subjective assumptions , this approach infers the category level importance of KPIs directly from literature. This ensures a transparent and evidence-based weighting framework.

Lastly, potential EoL pathway alternatives are ranked using the fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) model. This method, which combines fuzzy set theory with traditional TOPSIS ranking, is selected because of its capacity to handle uncertainties and imprecise information in decision making contexts. This enables the model to account for insufficient information and the ambiguity included in expert opinions. For example, an expert may assign a KPI a qualitative rating of "high importance", which fuzzy logic can translate into a range of numerical weights. In doing this, all the qualitative assumptions are converted to quantitative weights which is later used in the decision making process.

3.1 Qualitative Analysis of KPIs in the three seed papers

After studying and analysing the key drivers for decision making processes available in the literature (Section 2.4), 7 KPIs were selected as the criteria for this MCDM model. These include two technical KPIs (SoH, IR) and three economic KPIs (Refurbishment cost, scrap value/material recovery value and battery chemistry). For environmental KPIs, CO_2 emissions savings and hazard level were chosen. The importance of these KPIs in driving EoL decisions has been previosuly discussed in 2.4. In addition to that, refurbishment cost is introduced as a new KPI based on the inference from the study by Montes et. al [15] where it was discussed that a higher refurbishment cost negatively impacts the reusability of retired batteries. Additionally, the material recovery value or the scrap value of a battery is also introduced as an economic KPI. This is because, if the scrap value of a retired battery is economically higher, the batteries are almost always recycled. The battery chemistry hugely influences the scrap value and is hence treated as an economic KPI.

The seed papers adopted three different EoL decision frameworks which are illustrated in the figures A.2, A.3 and A.4 in Appendix A. These papers were critically analysed to understand how each KPI is emphasised within their respective EoL decision framework. Seika& Kubli [14], hereafter referred to as Paper 1 for the simplicity of this thesis, adopt a technical first framework. In their decision framework, reuse is only considered if the battery satisfies the technical thresholds for SoH, IR and RUL. Their logic prioritises safety and functionality before economics. Montes et al. (Paper 2 [15]) makes the decision primarily based on the economic aspects by comparing the refurbishment cost with the potential scrap value for different chemistries (NMC vs LFP). In this study, SoH is only used to categorise the batteries as high-quality ($80\% \geq SoH \geq 50\%$) and low-quality batteries (SoH $<$ 50 %)[15]. For this reason, Paper 2 was interpreted to give a higher weight to economic KPIs compared to technical KPIs.

Chakraborty & Saha (Paper 3 [6]) proposed a different approach by applying a fuzzy multi-criteria group decision making (MCGDM) method to rank recycling processes. Their framework includes envrionmental and safety KPIs such as hazard level, environmental impact and resource efficiency. They also include economic factors like recyling cost and material recovery. Even though the study does not evaluate reuse directly, it is the only one among the three that incorporates environmental KPIs into the main decision framework. Therefore, this paper was interpreted as having a higher impportance to envrionmental KPIs compared to Papers 1 and 2. For the purpose of this thesis, an important assumption was made: KPIs that are heavily weighted for recycling have a proportionately lower relevance for reuse. This assumption allows the environmental considerations in Paper 3 to be used for comparison against reuse and recycle scenarios.

From the critical analysis, it can be identified that SoH is the main technical filter guiding the decision for reuse. IR is a secondary technical KPI which indicates the quality of the battery. Lower resistance value improves reuse viability. Refurbishment cost and scrap value(or material recovery value) are major economic KPIs. A lower value of the former favours reuse, while a higher value of the latter favours recycle. Battery chemistry is a secondary economic KPI which affects both the reuse performance and recycling value. CO_2 savings and hazard are core environmental KPIs. A higher value for CO_2 savings and a lower value for hazard are preferred. Table 3.1 summarises how each source emphasises the KPIs.

Table 3.1: KPI interpretation across the three seed papers

KPI	**Paper 1** (Seika & Kubli[14])	**Paper 2** (Montes et al.[15])	**Paper 3** (Chakraborty & Saha[6])
SoH	Main technical filter (typically >70-80%)	Considered only for classification but not a key factor	Considered for suitability; not central to recycling decision
IR	Key check for safety and power	Assumed acceptable if SoH is fine	Considered to avoid high resistance
Refurbishment Cost	Considered after technical pass	Key economic factor; compared with scrap value	Included in cost analysis
Scrap Value	Mentioned but not the focus	Main factor; higher value supports recycling	Used to support recycling decision
Chemistry	Considered via battery ageing	Direct link to decision (e.g., LFP vs. NMC)	Included through process feasibility
CO_2 Savings	Briefly mentioned	Acknowledged but secondary to cost	Key environmental factor
Hazard (Safety)	Not included in decision logic	Not included in decision logic	Explicitly considered in decision logic

The importance of the three domains of KPIs across the three papers are interpreted in the following manner. Paper 1 focuses highly on technical KPIs followed by economic KPIs and there is a lower focus on environmental KPIs and it evaluated both reuse and recycling [14]. Paper 2 focuses first on the economic KPIs, followed by the technical KPIs and then environmental KPIs are acknowledged as important through policy considerations [15]. Paper 2 evaluated both reuse and recycling as well. Paper 3 only evaluates recycling but it explicitly mentions environmental KPIs, so it is considered as first importance followed by economic (being a recycling focused paper) and then followed by technical. This qualitative importance was converted into the respective approximate percentage distributions for each paper as shown in Table 3.2.

These values are an independent interpretation of how each seed paper emphasises the three KPI categories. This is a key assumption in the current model, as obtaining direct rankings from experts for KPIs across the reuse and recycle scenarios was not feasible within the scale and scope of this thesis. Regardless, the decision

Table 3.2: Qualitative Interpretation of KPI Importance values across the seed papers

Paper	Tech (%)	Economic (%)	Environmental (%)
Paper 1	50	42.3	7,7
Paper 2	28.6	57.1	14.3
Paper 3	10.4	37.5	52.1

framework of the model remains adaptable and can incorporate real expert inputs or case specific datasets for future applications. To reduce any potential bias in the weight assignment, the next section applies fuzzy logic to translate these qualitative assessments into triangular fuzzy numbers (TFNs), which are then defuzzified to derive weight criteria which are suitable for the TOPSIS model.

3.2 Constructing KPI Importance weights using fuzzy logic

In order to apply the TOPSIS model, each KPI needs a weight that reflects how important it is in the decision-making process. Since expert ranking of the weights were not possible within the time constraints of this thesis, the weights were instead derived from seed papers as seen in Section 3.1. The importance levels in Table 3.2 are shown as percentages. These were interpreted as the most probable or central values (denoted as m) of the fuzzy weights. To reduce bias in the qualitative assessments, fuzzy logic is applied by translating the qualitative assessments into triangular fuzzy numbers (TFNs)[6, 16].

Fuzzy Logic and Guiding Equations

A triangular fuzzy number(TFN) is defined by the triplet (l, m, u), where l denotes a lower bound, m the most feasible value, and u an upper bound. As discussed previously, m values correspond to the qualitative importance weights. The l and u values were defined based on a fixed tolerance range (+/- 0.05) from the central m value. The tolerance range is another assumption made in this thesis. The resulting TFNs for each KPI group are shown in Table 3.3.

Table 3.3: TFN weights for KPI groups

KPI Group	**Paper 1** [14]	**Paper 2** [15]	**Paper 3** [6]
Technical	(0.45, 0.50, 0.55)	(0.25, 0.286, 0.323)	(0.08, 0.10, 0.13)
Economic	(0.37, 0.42, 0.48)	(0.50, 0.571, 0.642)	(0.32, 0.375, 0.43)
Environmental	(0.06, 0.08, 0.09)	(0.10, 0.14, 0.19)	(0.45, 0.521, 0.592)

Step 1: Defuzzification

Once the TFNs were defined, they were then defuzzified using the centroid method using equation 3.1. This gives one number for each KPI group per paper. The defuzzified technical, economic and environmental weights for Paper 1 are (0.5,0.423,0.076); for Paper 2 are (0.286, 0.571, 0.143) and for Paper 3 are (0.103, 0.375, 0.521) respectively. These values are similar to the assumed median weights from section 3.1.

$$w = \frac{l + m + u}{3} \tag{3.1}$$

The defuzzified values are then normalised so that the seven KPI weights sum to unity for each perspective. This procedure permits minor yet justified differences between sources to be preserved at the KPI level, before later reconciliation into a unified weighting scheme. In line with [16], the triplet is interpreted as a conservative estimate (l), a central or modal assessment (m), and an upper credible bound (u) for the importance of a given KPI within a source.

Step 2: Distributing group KPI weights across individual KPIs

Individually, there are 2 technical KPIs (SoH, IR); 3 economic KPIs(Refurbishment cost, scrap value, battery chemistry) and two environmental KPIs (CO_2 savings, hazard). Since none of the seed papers rank these KPIs individually, the group-level weights were distributed equally among KPIs belonging to that particular domain. This was done to ensure internal consistency and to avoid prioritisation of any KPI group. For example, in Paper 1, the technical KPI was assigned a weight of 0.50, so for each individual technical KPI, the now assigned weight is 0.50/2=0.25. Thus, for Paper 1, SoH and IR both have an individual weight of 0.25. On distributing the weight across all individual KPIs with the same assumption, the final weights at this stage were obtained as in Table 3.4.

Table 3.4: Per-paper KPI weights after distributing group weights

Profile	**SoH**	**IR**	**Refurbish Cost**	**Scrap Value**	**Chemistry**	**CO_2 Savings**	**Hazard**
Paper 1 (Reuse-focused)	0.250	0.250	0.141	0.141	0.141	0.039	0.039
Paper 2 (Economic)	0.143	0.143	0.191	0.191	0.191	0.071	0.071
Paper 3 (Recycle-focused)	0.052	0.052	0.125	0.125	0.125	0.260	0.260
Reuse Average	0.196	0.196	0.166	0.166	0.166	0.055	0.055
Recycle Average	0.098	0.098	0.158	0.158	0.158	0.166	0.166

In the final step, the two weight sets that will be used in the TOPSIS model were defined. The first set was reuse oriented weights which were based on the average of Paper 1 [14] and Paper 2 [15] since both these papers model a decision framework between reuse and recycle. The second set was recycle oriented weights, which were an average of Paper 2 [15] and Paper 3[6], which both consider recycling. This was based on the literature analysis in Section 3.1. The reuse and recycle averages are presented in Table 3.4. These two matrices will be key inputs for the TOPSIS model discussed in the further sections.

3.2.1 Battery Pack Selection and Test Dataset

Four test battery packs (B-E) were built with reasonable values taken from research and representative of typical EoL battery characteristics in order to illustrate the methodology. These values were chosen to replicate common trade-offs between reuse and recycling that have been noted in the literature. Appendix C provides a thorough justification for the chosen ranges.

- **Pack B**: Lower SoH, high IR, high cost and scrap value(representing high-value recycling)
- **Pack C**: Higher SoH, low IR, lower scrap value(favours reuse over recycling)
- **Pack D**: Low SoH, high IR, high cost and scrap value(favours recycling over reuse)
- **Pack E**: Highest SoH, low IR, low scrap value(optimised for reuse)

Table 3.5: Raw scores for test battery packs (Input Decision Matrix)

Scenario	**SoH (%)**	**IR (mΩ)**	**Refurbish Cost (€/kWh)**	**Scrap Value (0-1)**	**Chemistry Value (0-1)**	**CO_2 Saved (kg/kWh)**	**Hazard (0-1)**
EV Pack B (10 yr)	65	28	38	0.55	0.72	12	0.32
EV Pack C (6 yr)	78	18	26	0.40	0.65	18	0.24
EV Pack D (12 yr)	60	30	42	0.60	0.75	10	0.40
EV Pack E (5 yr)	90	17.5	24	0.32	0.58	19.5	0.22

3.3 Defining as an MCDM problem

As discussed in the literature review, choosing the right EoL route for a battery requires considering several criteria(KPIs in this case) at the same time. These criteria often conflict or differ in importance based on the situation. This can be considered as a Multi Criteria Decision Making (MCDM) problem.

To address this problem, the TOPSIS method (Technique for Order Preference by Similarity to Ideal Solution) methodology was selected. This method ranks alternatives by evaluating their distance from the ideal best and ideal worst scenarios. The decision matrix used in TOPSIS consists of m alternatives (in this case, battery packs or scenarios) and n criteria (the selected KPIs) [16]. It is structured as follows:

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n}\, a_{21} & a_{22} & \dots & a_{2n} \vdots & \vdots & \ddots & \vdots\, a_{m1} \\ a_{m2} & \dots & a_{mn} \end{bmatrix} \tag{3.2}$$

where a_{ij} represents the performance score of alternative i against criterion j [6, 16].

Each column of the matrix corresponds to one of the seven KPIs identified:

- C_1: State of Health (SoH)
- C_2: Internal Resistance (IR)
- C_3: Refurbishment Cost
- C_4: Scrap Value
- C_5: Battery Chemistry
- C_6: CO_2 Savings
- C_7: Hazard Level

The matrix captures the multi-criteria nature of the problem, where each battery scenario is assessed based on these 7 different indicators. To account for the varying importance of the criteria, TFNs were assigned to each KPI category based on three seed papers (see Section 3.2). From this process, two sets of KPI weights were obtained to represent reuse and recycle perspectives:

$$w_{reuse} = [w_1, w_2, w_3, w_4, w_5, w_6, w_7] = [0.196, 0.196, 0.166, 0.166, 0.166, 0.055, 0.055] \tag{3.3}$$

$$w_{recycle} = [w_1, w_2, w_3, w_4, w_5, w_6, w_7] = [0.097, 0.097, 0.158, 0.158, 0.158, 0.166, 0.166] \tag{3.4}$$

where the order of w_j matches the criteria C_1 through C_7 listed above.

3.4 KPI categories (Benefit/Cost)

In a TOPSIS-based MCDM framework, each critera must be designated as either a benefit or a cost type. This is needed to determine the ideal best and worst values in the later steps of the methodology. A benefit type criterion is one where higher values are more desirable, while a cost type criterion is one where lower values are preferable.

The categorisation of the seven selected Key Performance Indicators (KPIs) is summarised in Table 3.6. The classification is interpreted based on literature [1, 6, 14] as discussed in Section 2.4.

Table 3.6: Classification of KPIs as Benefit or Cost Criteria

KPI Criteria	KPI Description	Type	Reasoning
C_1	State of Health (SoH)	Benefit	Higher SoH indicates better battery performance and suitability for reuse.
C_2	Internal Resistance (IR)	Cost	Lower resistance improves energy efficiency and output.
C_3	Refurbishment Cost	Cost	Reduced costs increase economic viability.
C_4	Scrap Value	Benefit	Higher residual value enhances recycling attractiveness.
C_5	Chemistry Value	Benefit	Valuable chemistries contribute to recovery economics.
C_6	CO_2 Savings	Benefit	Greater emissions reductions improve environmental impact.
C_7	Hazard Level	Cost	Higher hazard ratings increase health and safety risks.

3.5 TOPSIS Methodology

TOPSIS is used to evaluate battery end-of-life options by identifying which alternative is closest to the ideal and furthest from the least desirable solution. The methodology and the equations were replicated from [6] and [16]. This section outlines the step-by-step implementation of the method, and the guiding mathematical equations for each stage. Each step is elaborated in subsequent subsections.

1. Construct the normalised decision matrix
2. Generate the weighted decision matrix
3. Identify the ideal best and ideal worst solutions
4. Compute the Euclidean distances to the ideal best and worst solutions
5. Calculate the closeness coefficient
6. Rank the alternatives by comparing the closeness coefficient value

3.5.1 Stepwise Methodology and Guiding Equations

Step 1: Normalisation

To eliminate scale bias among KPIs, the raw decision matrix is normalised using vector normalisation as shown in Equation (3.5).

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}} \tag{3.5}$$

Here, a_{ij} denotes the original value of alternative i under criterion j, and r_{ij} is the resulting normalised score.

Step 2: Weighted Normalised Matrix

Each column of the normalised matrix is multiplied by the weight of the corresponding KPI to reflect its relative importance.

$$v_{ij} = w_j \cdot r_{ij} \tag{3.6}$$

Where w_j is the weight assigned to criterion j, and v_{ij} is the weighted normalised score.

Step 3: Ideal Best and Worst Solutions

The positive ideal solution (v_j^+) and the negative ideal solution (v_j^-) are determined as follows:

$$v_j^+ = \begin{cases} \max(v_{ij}) & \text{if } j \text{ is a benefit criterion} \\ \min(v_{ij}) & \text{if } j \text{ is a cost criterion} \end{cases} \qquad v_j^- = \begin{cases} \min(v_{ij}) & \text{if } j \text{ is a benefit criterion} \\ \max(v_{ij}) & \text{if } j \text{ is a cost criterion} \end{cases} \tag{3.7}$$

Step 4: Separation Measures

The Euclidean distance of each alternative from the ideal best and ideal worst solution is calculated using:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2}, \quad S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \tag{3.8}$$

Where S_i^+ and S_i^- are the distances of alternative i to the ideal and anti-ideal solutions, respectively.

Step 5: Closeness Coefficient

The closeness coefficient C_i is then computed to represent the relative performance of each alternative:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{3.9}$$

Higher values of C_i indicate greater proximity to the ideal solution, making the corresponding alternative more desirable.

3.5.2 Normalisation

The first step in applying the TOPSIS method is the construction of a normalised decision matrix. Since the original performance scores of battery packs are expressed in different units and scales (e.g., Euros, percentages, hazard index), direct comparison is not meaningful. Normalisation resolves this issue by transforming all scores into a dimensionless scale while preserving proportionality.

Vector normalisation is applied as shown in Equation (3.5), where each value a_{ij} in the original decision matrix is divided by the Euclidean norm of its column:

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}} \tag{3.5}$$

This results in a normalised matrix $R = [r_{ij}]$, in which all values fall within the range $[0, 1]$. Each column now represents the relative strength of an alternative against a particular criterion, independent of units.

Application to the Test Battery Packs

Using the raw scores in Table 3.5, the denominator for each column is computed by summing the squares of that column and taking the square root. The result is used to normalise the entries across all four battery packs.

As an example, for the State of Health (SoH) column:

$$\text{Denominator} = \sqrt{65^2 + 78^2 + 60^2 + 90^2} = \sqrt{22{,}008.9} \approx 148.354$$

$$r_{B,\text{SoH}} = \frac{65}{149.78} \approx 0.438$$

This process is repeated for each KPI column. The complete normalised matrix is then used in the next step to generate the weighted decision matrix 3.7.

Table 3.7: Normalised Decision Matrix ($R = [r_{ij}]$)

Pack	SoH	IR	Cost	Scrap	Chem	CO_2	Hazard
B	0.438	0.582	0.569	0.572	0.531	0.390	0.527
C	0.526	0.374	0.389	0.416	0.479	0.585	0.395
D	0.404	0.624	0.629	0.624	0.553	0.325	0.659
E	0.607	0.364	0.359	0.333	0.428	0.633	0.362

Weighted Matrix

After normalisation, each value is multiplied by its corresponding criterion weight to reflect the relative importance assigned to each KPI. The resulting matrix, $V = [v_{ij}]$, is known as the weighted normalised decision matrix. This step ensures that criteria with higher weights exert greater influence on the final ranking.

The operation is defined by Equation (3.5):

$$v_{ij} = w_j \cdot r_{ij} \tag{3.5}$$

Two different weight configurations were applied: one with respect to a reuse-focused strategy and another prioritising recycling. These configurations were derived from defuzzified weights discussed in earlier sections.

Reuse Scenario Weights:

$$w_{\text{reuse}} = [0.196, 0.196, 0.166, 0.166, 0.166, 0.055, 0.055]$$

Recycle Scenario Weights:

$$w_{\text{recycle}} = [0.097, 0.097, 0.158, 0.158, 0.158, 0.166, 0.166]$$

Weighted Matrix: Reuse Scenario

Table 3.8: Weighted Normalised Matrix - Reuse Scenario

Pack	**SoH**	**IR**	**Cost**	**Scrap**	**Chem**	**CO_2**	**Hazard**
EV_Pack_B	0.0861	0.1143	0.0943	0.0948	0.0880	0.0214	0.0290
EV_Pack_C	0.1033	0.0735	0.0645	0.0689	0.0794	0.0321	0.0217
EV_Pack_D	0.0794	0.1225	0.1042	0.1034	0.0916	0.0178	0.0362
EV_Pack_E	0.1192	0.0715	0.0596	0.0552	0.0709	0.0348	0.0199

Weighted Matrix: Recycle Scenario

Table 3.9: Weighted Normalised Matrix-Recycle Scenario

Pack	**SoH**	**IR**	**Cost**	**Scrap**	**Chem**	**CO_2**	**Hazard**
EV_Pack_B	0.0427	0.0567	0.0898	0.0902	0.0837	0.0647	0.0875
EV_Pack_C	0.0512	0.0365	0.0614	0.0656	0.0756	0.0970	0.0656
EV_Pack_D	0.0394	0.0608	0.0992	0.0984	0.0872	0.0539	0.1093
EV_Pack_E	0.0591	0.0355	0.0567	0.0525	0.0674	0.1051	0.0601

These weighted matrices form the basis for calculating ideal best and worst solutions in the next step of the TOPSIS process.

3.5.3 Ideal Best and Worst Case

The third step in the TOPSIS procedure is to identify the ideal best and ideal worst solutions, denoted as A^+ and A^- respectively. The ideal best solution is composed of the best achievable value for each criterion, while the ideal worst represents the least desirable outcomes.

These are computed from the weighted normalised matrix according to Equation (3.7):

$$v_j^+ = \begin{cases} \max(v_{ij}), & \text{if } j \text{ is a benefit criterion} \\ \min(v_{ij}), & \text{if } j \text{ is a cost criterion} \end{cases} \quad v_j^- = \begin{cases} \min(v_{ij}), & \text{if } j \text{ is a benefit criterion} \\ \max(v_{ij}), & \text{if } j \text{ is a cost criterion} \end{cases} \tag{3.7}$$

This classification depends on whether a criterion is to be maximised (benefit) or minimised (cost), as previously identified in Table 3.6.

Ideal Best and Worst Solutions : Reuse Scenario

Table 3.10: Ideal and Anti-Ideal Vectors - Reuse Scenario

Solution	**SoH**	**IR**	**Cost**	**Scrap**	**Chem**	$\mathbf{CO_2}$	**Hazard**
Ideal Best (A^+)	0.1192	0.0715	0.0596	0.1034	0.0916	0.0348	0.0199
Ideal Worst (A^-)	0.0794	0.1225	0.1042	0.0552	0.0709	0.0178	0.0362

Ideal Best and Worst Solutions : Recycle Scenario

Table 3.11: Ideal Best and Worst Vectors : Recycle Scenario

Solution	**SoH**	**IR**	**Cost**	**Scrap**	**Chem**	$\mathbf{CO_2}$	**Hazard**
Ideal Best (A^+)	0.0591	0.0355	0.0567	0.0984	0.0872	0.1051	0.0601
Ideal Worst (A^-)	0.0394	0.0608	0.0992	0.0984	0.0872	0.0539	0.1093

These values serve as reference points for evaluating how close each battery pack is to the optimal or least favourable scenario in the next step while finding the closeness value.

3.5.4 Distance and Closeness Coefficient

In the final step of the TOPSIS method, the distance of each alternative from the ideal best and worst solutions is calculated using Euclidean distance. These distances are then used to compute the closeness coefficient (C_i), which indicates how close each alternative is to the ideal scenario.

The separation measures are calculated using Equation (3.6):

$$S_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^+)^2}, \quad S_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2} \tag{3.6}$$

The closeness coefficient is computed for each alternative using Equation (3.7):

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{3.7}$$

A higher value of C_i indicates a more favourable alternative, as it is closer to the ideal solution and farther from the worst-case outcome.

Scores: Reuse Scenario

Table 3.12: Separation Distances and Closeness Coefficient: Reuse Scenario

Pack	S_i^+	S_i^-	C_i
EV_Pack_B (10yr)	0.0670	0.0462	0.4083
EV_Pack_C (6yr)	0.0404	0.0723	0.6416
EV_Pack_D (12yr)	0.0820	0.0525	0.3904
EV_Pack_E (5yr)	0.0525	0.0820	0.6096

Scores : Recycle Scenario

Table 3.13: Separation Distances and Closeness Coefficient : Recycle Scenario

Pack	S_i^+	S_i^-	C_i
EV_Pack_B (10yr)	0.0654	0.0281	0.3007
EV_Pack_C (6yr)	0.0373	0.0845	0.6937
EV_Pack_D (12yr)	0.0888	0.0000	0.0000
EV_Pack_E (5yr)	0.0500	0.1019	0.6708

Under the reuse scenario, EV Pack C achieves the highest closeness coefficient, indicating its strong suitability for second-life applications. In contrast, under the recycle weighting scheme, both EV Pack C and EV Pack E stand out as optimal candidates due to favourable environmental and hazard values, despite cost trade-offs.

Chapter 4

Results and Discussions

4.1 TOPSIS Results

In this section, the final closeness coefficient (C_i) values calculated under both reuse and recycle weighting scenarios are interpreted. These values serve as the basis for recommending the most suitable EoL route for each synthetic battery pack, based on their proximity to ideal decision profiles.

Table 4.1: Final TOPSIS Scores and EoL Recommendations

Pack	C_i^{Reuse}	C_i^{Recycle}	$\Delta = C_i^{\text{Reuse}} - C_i^{\text{Recycle}}$	**Decision**
EV_Pack_B (10yr)	0.4083	0.3007	+0.1077	Reuse
EV_Pack_C (6yr)	0.6416	0.6937	− 0.0521	Recycle
EV_Pack_D (12yr)	0.3904	0.0000	+0.3904	Reuse
EV_Pack_E (5yr)	0.6096	0.6708	− 0.0612	Recycle

The results indicate that EV Pack C and EV Pack E are more favourable for recycling, while EV Pack B and EV Pack D are better suited to reuse pathways. These decisions align with their relative performance on technical, economic, and environmental KPIs.

4.1.1 Discussion and Interpretation

Each battery pack was originally designed to reflect diversity in age, chemistry, and remaining technical health, based on parameter ranges found in industry and academic literature (See Appendix C). For instance, EV Pack C (6 years old) was modelled with good SoH and moderate internal resistance, but with strong scores in environmental KPIs. This pack demonstrated a high closeness coefficient under the recycling scenario, which places significant weight on CO_2 savings and hazard mitigation. This pack benefits from favourable material recovery and low associated risk, making recycling a sensible route.

Conversely, EV Pack D (12 years old) received a C_i of zero under the recycle scenario. This outcome comes from the effect of high refurbishment costs, elevated internal resistance, and low environmental performance. However, because of its moderate scrap value and comparatively better reuse profile, it is not entirely ruled out under the reuse model. Its significant positive C_i value (+0.3904) reflects this divergence, favouring reuse despite its age. Such a result could be viewed as counter-intuitive at first glance, yet it mirrors cases described in Montes et al. [15] , where older packs still present economic feasibility in low-demand second-life applications.

EV Pack B (10 years) shows a modest but positive preference for reuse. This is consistent with its balanced performance: strong technical health and manageable cost, even if its environmental attributes are not exceptional. This reinforces the first seed paper's threshold logic which showed that batteries with sufficient SoH (typically above 80%) and manageable costs are prioritised for reuse [14]. The C_i gap of +0.1077 illustrates that even if environmental benefits are modest, technical-economic suitability remains decisive.

EV Pack E (5 years), the youngest battery in the dataset, was expected to favour reuse. However, its low technical performance (e.g., lower SoH and higher hazard index) diminished its reuse score, despite age-based assumptions. Under the recycling scenario, its material recovery values and environmental performance improved its overall rank. This serves as a reminder that age alone is insufficient as a proxy for reuse potential. The technical condition and configuration seem to drive outcomes more strongly, a notion which is reinforced by Seika and Kubli [14].

4.1.2 Comparison to Seed Papers

The patterns observed here reflect and extend the logic proposed by the seed papers. Paper 1's framework, which prioritises technical screening followed by economic viability, aligns well with the reuse selections of Packs B and D. Paper 2's model, driven by long-term economic profitability and policy conditions, supports recycling outcomes like that of Pack C, especially when environmental and hazard parameters are weighed heavily.

The inclusion of Paper 3's sustainability-oriented fuzzy model is evident in the elevation of recycling outcomes for Packs C and E. Their methodology assigns substantial importance to social and environmental indicators. These specific KPIs improved the C_i values for recycling in this model.

4.1.3 Discussion

The results confirm that the TOPSIS framework, when adapted for reuse vs. recycle decision contexts, is sensitive to subtle differences in KPI importance rankings. More importantly, the model is capable of producing results that are consistent with expert insights from the literature while also revealing nuanced outcomes that may not be immediately intuitive.

If the seed papers had been applied directly as rigid decision rules, Pack D might have been ruled out for both reuse and recycling due to its age. Similarly, Pack E might have been wrongly assumed fit for second-life based on age alone. This analysis, by considering a weighted multi-criteria perspective, avoids such oversimplifications and supports a more dynamic and evidence-based routing of EoL batteries.

4.1.4 Limitations

While the proposed decision-support framework offers a structured and transparent approach to selecting end-of-life pathways for BESS, it still remains an early-stage, exploratory model. A key limitation of this study is the exclusive reliance on literature-derived weights for KPI prioritisation. The fuzzy weights used in the TOPSIS methodology are extracted from three representative seed papers, each reflecting a different strategic emphasis (technical, economic, and environmental). Although this approach ensures methodological consistency and alignment with the literature, it does not incorporate primary data from industry practitioners or subject-matter experts.

Additionally, the battery pack profiles used in the case analysis are constructed based on indicative values from published datasets and do not reflect real-world operational diagnostics or manufacturer-supplied data. As such, the findings demonstrate the potential of the model rather than stating definitive recommendations for specific batteries. Moreover, the model does not yet account for dynamic market conditions, regulatory changes, or region-specific cost factors which could significantly influence EoL decisions. These simplifications constrain the immediate applicability of the tool in commercial or policy environments.

Nonetheless, this limitation also reflects a deliberate research choice: to build a replicable and generalisable framework that can later be customised with context-specific data.

Chapter 5

Conclusion

The growing number of LIBs reaching the end of their usable life, especially those from EVs, presents both a notable challenge and a unique opportunity for circular economy initiatives. This thesis tackles the gap in having a systematic and replicable decision-making tool for determining battery EoL options by creating an MCDM framework based on fuzzy TOPSIS. By drawing on weights from three foundational studies and evaluating KPIs related to technical, economic, and environmental factors, the model provides a way to choose the best EoL routes. When the model was applied to four representative battery packs with realistic hypothetical values, it became clear that the decisions made are reasonably sensitive to the priorities given to different factors. In reuse-focused scenarios, battery packs which had higher SoH and lower IR values performed better. In the case of recycling scenarios, batteries that posed greater hazards and contained valuable materials were favoured. These insights highlight that the best EoL choices are not standard; they should vary based on the goals of different stakeholders and the specific context.

While the study effectively showcases how fuzzy MCDM methods can be applied to battery EoL decisions, it also recognises some limitations. The current model is based solely on secondary data and literature derived weights, without incorporating real world data or input from industry experts. As a result, it should be viewed more as an exploratory framework than a fully operational tool.

By offering a method for comprehensive EoL assessments, this thesis makes a valuable contribution to both academic research and industry discussions. This lays the foundation for more integrated, data driven systems that support battery circularity.

5.0.1 Future Scope of Work

The current version of the MCDM tool is a foundational prototype and its capabilities can be improved in future iterations. The literature derived weights can be replaced by data collected through expert interviews and surveys. The KPI weights would then be more refined by gathering insights from stakeholders and capturing their experiential knowledge. By doing this, the framework presented can transition from a theoretical concept to a useful operational tool which would reflect real world trade-offs, operational challenges, and decision making priorities.

Besides, applying the tool to actual battery datasets from battery management systems (BMS), lab tests, or reported manufacturer diagnostics would strengthen its predictive accuracy. This would enable the decision making model to represent better real battery degradation trends and contextual factors, such as chemistry-related risks, refurbishment expenses, and local recycling economics. There is also potential to expand the framework to allow for dynamic assessments that revisit EoL decisions as economic conditions, policy frameworks, or technical standards evolve. Additionally, integrating lifecycle carbon pricing, extended producer responsibility, or information from digital battery passports could greatly improve the relevance of the tool to current policies aligning it with emerging EU regulations.

Appendix A

Appendix A

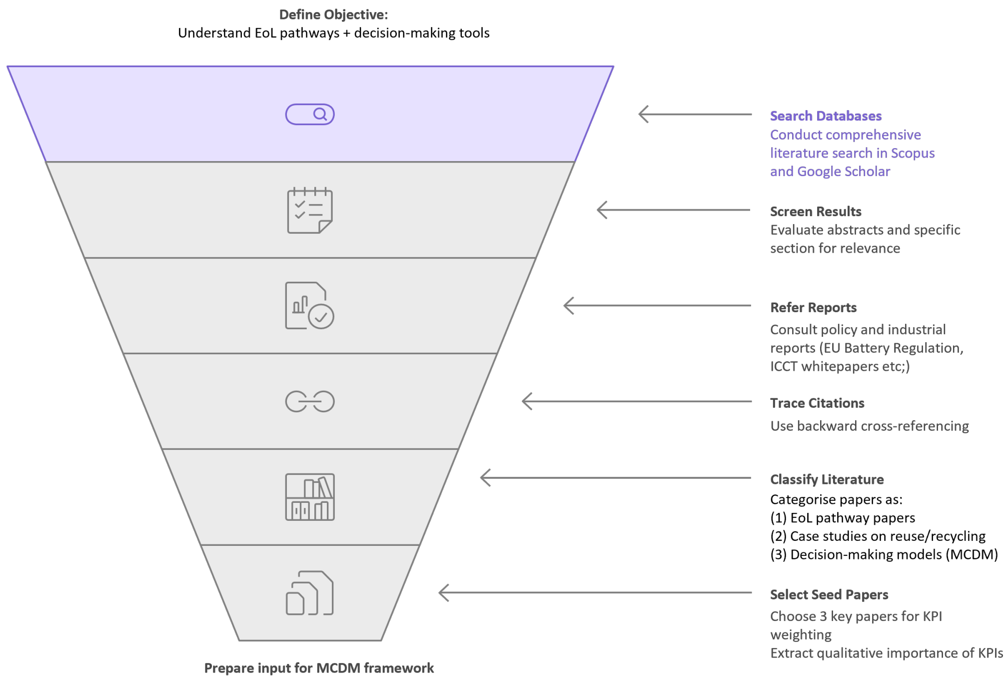

Figure A.1: Flowchart of the methodology used for Literature Review

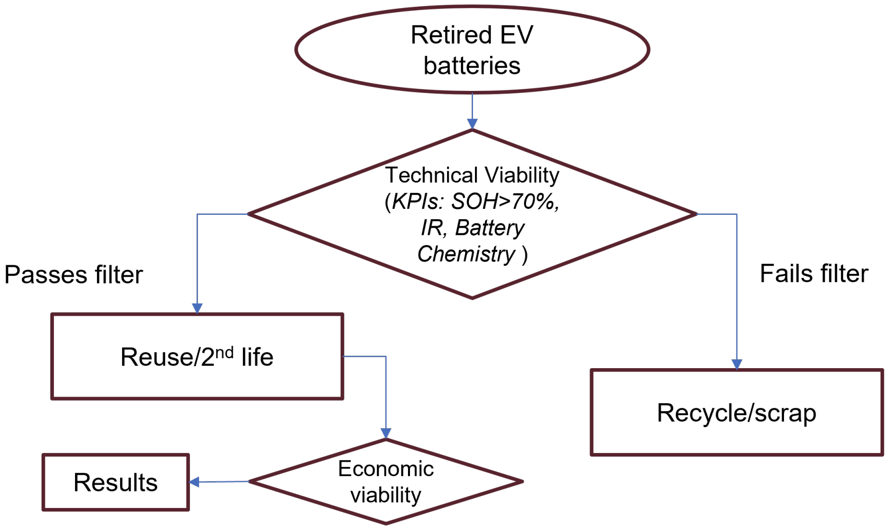

Figure A.2: Flowchart of the methodology used in the Montes et al. study [15]

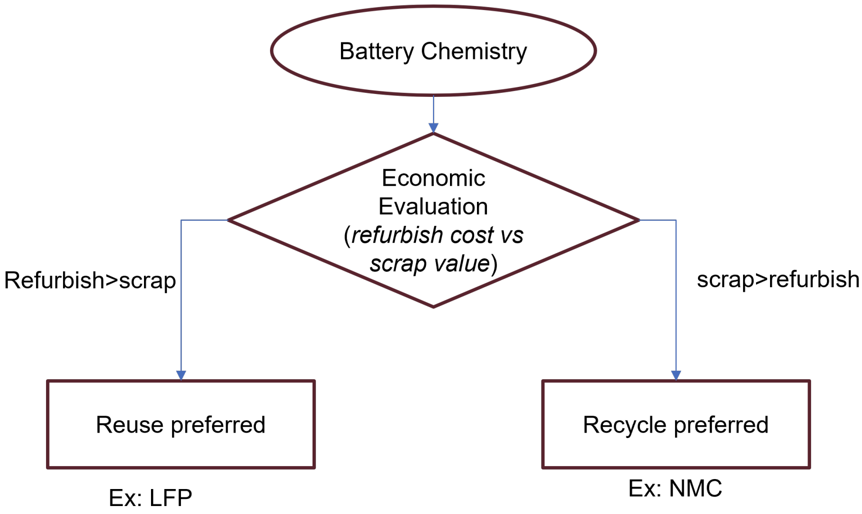

Figure A.3: Flowchart of Seika and Kubli's approach for battery end-of-life assessment [14]

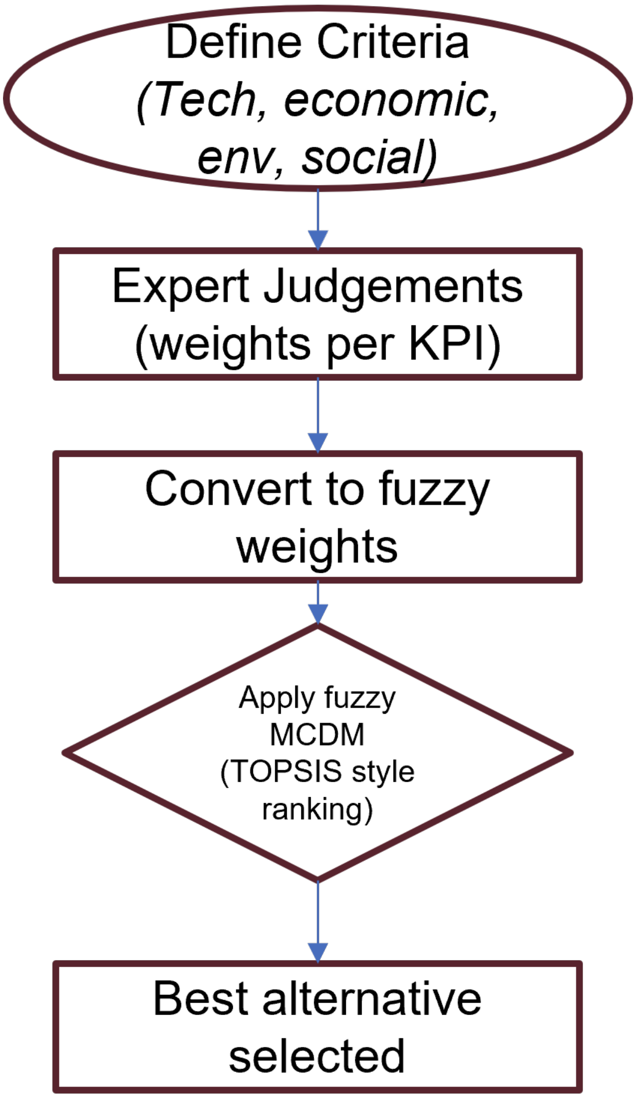

Figure A.4: Flowchart of Chakraborty and Saha's decision framework [6]

Appendix B

Appendix B

Table B.1: Comparison of operational parameters between first-life EV batteries and second-life stationary applications (adapted from [9]).

Parameter	First-Life in Electric Vehicles (EVs)	Second-Life in Stationary Systems
Nominal Voltage	∼400 V	∼800-1000 V
Operating Hours (for 10A)	Up to 16,800 h	Up to 87,800 h
Ambient Temperature Range	−40°C to 60°C	10°C to 35°C
C-Rate (Continuous / Peak)	2-3 C / >5 C	<0.5 C / 0.2-2 C
Thermal Management	Active (air or liquid cooling)	Passive (active only in critical cases)
Vibration Conditions	Present (due to EV motion)	None (stationary installation)
State of Health (SOH)	100% (beginning of 1st life)	70-90% (beginning of 2nd life)

Appendix C

Appendix C

Table C.1: Justification of Raw Score Ranges for Test Battery Packs (Part 1)

KPI (Unit)	**Range/Value Used**	**Supporting Context and Sources**
SoH (%)	50 to 80%	Based on Montes et al. [15], batteries with SoH ≤50% were considered low-quality and 70-80% as high-quality.
IR (mΩ)	∼17 to 30	IR increases with degradation, indicating power fade. Sorting is often based on deviation from nominal IR (e.g., 100-120% or >200%) [14].
Refurb. Cost (€/kWh)	24-42	Based on dismantling costs and literature estimates. Disassembly costs ∼€35.26/kWh; EV removal €6.68/kWh. Costs decline at module level due to less manual labour [14].

Table C.2: Justification of Raw Score Ranges for Test Battery Packs (Part 2)

KPI (Unit)	**Range/Value Used**	**Supporting Context and Sources**
Scrap Value (0-1)	0.3-0.6	Based on the economic criteria set by Montes et al. [15]. If reuse value < recycling price (Pr), battery is recycled
Chemistry Value (0-1)	0.4-0.75	NMC has high-value metals for recycling; LFP is safer with longer RUL. Reflects reuse/recycling potential [15].
CO_2 Saved (kg/kWh)	10-20	Literature shows 10-20 kg CO_2-eq savings per kWh in reuse scenarios. Survey median was 41.5% reduction [65].
Hazard Score (0-1)	0.2-0.4	Hazard scores are derived from risk assessments of chemical and fire safety. The closely related KPI, State of Safety (SoS), was rated as the single most important KPI (median of 1.0 on a 1-5 importance scale) [65]

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Dedications

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