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Subject

**Deterministic and Stochastic Modelling
of a Multi-Type Human–Robot Collaborative
Disassembly Line
for End-of-Life Electric Vehicle Batteries**

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بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

Dedication

I dedicate this work, first and foremost, to myself, for all the times I kept going despite fatigue, doubts, and difficult moments. To the version of myself that learned, grew, resisted, and continued until the end of this journey.

To my beloved parents, my father and my mother, to whom I owe everything. No words can truly express my gratitude for your love, sacrifices, patience, and endless support. You have always been my strength, my refuge, and my greatest source of motivation. If I have reached this point today, it is thanks to you, your prayers, your trust, and everything you have done for me.

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Abstract

This thesis addresses the organization of a multi-product human–robot collaborative disassembly line for end-of-life electric vehicle batteries. The objective is to support circular economy strategies by improving the planning of battery disassembly operations, which are essential for reuse, remanufacturing, repurposing and recycling. The studied problem considers several battery types, each with its own tasks, precedence relations, operation times and execution constraints. A deterministic mixed-integer linear programming model is first proposed to determine station opening, task assignment, execution mode selection and resource allocation. Then, a stochastic scenario-based extension is developed to account for the uncertainty of human operation times. The models are tested on instances involving one, two and three battery types. The results show that the deterministic model provides a structured baseline solution, while the stochastic model gives additional information about station-load variability and recourse under uncertainty. The computational study also highlights the limits of exact MILP models for larger instances involving four and five battery types.

Key words: End-of-life electric vehicle batteries, Disassembly line balancing, Human–robot collaboration, Multi-product disassembly, Stochastic optimization, Mixed-integer linear programming.

Résumé

Ce mémoire traite l'organisation d'une ligne de désassemblage collaborative humain-robot pour plusieurs types de batteries de véhicules électriques en fin de vie. L'objectif est de soutenir les stratégies d'économie circulaire en améliorant la planification des opérations de désassemblage, qui sont nécessaires pour la réutilisation, le remanufacturing, la reconversion et le recyclage. Le problème étudié considère plusieurs types de batteries, chacune ayant ses propres tâches, relations de précédence, temps opératoires et contraintes d'exécution. Un modèle déterministe de programmation linéaire en nombres entiers mixtes est d'abord proposé afin de déterminer l'ouverture des stations, l'affectation des tâches, le choix du mode d'exécution et l'allocation des ressources. Ensuite, une extension stochastique basée sur des scénarios est développée afin de prendre en compte l'incertitude des temps opératoires humains. Les modèles sont testés sur des instances comportant une, deux et trois batteries. Les résultats montrent que le modèle déterministe fournit une solution de référence structurée, tandis que le modèle stochastique apporte des informations supplémentaires sur la variabilité des charges des stations et le recours sous incertitude. L'étude met également en évidence les limites des modèles MILP exacts pour les grandes instances comportant quatre et cinq types de batteries.

Mots clés : Batteries de véhicules électriques en fin de vie, Équilibrage de ligne de désassemblage, Collaboration humain-robot, Désassemblage multi-produit, Optimisation stochastique, Programmation linéaire en nombres entiers mixtes.

الملخص

يتناول هذا العمل تنظيم خط تفكيك تعاوني بين الإنسان والروبوت لعدة أنواع من بطاريات المركبات الكهربائية في نهاية عمرها. يهدف هذا البحث إلى دعم مبادئ الاقتصاد الدائري من خلال تحسين تخطيط عمليات التفكيك، باعتبارها خطوة أساسية لإعادة الاستخدام، وإعادة التصنيع، وإعادة التوظيف، وإعادة التدوير. تعتمد الدراسة على عدة أنواع من البطاريات، حيث يتميز كل نوع بمجموعة خاصة من المهام، وعلاقات الأسبقية، وأزمنة التشغيل، وقيود التنفيذ. في البداية، تم اقتراح نموذج حتمي باستعمال البرمجة الخطية بالأعداد الصحيحة المختلطة من أجل تحديد المحطات المفتوحة، وتوزيع المهام، واختيار نمط التنفيذ، وتخصيص الموارد البشرية والروبوتية. بعد ذلك، تم تطوير نموذج احتمالي قائم على السيناريوهات لأخذ عدم اليقين في أزمنة تنفيذ المهام البشرية بعين الاعتبار. تم اختبار النموذجين على حالات تضم بطارية واحدة، وبطارتين، وثلاث بطاريات. أظهرت النتائج أن النموذج الحتمي يوفر حلاً مرجعياً منظماً، في حين يسمح النموذج الاحتمالي بتحليل تغير أحمال المحطات وتقييم الحاجة إلى متغيرات المعالجة تحت تأثير عدم اليقين. كما بينت الدراسة أن النماذج الدقيقة تصبح محدودة حسابياً عند التعامل مع حالات أكبر تضم أربعة أو خمسة أنواع من البطاريات.

الكلمات المفتاحية: بطاريات المركبات الكهربائية في نهاية العمر، موازنة خط التفكيك، التعاون بين الإنسان والروبوت، التفكيك متعدد المنتجات، التحسين الاحتمالي، البرمجة الخطية بالأعداد الصحيحة المختلطة.

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Abbreviations list

Acronym	Meaning
AI	Artificial Intelligence
AND	Mandatory precedence relation
BMS	Battery Management System
CT	Cycle Time
DLBP	Disassembly Line Balancing Problem
EOL	End-of-Life
EV	Electric Vehicle
GWh	Gigawatt-hour
HRC	Human–Robot Collaboration
LFP	Lithium Iron Phosphate
LHS	Latin Hypercube Sampling
MILP	Mixed-Integer Linear Programming
NCA	Nickel Cobalt Aluminum
NMC	Nickel Manganese Cobalt
NSGA-II	Non-dominated Sorting Genetic Algorithm II
OR	Alternative precedence relation

General Introduction

The rapid development of electric mobility has transformed electric vehicle batteries into one of the most strategic components of the current industrial and energy transition. These batteries are essential for reducing dependence on fossil fuels and supporting the deployment of cleaner transportation systems. However, their growing use also creates new challenges at the end of their life. Electric vehicle batteries are complex technical products that contain valuable materials, high-value components, and potentially hazardous elements. For this reason, their end-of-life management cannot be reduced to simple waste treatment.

From a circular economy perspective, end-of-life electric vehicle batteries represent both an environmental challenge and an industrial opportunity. When properly managed, they can support reuse, second-life applications, refurbishment, remanufacturing, and recycling. These recovery strategies make it possible to preserve value, reduce material losses, and limit dependence on primary raw materials. Nevertheless, the implementation of these strategies requires the battery pack to be identified, inspected, opened, disassembled, and directed toward the most appropriate recovery route.

Battery disassembly is therefore a key step in the recovery process. It provides access to modules, cells, busbars, cooling systems, electronic components, casing parts, and other elements that may be reused, remanufactured, or recycled. However, disassembly is not a simple reverse assembly operation. Electric vehicle batteries are characterized by high structural diversity, different chemistries, various fastening methods, compact architectures, and safety risks related to residual energy, high-voltage components, chemical exposure, and possible thermal events. These difficulties become even more important when batteries arrive at the end of life with uncertain conditions, such as degradation, corrosion, deformation, or previous accident damage.

In industrial practice, the treatment of end-of-life batteries also raises organizational problems. A recovery facility may receive several battery types with different structures, task sequences, operation times, and resource requirements. A disassembly line must therefore be flexible enough to handle product diversity, while remaining efficient, safe, and economically viable. Some disassembly tasks require human dexterity, perception, and judgment, whereas others are repetitive, heavy, hazardous, or suitable for robotic execution. Human–robot collaboration appears as a promising approach because it combines human adaptability with robotic assistance, precision, and safety support.

Despite the growing interest in battery disassembly, several limitations remain in the existing literature. Many studies focus on a single battery type, even though real recovery systems may process several products. Other works consider human–robot collaboration, but often under deterministic assumptions. In addition, uncertainty is frequently simplified, although human operation times may vary significantly depending on the actual condition of the end-of-life battery. These observations motivate the development of a modelling framework that integrates multi-product battery disassembly, human–robot collaborative execution, and uncertainty in human operation times.

The objective of this thesis is to formulate and analyze a multi-product human–robot collaborative disassembly line balancing problem for end-of-life electric vehicle batteries. Several battery types are considered, each one described by its own set of tasks, precedence relations, execution modes, operation times, and cost parameters. The line contains a maximum number of potential workstations, and the model determines which stations

should be opened, which resources should be installed, how tasks should be assigned, and how the technological precedence constraints should be respected.

The proposed approach is developed in two stages. First, a deterministic mixed-integer linear programming model is formulated. In this model, all operation times are assumed to be known and fixed. This formulation provides a rigorous baseline for representing the main structural decisions of the disassembly line, including station opening, task assignment, execution mode selection, resource allocation, precedence satisfaction, cycle time feasibility, and non-overlap of human and robotic resources.

Second, the deterministic model is extended into a stochastic scenario-based formulation. In this extension, uncertainty is introduced through human operation times, while robot and collaborative operation times remain deterministic. The main structural decisions remain common to all scenarios, whereas scheduling variables, station loads, and recourse variables become scenario-dependent. A bounded recourse mechanism is used to allow limited station overloads under uncertainty while penalizing them economically. This stochastic formulation aims to provide a more realistic evaluation of the line configuration under uncertain human task durations.

The thesis is organized as follows. Chapter 1 introduces the circular economy framework and discusses the value recovery of end-of-life electric vehicle batteries. It explains the transition from a linear economy to circular value preservation and presents the main recovery strategies, including reuse, refurbishment, remanufacturing, and recycling. Chapter 2 focuses on the disassembly of end-of-life electric vehicle batteries. It presents battery pack structures, disassembly levels, typical operations, disassembly approaches, and the main challenges of multi-type human-robot battery disassembly.

Chapter 3 reviews the scientific literature related to disassembly planning, electric vehicle battery disassembly, disassembly sequence planning, disassembly line balancing, human-robot collaboration, uncertainty, and multi-product disassembly lines. This review identifies the main research gaps and positions the present work within the existing literature. Chapter 4 presents the problem formulation and the mathematical models. It describes the input data, the deterministic formulation, and the stochastic scenario-based extension. Finally, Chapter 5 presents the computational results, compares the deterministic and stochastic formulations, analyzes the Gantt charts, and discusses the computational limits of the exact models.

CIRCULAR ECONOMY AND VALUE RECOVERY OF END-OF-LIFE ELECTRIC VEHICLE BATTERIES

1.1 Introduction

The growth of electric mobility has changed the way industrial systems think about products at the end of their life. End-of-life electric vehicle batteries are not ordinary waste: they are expensive, technically complex, and made of materials that remain valuable after their automotive use. At the same time, their recovery is not straightforward. A battery pack contains electrical, mechanical, thermal, and electronic subsystems that must be identified, evaluated, accessed, and handled under strict safety conditions. For this reason, the recovery of end-of-life batteries cannot be reduced to recycling alone. It must be considered as part of a broader circular economy approach.

For many decades, industrial production has mainly followed a linear model, in which resources are extracted, transformed into products, used, and finally discarded. This model has supported economic development, but it also increases pressure on raw materials, energy consumption, and waste management systems. The circular economy proposes a different logic. Instead of treating products as waste at the end of their use phase, it seeks to preserve their value for as long as possible through maintenance, reuse, repair, refurbishment, remanufacturing, and recycling [31, 32]. This change is especially important for technical products whose value is not only contained in their raw materials, but also in their components, design, manufacturing effort, and functional condition.

Electric vehicle batteries are a representative example of this issue. Their production requires materials such as lithium, nickel, cobalt, manganese, graphite, copper, aluminum, and steel. Some of these materials are economically strategic and supply-sensitive, while battery manufacturing itself requires important industrial and energy inputs. In 2024, global demand for electric vehicle batteries exceeded 950 GWh, which reflects the rapid expansion of electric mobility and suggests that the number of batteries reaching end of life will also increase in the coming years [26]. This evolution creates both an environmental challenge and an industrial opportunity.

From a circular economy perspective, an end-of-life battery may follow different recovery routes depending on its condition. If the battery still satisfies technical and safety requirements, it may be reused or repurposed for a second-life application. If only some modules or components are degraded, refurbishment or remanufacturing may allow part of the battery value to be preserved. When functional recovery is no longer possible, recycling remains necessary to recover valuable materials and reduce dependence on primary extraction [37, 27, 44]. These recovery routes are complementary rather than interchangeable, and selecting the appropriate one requires information about the battery state, structure, degradation level, and safety condition.

However, none of these strategies can be effectively implemented without suitable technical and organizational decisions. In most cases, the battery pack must first be inspected, secured, opened, and prepared before modules, cells, electronics, cooling elements, or casing parts can be directed toward reuse, remanufacturing, or recycling. This

practical reality creates a connection between circular economy objectives and the industrial organization of recovery systems. The difficulty becomes even higher when several battery types are treated in the same facility, because each model may differ in geometry, module layout, fastening methods, cooling architecture, and accessibility [43, 47].

This chapter introduces the circular economy concepts required to understand the value recovery of end-of-life electric vehicle batteries. It first presents the transition from the linear economy to the circular economy and explains the main principles of circular value preservation. It then discusses electric vehicle batteries as strategic circular economy products and presents the main recovery strategies: reuse, refurbishment, remanufacturing, and recycling. Finally, the chapter highlights how circular recovery becomes an industrial organization problem, preparing the transition toward the next chapter, which focuses on the disassembly of end-of-life electric vehicle batteries.

1.2 From Linear Economy to Circular Economy

The circular economy is often introduced as an alternative to the traditional linear economy. However, the difference between the two models is not only a matter of waste treatment. It concerns the way products are designed, used, maintained, recovered, and reintegrated into industrial systems. This distinction is important in the case of end-of-life electric vehicle batteries because their value does not disappear when they are removed from vehicles. A battery pack may no longer satisfy the requirements of vehicle propulsion, but it may still contain usable modules, recoverable components, and valuable materials. The challenge is therefore to organize the transition from a product that is no longer suitable for its first use toward a product, component, or material that can enter another value cycle.

1.2.1 Limits of the Linear Model

The linear economy is generally described as a “take–make–use–dispose” model. Raw materials are extracted, transformed into products, sold to users, and finally discarded when the product is no longer needed or no longer functional. This model has supported industrial growth for a long period because it is simple to organize and compatible with mass production. Nevertheless, it becomes increasingly problematic when products are complex, material-intensive, and difficult to treat at the end of life.

The main limitation of the linear model is that it assumes a continuous availability of virgin resources and a sufficient capacity to absorb waste. In practice, both assumptions are fragile. Extraction of raw materials can create environmental impacts, geopolitical dependency, and supply uncertainty. At the same time, waste management becomes more difficult when products contain mixed materials, hazardous substances, or components that require specific treatment. For technical products, the linear model also destroys part of the value that was previously created during design, manufacturing, assembly, testing, transport, and use.

This loss of value is particularly visible in electric vehicle batteries. A battery pack is not only a mass of metals and plastics. It is a structured system composed of cells, modules, busbars, casing elements, sensors, thermal management components, electronic control units, and safety devices. Treating such a product only as waste would ignore the value contained in its functional components and the possibility of recovering them through reuse, refurbishment, remanufacturing, or recycling. Therefore, the limits of the

linear model are not only environmental; they are also economic and industrial.

Several authors have shown that circular economy should not be reduced to end-of-pipe recycling. Kirchherr et al. [31] analyzed a large set of definitions and showed that the concept includes reducing, reusing, recycling, and recovering materials in a systemic way. Geissdoerfer et al. [18] also emphasize that circular economy is closely related to sustainability, although the two concepts should not be confused. Sustainability is a broader objective, while circular economy can be seen as one practical framework for reducing resource consumption and closing material loops.

1.2.2 Circular Economy Principles

Circular economy proposes a different way of thinking about value creation. Instead of considering the end of use as the end of value, it aims to keep products, components, and materials in circulation for as long as possible. The Ellen MacArthur Foundation presents circular economy around three main principles: eliminating waste and pollution, circulating products and materials at their highest value, and regenerating natural systems [13, 12]. These principles are useful because they show that circularity must be considered from the design stage and not only when the product becomes waste.

The first principle is to eliminate waste and pollution by design. This means that waste should not be considered as an unavoidable consequence of production, but as a sign that the product or process was not designed for circularity. In industrial systems, this principle concerns material selection, product architecture, fastening methods, accessibility of components, and the possibility of future maintenance or recovery. For electric vehicle batteries, design choices such as adhesives, welded connections, sealed casings, or inaccessible modules can make later recovery operations more difficult, slower, and riskier.

The second principle is to circulate products and materials at their highest possible value. This principle is essential for understanding the hierarchy of recovery strategies. Reuse and repair generally preserve more value than recycling because they keep the product or component close to its original function. Remanufacturing can also preserve a high level of value when defective elements are replaced and the product is restored to a reliable condition. Recycling remains necessary, but it usually recovers material value rather than the full value embedded in the product [44]. For batteries, this means that the preferred recovery route should depend on the technical condition of the pack, modules, and cells.

The third principle is to regenerate natural systems. This principle is easier to understand for biological materials, but it also has meaning for technical products. In the case of batteries, regeneration can be supported indirectly by reducing the extraction of primary materials, improving resource efficiency, increasing recycled content, and limiting environmental impacts associated with mining, processing, and waste treatment. Circularity in the battery sector is therefore not only a technical issue. It also contributes to resource security, environmental protection, and the development of more resilient industrial supply chains.

At the same time, circular economy should not be presented as a perfect or automatic solution. Korhonen et al. [32] point out that the concept has practical limitations, especially when energy use, material losses, rebound effects, and economic feasibility are considered. This observation is important for the present work. In the case of end-of-life electric vehicle batteries, circularity requires more than an intention to recover value. It requires safe operations, reliable information, suitable technologies, trained operators, and an efficient

organization of recovery processes.

1.2.3 Technical Loops and Value Preservation

Circular economy distinguishes between biological and technical cycles. Biological cycles concern materials that can safely return to natural systems. Technical cycles concern products, components, and materials that should remain in industrial circulation through maintenance, reuse, repair, refurbishment, remanufacturing, and recycling. Electric vehicle batteries clearly belong to the technical cycle because they are engineered products composed of high-value components and materials that cannot simply be returned to nature.

In the technical cycle, the position of a recovery strategy matters. Inner loops, such as maintenance, reuse, and repair, generally preserve more value because they require fewer transformations. Outer loops, such as recycling, are still important, but they usually involve more processing and more loss of functional value. Bocken et al. [7] explain that product design and business model choices strongly influence the ability to maintain products in these loops. For batteries, this means that circularity depends not only on recycling technologies, but also on how the pack is designed, documented, diagnosed, opened, and treated.

For an end-of-life electric vehicle battery, value preservation can occur at different levels. At the pack level, a battery may be reused directly if its state of health and safety condition are sufficient. At the module level, some modules may be extracted and tested for second-life applications. At the cell level, recovery becomes more complex because cells may be welded, glued, or strongly integrated into the module structure. If the battery is too degraded or unsafe for functional recovery, recycling becomes the appropriate route for material recovery. These different possibilities show that the battery does not have a single end-of-life pathway.

This multi-level structure also explains why recovery requires more than a general sustainability intention. Without access to internal information and components, it is difficult to evaluate the condition of the battery, separate valuable parts, or direct them toward the appropriate recovery route. A battery pack must often be opened and examined before the real decision can be made: reuse, remanufacture, recycle, or reject a specific part. In this sense, value recovery is not only a material problem. It is also an information and organization problem.

Figure 1.1 summarizes the difference between a linear logic and a circular value-preservation logic for electric vehicle batteries. The linear model ends with disposal after the use phase, while the circular model introduces several loops after the automotive use phase. These loops depend on diagnosis, sorting, and technical treatment before choosing the most suitable recovery strategy.

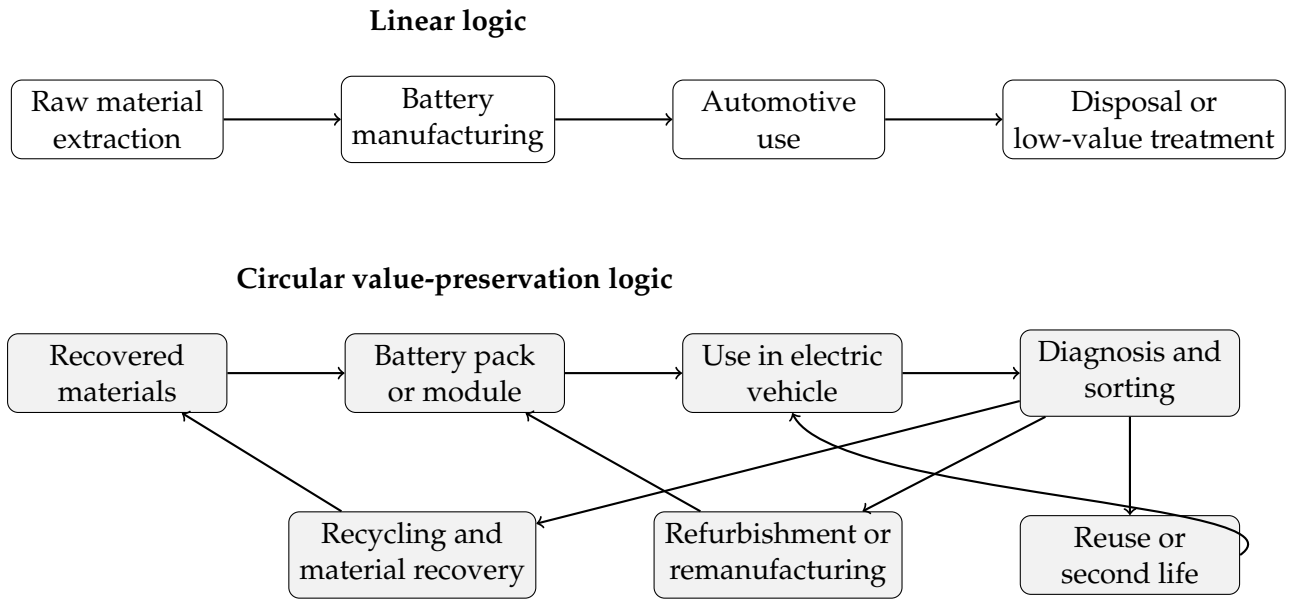


Figure 1.1: From a linear logic to circular value preservation for electric vehicle batteries.

In the context of this thesis, this circular logic is important because it leads directly to an operational problem. If several battery types must be treated in the same recovery system, the process must handle different structures, different recovery decisions, and different resource requirements. Some operations may require human judgment, perception, or adaptation. Others may benefit from robotic assistance because they are repetitive, heavy, precise, or hazardous. Therefore, the circular economy perspective naturally leads to the need for a structured industrial recovery system, which will be developed through the study of end-of-life battery disassembly in the next chapter.

1.3 Electric Vehicle Batteries in the Circular Economy

Electric vehicle batteries occupy a particular position in the circular economy. They are not simple consumable products, and they are not ordinary waste at the end of their use phase. A traction battery pack is a high-value technical system that combines electrochemical cells, modules, electrical connections, thermal management devices, mechanical protection, electronic control units, and safety components. This combination makes the battery essential for electric mobility, but it also makes its recovery difficult when it reaches the end of its automotive life.

The circular economy perspective is therefore useful because it does not look at an end-of-life battery only through its remaining material content. It also considers the value that may still exist at the pack, module, cell, and component levels. In some cases, a battery may be reused in a less demanding application. In other cases, some modules may be recovered while degraded or unsafe elements are removed. If functional recovery is no longer possible, recycling remains necessary to recover materials and reduce the need for primary extraction. The circular value of a battery is therefore distributed across several possible recovery routes, and the choice between them depends on technical, economic, and safety conditions.

1.3.1 Strategic Role of Electric Vehicle Batteries

The development of electric mobility has made lithium-ion batteries one of the central technologies of the energy transition. In an electric vehicle, the battery pack determines a large part of the vehicle range, cost, mass, performance, and safety. It is also one of the most expensive components of the vehicle, which explains why its recovery is a major industrial issue. From a circular economy point of view, losing the value embedded in such a component at the end of its automotive use would represent both an environmental and economic inefficiency.

The scale of battery deployment reinforces this issue. According to the International Energy Agency, global battery demand for the energy sector reached the milestone of 1 TWh in 2024, and electric vehicle battery demand exceeded 950 GWh, representing an increase of about 25% compared with 2023 [26]. This growth means that the number of batteries entering the market is increasing rapidly. Even if most of these batteries will reach end of life only after several years of use, recovery systems must be prepared before large volumes of retired battery packs arrive.

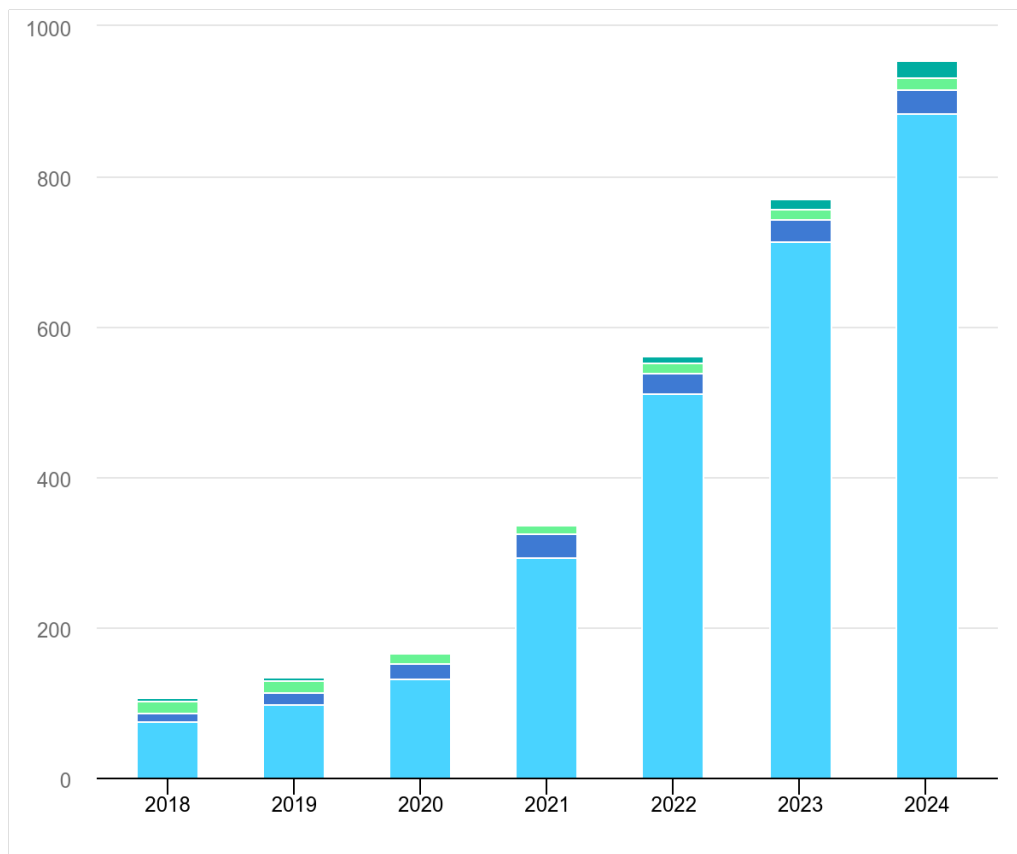


Figure 1.2: Electric vehicle battery demand by mode, 2018–2024. [26].

The increase in demand also changes the way end-of-life management should be considered. When electric vehicles were produced in smaller volumes, battery recovery could be treated as a limited technical issue. With the expansion of the market, it becomes a production and logistics problem. Recovery facilities must be able to receive different types of batteries, identify their characteristics, evaluate their condition, and direct them toward suitable treatment processes. This creates a need for organized recovery systems rather than isolated manual decisions.

Another important aspect is the evolution of battery technologies. Lithium-ion batter-

ies are not all identical. They may differ in chemistry, format, architecture, cooling system, safety design, and joining methods. For example, lithium iron phosphate batteries and nickel manganese cobalt batteries have different material compositions and performance characteristics. The International Energy Agency reports that lithium iron phosphate batteries represented nearly half of the global electric vehicle battery market in 2024, which shows that battery chemistry is evolving with cost, performance, and supply-chain considerations [26]. This technological diversity directly affects circular recovery because the value, risk, and treatment route of a battery depend partly on its chemistry and design.

1.3.2 Material Criticality and Supply Concerns

Electric vehicle batteries are strongly connected to the issue of critical materials. Depending on the chemistry, a battery may contain lithium, nickel, cobalt, manganese, graphite, copper, aluminum, iron, phosphorus, and other materials used in cells, current collectors, busbars, cooling systems, casing structures, and electronic components. These materials do not have the same economic value, availability, environmental impact, or recovery difficulty. For this reason, battery circularity is also a question of material security.

The demand for battery-related minerals is expected to increase with the deployment of electric vehicles and stationary storage systems. The International Energy Agency notes that, in the Stated Policies Scenario, lithium demand is projected to grow fivefold by 2040, while graphite and nickel demand are projected to double, with battery deployment being one of the main drivers of this growth [25]. This situation explains why battery recycling and recovery are increasingly viewed as strategic activities. Recovering materials from end-of-life batteries can reduce part of the pressure on primary extraction, even if recycling alone cannot immediately replace mining.

Material criticality is not limited to the quantity of minerals available in the ground. It also concerns refining capacity, geographical concentration, supply-chain dependency, price volatility, environmental constraints, and social concerns related to extraction. Some battery materials are associated with high environmental burdens during mining and processing. Others are affected by supply concentration in a limited number of countries or industrial actors. In this context, circular recovery can contribute to a more resilient battery value chain by keeping materials and components in use for longer periods.

However, the circular recovery of these materials is technically difficult. A battery pack is not a homogeneous block of material. It is a layered and assembled product in which materials are distributed across cells, modules, connectors, cooling plates, protection systems, adhesives, sealants, electronics, and structural elements. Before materials can be recycled efficiently, the pack often needs to be dismantled, separated, sorted, and prepared. This is one of the reasons why the industrial organization of battery recovery is essential in the circular economy of electric vehicle batteries.

1.3.3 End-of-Life Concerns and Recovery Potential

The end of the automotive life of a battery does not necessarily mean the end of its usefulness. In many cases, a battery is considered no longer suitable for vehicle traction when its state of health has decreased below the level required for automotive performance. This can affect driving range, power delivery, charging behavior, reliability, and user acceptance. Nevertheless, the same battery may still have enough remaining capacity for a less demanding application, such as stationary storage, backup power, renewable energy integration, or charging support [45, 19].

This creates an important distinction between end of automotive life and end of technical life. End of automotive life refers to the moment when the battery no longer satisfies its original vehicle requirements. End of technical life refers to the moment when the battery can no longer be used safely or economically in any functional application. Between these two moments, there may be opportunities for reuse, repurposing, refurbishment, or remanufacturing. These opportunities depend on the condition of the pack, the state of health of its modules and cells, the availability of product information, and the cost of diagnosis and treatment.

Safety remains a central concern in all end-of-life battery recovery routes. A retired battery may still contain a significant amount of electrical energy. It may also be damaged, swollen, corroded, thermally stressed, or affected by previous operating conditions. Opening a battery pack without adequate procedures can expose operators to electrical, thermal, chemical, and mechanical hazards. For this reason, recovery cannot be separated from safety management. Identification, discharge or isolation, inspection, handling, and controlled treatment are necessary before any recovery decision can be implemented.

Regulation also reinforces the importance of battery circularity. The European Union Battery Regulation 2023/1542 introduces requirements related to sustainability, safety, labelling, due diligence, collection, recycling efficiency, material recovery, recycled content, and information systems for batteries [14]. Such regulatory developments show that battery recovery is not only a voluntary environmental practice. It is becoming part of an organized industrial and legal framework.

From the perspective of this thesis, these elements lead to a clear conclusion. End-of-life electric vehicle batteries contain value after their automotive use, but this value cannot be recovered automatically. It must be accessed through technical operations that are safe, organized, and adapted to product variability. Since battery packs differ from one manufacturer to another, and since each recovery route may require different levels of treatment, the management of end-of-life batteries becomes a complex industrial problem. This problem becomes even more difficult when several battery types are processed on the same line with both human and robotic resources. Therefore, the circular economy of electric vehicle batteries naturally leads to the study of multi-type battery recovery systems.

1.4 Battery Value Recovery Strategies

End-of-life electric vehicle batteries can follow several recovery strategies depending on their technical condition, safety state, residual performance, and economic value. In this thesis, the expression end-of-life battery refers to a battery pack that has been removed from its automotive application and enters a recovery system. This does not necessarily mean that the battery has lost all value. It means that the battery is no longer considered suitable for its original use in the vehicle, and that a decision must be made regarding its next destination.

The possible recovery routes are not equivalent. Some strategies aim to preserve the functional value of the battery, while others focus mainly on material recovery. Reuse and second-life applications try to keep the battery, module, or cell in operation. Refurbishment and remanufacturing involve technical interventions to restore part of the product performance or reliability. Recycling, on the other hand, generally destroys the product structure in order to recover valuable materials. These strategies form a hierarchy of value preservation, where inner loops usually retain more value than outer loops [44, 24].

For end-of-life EV batteries, the choice of a recovery strategy cannot be made only from a theoretical circular economy perspective. It requires practical information about the state of health, degradation history, safety condition, chemistry, architecture, and accessibility of the pack. This is why diagnosis and product evaluation are closely connected to value recovery. Without inspecting and separating the battery pack, it is difficult to know whether a module should be reused, repaired, remanufactured, recycled, or rejected.

1.4.1 Reuse and Second-Life Applications

Reuse is one of the most direct strategies for preserving the value of an end-of-life battery. It consists of using the battery, module, or cell again without breaking it down into raw materials. In the case of electric vehicle batteries, reuse is often discussed through the concept of second-life applications. A battery that no longer satisfies automotive requirements may still be able to operate in applications where energy density, power demand, and dynamic performance are less severe than in a vehicle.

Typical second-life applications include stationary energy storage, renewable energy integration, backup power systems, microgrids, and support for charging infrastructure [45, 19, 2]. These applications are attractive because they can extend the useful lifetime of the battery and delay recycling. From a circular economy point of view, this is valuable because the battery continues to provide a function instead of being immediately transformed into material feedstock.

However, reuse is not automatic. An end-of-life battery must be tested before it can be used again. Its state of health, remaining capacity, internal resistance, thermal behavior, safety condition, and history of use must be assessed. Two batteries of the same model may behave differently because they may have experienced different temperatures, charging rates, depths of discharge, storage conditions, and mechanical stresses. For this reason, second-life use requires reliable diagnosis and classification.

Reuse can be considered at different levels. At the pack level, the complete battery may be reused if its condition is sufficiently homogeneous and safe. At the module level, modules may be extracted, tested, and reassembled into a new system. At the cell level, reuse becomes more delicate because cells are often strongly integrated and may require more detailed testing and handling. In practice, the deeper the level of reuse, the more recovery effort is required.

The main advantage of reuse is value preservation. The product remains close to its functional form and avoids the energy and material losses associated with recycling. Nevertheless, reuse also faces several limitations. These include uncertainty about remaining lifetime, lack of standardization between battery packs, difficulty of accessing reliable usage data, safety certification requirements, and the cost of testing and repackaging. These limitations explain why reuse is not always the best solution, even when the battery still contains residual capacity.

1.4.2 Refurbishment and Remanufacturing

Refurbishment and remanufacturing are recovery strategies that require more intervention than simple reuse. They are relevant when the battery or one of its subassemblies is no longer directly reusable, but still contains components that can be restored, replaced, or reconfigured. In this case, the objective is not only to extend the life of the product, but also to recover a reliable level of performance through controlled technical operations.

Refurbishment generally refers to operations that improve the condition of a used product without necessarily restoring it to a like-new condition. For a battery pack, this may include cleaning, inspection, replacement of damaged connectors, correction of minor faults, replacement of auxiliary components, or reconfiguration for another use. Remanufacturing is usually more demanding. It involves a structured industrial process that may include disassembly, cleaning, inspection, diagnosis, replacement of defective parts, reassembly, and final testing [41, 44].

In the context of electric vehicle batteries, remanufacturing may be applied at the pack, module, or cell level. For example, a battery pack may contain some degraded modules while other modules remain usable. Instead of recycling the whole pack, the defective modules can be removed and replaced, while the remaining modules are preserved. This approach can reduce material waste and retain part of the manufacturing value embedded in the battery.

The feasibility of refurbishment or remanufacturing depends strongly on the design of the battery pack. If modules are accessible, fasteners are removable, and product information is available, the recovery process becomes easier. In contrast, welded connections, structural adhesives, sealed covers, and poor documentation can increase operation time, risk, and cost. Battery remanufacturing is therefore not only a question of technical skill. It is also directly linked to design for recovery, product information, and process planning.

For this thesis, refurbishment and remanufacturing are important because they require selective recovery. The objective is not simply to destroy the product, but to access specific components while preserving their integrity when possible. This creates operational constraints: some tasks must be performed in a specific order, some components must not be damaged, and some operations require human judgment or robotic assistance. These characteristics are consistent with the need to study human–robot collaborative organization in end-of-life battery recovery.

1.4.3 Recycling and Material Recovery

Recycling is necessary when an end-of-life battery can no longer be reused, refurbished, or remanufactured in a safe and economically reasonable way. Unlike reuse or remanufacturing, recycling does not preserve the functional structure of the battery. Its main objective is to recover valuable materials and reintegrate them into industrial supply chains.

Electric vehicle batteries contain materials that can be recovered, such as lithium, cobalt, nickel, manganese, copper, aluminum, graphite, steel, and plastics. The economic and environmental interest of recycling depends on the chemistry of the battery, the concentration of valuable materials, the recycling process used, and market conditions. For example, batteries rich in cobalt and nickel may have a different recycling value compared with lithium iron phosphate batteries, which contain less high-value cathode material but remain important from a resource and waste management perspective [24, 10].

Several recycling routes are discussed in the literature. Mechanical pretreatment is often used to open, crush, separate, or sort battery materials before further processing. Pyrometallurgical recycling uses high-temperature treatment to recover metals, but it can involve high energy consumption and may lose some materials. Hydrometallurgical recycling uses chemical leaching and separation processes to recover metals with higher selectivity. Direct recycling aims to preserve or regenerate active materials more directly, but it remains more sensitive to battery chemistry, sorting quality, and process control

[37, 27, 48].

Although recycling is essential, it should not be considered as the only circular economy strategy. If a battery module can still be safely used, recycling it too early may destroy functional value. On the other hand, if the battery is damaged, unsafe, deeply degraded, or economically unsuitable for reuse, recycling becomes the most appropriate route. The circular economy does not impose a single recovery path; it requires choosing the most suitable path based on the condition of the battery and the expected value recovery.

The recycling stage also benefits from upstream preparation. Removing casing parts, electronics, cables, cooling elements, and modules can improve sorting quality and reduce safety risks before mechanical or chemical treatment. In some cases, upstream preparation allows the separation of components that follow different recovery routes. For example, electronic boards, aluminum structures, copper busbars, and modules may require different treatments. Therefore, even when the final destination is recycling, organized treatment remains important for improving recovery efficiency and safety.

1.4.4 Comparison of Recovery Strategies

The main recovery strategies differ in terms of objective, value preservation, technical requirements, and dependence on product information. Table 1.1 summarizes these differences for end-of-life electric vehicle batteries.

Table 1.1: Comparison of value recovery strategies for end-of-life EV batteries.

Strategy	Main objective	Value preserved	Main requirements
Reuse / second life	Use the battery, module, or cell in another application when its condition allows it.	High functional value.	Diagnosis, safety validation, state-of-health assessment, and possible repackaging.
Refurbishment	Improve the condition of a used battery or component without necessarily restoring it to a like-new state.	Functional and component value.	Inspection, minor repair, replacement of auxiliary parts, and quality control.
Remanufacturing	Restore the battery pack or subassembly through a controlled industrial process.	High component and manufacturing value.	Disassembly, cleaning, diagnosis, replacement of defective parts, reassembly, and final testing.
Recycling	Recover materials when functional recovery is no longer safe, feasible, or economically justified.	Material value.	Sorting, safe handling, mechanical pretreatment, and pyrometallurgical or hydrometallurgical processing.

This comparison shows that the recovery of end-of-life batteries is not a single operation but a decision process. The best strategy depends on the state of the battery and on the balance between safety, cost, technical feasibility, and expected value. In all cases,

the recovery system requires information about the product and, very often, some level of technical preparation.

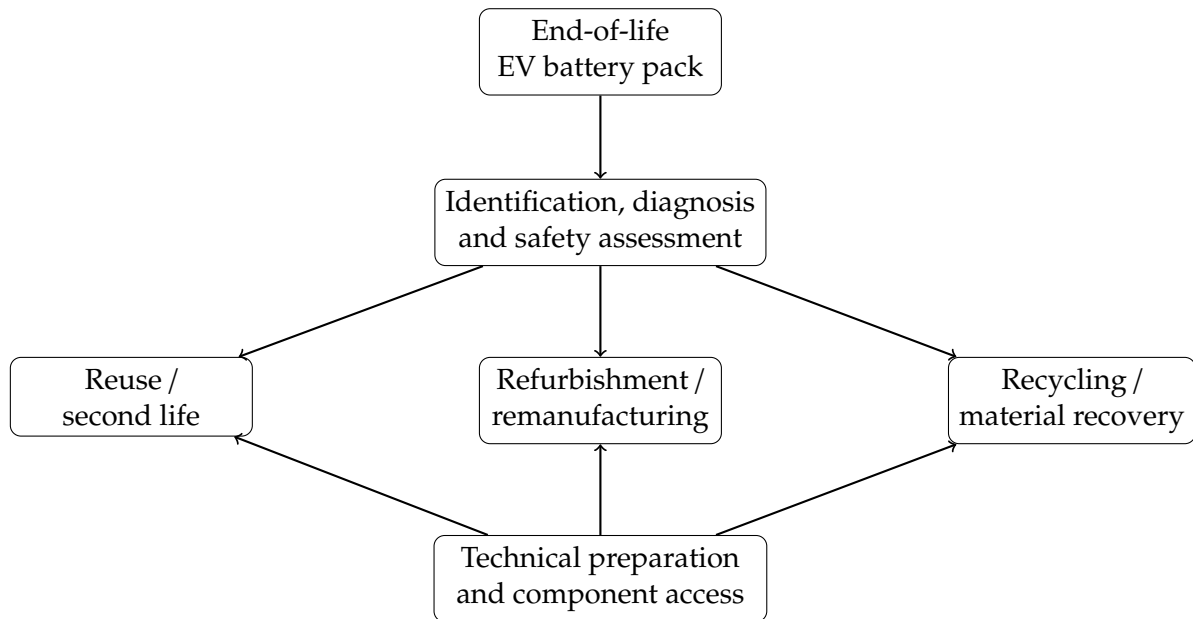


Figure 1.3: Recovery routes for end-of-life electric vehicle batteries.

The figure highlights the central idea of this chapter: end-of-life EV battery recovery depends on the ability to identify the battery condition and organize the appropriate recovery route. If the battery pack can be safely assessed and prepared, its modules, cells, electronics, connectors, and structural elements can be directed toward the most suitable option. If preparation is slow, unsafe, or poorly organized, the potential value of the battery may be lost. This observation prepares the transition toward the next section, which explains why circular recovery becomes an industrial organization problem.

1.5 From Circular Recovery to an Industrial Organization Problem

The previous sections showed that end-of-life electric vehicle batteries can still contain value after their automotive use. This value may exist at several levels: the complete pack, the modules, the cells, the electronic components, the casing, or the materials themselves. However, this value is not directly available. It must first be identified, evaluated, accessed, and directed toward an appropriate recovery route. This is where the circular economy becomes an industrial organization problem.

In theory, circular economy strategies are often presented as loops: reuse, refurbishment, remanufacturing, and recycling. In practice, these loops require concrete operations, resources, tools, information, and decisions. An end-of-life battery pack does not automatically enter the correct loop. It must be received, identified, inspected, classified, and treated according to its condition. The recovery system must therefore decide whether the battery should be reused as a pack, partially recovered at module level, prepared for remanufacturing, or sent to recycling. These decisions depend on technical feasibility, economic value, safety constraints, and available recovery capacity.

This practical dimension is particularly important for electric vehicle batteries because they are heterogeneous products. Battery packs differ from one manufacturer to another in chemistry, architecture, mass, dimensions, module arrangement, joining methods, cooling system, and accessibility of internal parts. Even batteries of the same model may arrive in different conditions depending on their age, usage history, degradation level, accident exposure, and storage conditions. As a result, a recovery process designed for a single standardized product may not be sufficient when several battery types must be treated in the same facility.

Another difficulty is that value recovery requires both technical knowledge and operational flexibility. Product information can help identify the battery structure, the location of components, the type of fasteners, the chemistry, and the safety procedures required before treatment. When this information is incomplete or unavailable, additional inspection and reverse engineering may be needed to understand the product before deciding how to recover it. Reverse engineering is therefore useful in a circular economy context because it transforms a physical product into usable knowledge for recovery planning [6, 15, 65].

The industrial organization of battery recovery must also consider the availability of resources. Some operations require human judgment, visual interpretation, adaptation, and careful handling. Other operations may benefit from robotic assistance because they are repetitive, physically demanding, hazardous, or require precision. Therefore, the recovery of end-of-life batteries is not only a technological problem, but also a resource allocation problem. It requires deciding which tasks should be performed, in which order, at which station, and by which type of resource.

This observation is directly related to the objective of this thesis. The treatment of multiple battery types on the same line requires a system capable of managing product variability while maintaining safety, cost control, and workload balance. A human-robot collaborative line can be a relevant solution because it combines the adaptability of human operators with the repeatability and physical assistance of robotic systems. However, such a line must be properly organized. Tasks must be assigned to stations and execution modes, precedence relations must be respected, and the use of human and robotic resources must be coordinated.

At this stage, the role of the next chapter becomes clear. The present chapter introduced the circular economy logic and the main value recovery strategies for end-of-life electric vehicle batteries. The next chapter will focus on the technical process that makes these strategies possible: battery disassembly. It will present the structure of EV battery packs, the specificities of end-of-life batteries, the main disassembly approaches, and the planning and scheduling issues that lead to the mathematical model developed later in this work.

1.6 Conclusion

This chapter presented the circular economy as the general framework in which the recovery of end-of-life electric vehicle batteries can be understood. The discussion first showed the limits of the linear economy, where products are produced, used, and discarded, and then introduced the circular economy as a way to preserve value through reuse, refurbishment, remanufacturing, and recycling. For technical products such as electric vehicle batteries, this perspective is particularly relevant because value is not only contained in raw materials, but also in components, assemblies, product information, and remaining

functional capacity.

The chapter also highlighted the strategic importance of electric vehicle batteries in current industrial and environmental transitions. The rapid growth of electric mobility increases the demand for battery materials and will progressively lead to larger flows of end-of-life battery packs. These batteries contain valuable materials such as lithium, nickel, cobalt, manganese, graphite, copper, aluminum, and steel, but they also present technical and safety challenges. Their recovery is therefore not only an environmental requirement, but also an industrial issue related to resource security, cost, regulation, and process organization.

Several recovery strategies were then discussed. Reuse and second-life applications aim to extend the functional use of batteries or modules when their condition allows it. Refurbishment and remanufacturing can preserve part of the product value by restoring, replacing, or reconfiguring components. Recycling remains necessary when functional recovery is no longer feasible, as it enables the recovery of materials and their reintegration into industrial supply chains. These strategies are complementary, but they require reliable information about the battery condition, structure, chemistry, and safety state.

A central conclusion of this chapter is that circular recovery cannot be treated only as a conceptual loop. In practice, it requires organized industrial operations. End-of-life electric vehicle batteries must be identified, assessed, classified, and directed toward the most suitable recovery route. This becomes more complex when several battery types are treated in the same recovery system, since each type may have its own architecture, components, material composition, and accessibility constraints. Product variability therefore creates a need for flexible and well-structured recovery processes.

This observation prepares the transition toward the next chapter. Since the value contained in an end-of-life battery is not directly accessible, the recovery process must rely on technical operations capable of accessing, separating, and preparing the battery components for the selected recovery route. The following chapter will therefore focus on the disassembly of end-of-life electric vehicle batteries. It will introduce the structure of battery packs, the specific challenges of end-of-life batteries, and the main concepts needed to understand disassembly planning, scheduling, and human–robot collaborative organization.

DISASSEMBLY OF END-OF-LIFE ELECTRIC VEHICLE BATTERIES

2.1 Introduction

The previous chapter showed that end-of-life electric vehicle batteries can still contain value after their first automotive use. However, this value cannot be recovered directly. Before a battery pack can be reused, refurbished, remanufactured, or recycled, its structure must be understood, its condition must be assessed, and its components must be accessed safely. Disassembly is therefore one of the key technical steps that connects circular recovery objectives with practical industrial operations.

End-of-life EV battery packs are complex products. They are composed of cells, modules, electrical connections, busbars, sensors, cooling elements, casing parts, protection systems, and a Battery Management System. These components are assembled in a compact structure designed mainly for performance, safety, and integration inside the vehicle. In many cases, the battery pack was not designed with easy end-of-life disassembly as the main priority. As a result, opening and separating its components may involve screws, welded joints, adhesives, sealants, clips, cables, cooling circuits, and high-voltage connections [47, 43].

The difficulty of battery disassembly increases because battery packs are not standardized across manufacturers. Their geometry, chemistry, module layout, cooling architecture, fastening methods, accessibility, and safety design may vary from one vehicle model to another. Moreover, batteries arriving at the end-of-life stage may have different histories. Some packs may simply be degraded after normal use, while others may be damaged after accidents, exposed to humidity, or affected by thermal or mechanical stress. This variability makes it difficult to define a single fixed disassembly procedure for all battery types.

Safety is another major concern. Even after removal from the vehicle, a battery pack may still contain significant electrical energy. Disassembly may expose operators and equipment to high-voltage risks, short circuits, chemical leakage, fire, thermal runaway, or mechanical hazards. For this reason, battery disassembly cannot be considered as a simple reverse assembly operation. It requires identification, preparation, safe handling, suitable tools, and a sequence of operations that respects both technological and safety constraints [28, 33].

At the industrial level, disassembly also raises organizational issues. If several battery types have to be processed on the same line, the system must handle different task sequences, processing times, tools, and resource requirements. Some tasks may require human perception, judgment, and adaptability, while others may be suitable for robotic execution because they are repetitive, heavy, precise, or hazardous. This explains the growing interest in human–robot collaborative disassembly, where humans and robots contribute to the same recovery process according to their respective strengths [47, 33].

This chapter introduces the technical and organizational concepts required to understand the disassembly of end-of-life EV batteries. It first presents the structure and specific characteristics of EV battery packs from a disassembly perspective. It then defines battery disassembly, its levels, and its typical operations. After that, the main disassembly

approaches are discussed, including manual, automated, and human–robot collaborative disassembly. Finally, the chapter introduces disassembly planning, task allocation, and multi-type disassembly line issues, which prepare the formulation of the considered problem in the next chapter.

2.2 Structure and Specificity of End-of-Life EV Battery Packs

Before studying battery disassembly operations, it is necessary to understand the structure of the product being treated. An end-of-life EV battery pack is not a single component, but a multi-level technical system. Its architecture combines electrochemical, electrical, thermal, mechanical, and electronic elements. These elements are assembled to satisfy vehicle requirements such as energy capacity, power delivery, crash protection, thermal regulation, electrical safety, and compact integration inside the vehicle.

From a disassembly point of view, this structure is important because each level of the battery pack creates specific access constraints. The external casing protects the battery against mechanical shocks and environmental conditions, but it also creates the first physical barrier to internal components. Modules and cells contain the main electrochemical value, but they may be connected through busbars, welded joints, adhesives, or mechanical fasteners. Cooling plates, hoses, sensors, wiring harnesses, and Battery Management System components must also be considered because they influence the accessibility and safety of the disassembly process.

2.2.1 Battery Pack Architecture

The conventional architecture of an electric vehicle battery is commonly described through a hierarchical structure: cells are assembled into modules, and modules are integrated into the complete battery pack. The cell is the elementary electrochemical unit that stores and releases electrical energy. Several cells are connected in series and/or in parallel to form a module with the required voltage and capacity. Several modules are then integrated into the battery pack, together with structural, electrical, thermal, and control components [29, 47].

The complete battery pack must ensure more than energy storage. It must also protect the cells, maintain acceptable operating temperatures, monitor electrical and thermal parameters, isolate high-voltage circuits when needed, and interface with the vehicle. For this reason, a pack generally includes a housing or tray, top and bottom covers, module frames, busbars, wiring harnesses, fuses, contactors, sensors, cooling channels or plates, and a Battery Management System. In many battery electric vehicles, the pack is located in the underbody of the vehicle, where it contributes to vehicle packaging and may interact with structural and safety requirements [5].

Recent battery architectures are also evolving. In addition to the traditional cell–module–pack architecture, manufacturers increasingly develop cell-to-pack and cell-to-chassis concepts. In cell-to-pack architectures, the intermediate module level is reduced or eliminated, and cells are integrated more directly into the pack. In cell-to-chassis or structural battery concepts, the battery becomes more strongly integrated with the vehicle structure [29]. These evolutions can improve energy density and reduce the number of components, but they may also change the way end-of-life batteries are accessed, separated, and recovered.

For end-of-life batteries, this architecture has a direct consequence. The recovery

process may target different levels depending on the selected objective. If the complete pack can be reused, only limited intervention may be required. If modules must be extracted, the pack has to be opened and internal connections must be accessed. If cells or materials are targeted, a deeper level of treatment is required. Therefore, the structure of the battery pack determines both the difficulty and the possible depth of disassembly.

2.2.2 Components Relevant to Disassembly

The components of an EV battery pack do not all have the same role during disassembly. Some components mainly act as barriers that must be removed to access the internal structure, while others represent valuable elements that should be preserved whenever possible. In addition, several components introduce safety constraints because they are connected to high-voltage circuits, cooling systems, or monitoring and control functions. For this reason, understanding the main components of a battery pack is necessary before defining disassembly tasks, precedence relations, and suitable execution resources.

Figure 2.1 illustrates the main components of an electric vehicle battery pack from a disassembly perspective. It highlights the elements that are usually encountered during pack opening, electrical disconnection, thermal interface handling, and module extraction.

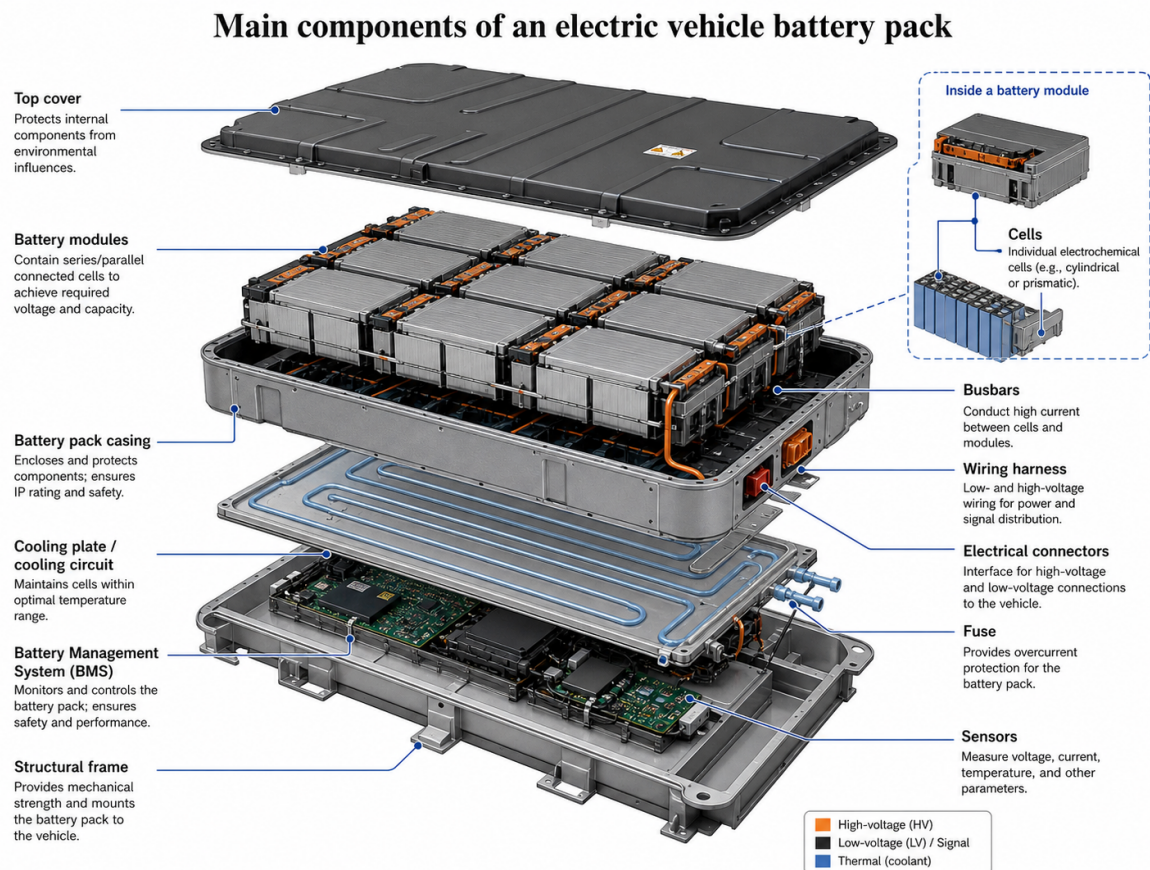


Figure 2.1: Main components of an electric vehicle battery pack

The external casing, structural frame, and top cover protect the battery pack against mechanical shocks, dust, water, and environmental influences. These elements are usually among the first barriers encountered during disassembly. Their design strongly influences accessibility to the internal modules and the difficulty of opening the pack. Depending

on the manufacturer and the battery generation, covers may be bolted, sealed, glued, or integrated with structural elements. This directly affects the time, tools, and precautions required before internal components can be reached.

The modules and cells represent the core electrochemical part of the battery. They contain most of the energy storage value and are therefore central to reuse, remanufacturing, and recycling decisions. However, they can also be hazardous if damaged, overcharged, short-circuited, or thermally unstable. Their arrangement, spacing, fixation method, and connection type influence whether they can be removed safely and without damage.

Electrical components such as busbars, fuses, contactors, terminals, and wiring harnesses ensure the circulation and control of electrical energy. From a disassembly perspective, these components are important because they may carry residual electrical risk and because they often create precedence constraints. In many cases, electrical isolation and disconnection must be considered before mechanical extraction of modules.

Thermal management components are also important. EV battery packs may use air cooling, liquid cooling, cooling plates, channels, hoses, or thermal interface materials. These components are often placed close to modules or cells. Their presence can complicate access, especially when cooling plates are integrated into the structure or when thermal interface materials increase adhesion between components.

Finally, the Battery Management System and sensing elements provide monitoring and control functions. They may include electronic boards, voltage sensing wires, temperature sensors, current sensors, and communication interfaces. These elements are usually small compared with modules or covers, but they are important during disassembly because they are fragile, connected to several parts of the pack, and sometimes valuable for diagnosis or reuse.

Table 2.1 summarizes the main component groups of an EV battery pack and their relevance for end-of-life disassembly.

Table 2.1: Main EV battery pack component groups and their relevance for end-of-life disassembly.

Component group	Main function in the battery pack	Relevance for disassembly
Casing, tray and covers	Mechanical protection, sealing, structural support and vehicle integration.	First access barrier; may involve bolts, sealants, adhesives or structural connections.
Modules and cells	Energy storage and power delivery.	Main value carrier; may be targeted for reuse, remanufacturing or recycling; requires careful handling.
Busbars and high-voltage connections	Electrical connection between cells, modules and pack terminals.	Create electrical risk and precedence constraints; usually require safe disconnection before extraction.
Battery Management System and sensors	Monitoring of voltage, current, temperature, state of charge and safety functions.	Important for diagnosis; fragile components connected through wiring and sensing circuits.
Cooling system	Thermal regulation of cells and modules during operation.	Can limit access to modules; may involve hoses, plates, fluids or thermal interface materials.
Fasteners, adhesives and sealants	Assembly, fixation, sealing and mechanical stability.	Strongly influence disassembly time, tool selection and risk of component damage.

This component view is useful for the rest of the thesis because it allows battery disassembly to be described as a set of tasks rather than as a vague operation. Each component group can generate one or several tasks, and each task may require a specific resource, tool, execution mode, and precedence relation. This is consistent with the modelling perspective adopted later, where each battery type is represented by a set of disassembly tasks subject to precedence and resource constraints.

2.2.3 Variability Between Battery Types

One of the main difficulties in end-of-life EV battery disassembly is product variability. Battery packs are not designed according to a single universal architecture. They differ between manufacturers, vehicle models, battery chemistries, and technological generations. This variability is a key reason why a fixed disassembly process is difficult to apply in industrial conditions.

Variability appears first at the cell level. Cells may be cylindrical, prismatic, or pouch-shaped. These formats differ in geometry, packaging, mechanical behavior, connection method, and integration inside modules or packs. Variability also appears in chemistry. Lithium iron phosphate, nickel manganese cobalt, nickel cobalt aluminum, and other chemistries can lead to different material values, safety considerations, and recycling

interests.

At the pack level, differences concern the number of modules, module arrangement, casing geometry, cooling system, fastening methods, accessibility of components, and degree of structural integration. Some packs are relatively modular and allow modules to be removed after opening the cover and disconnecting electrical links. Other designs are more integrated and may use adhesives, sealants, welded joints, or cell-to-pack structures that reduce the number of removable subassemblies.

End-of-life condition adds another layer of variability. A retired battery may be normally aged, mechanically damaged, thermally stressed, corroded, partially dismantled, or missing information. Two batteries with the same nominal design may therefore require different precautions and treatment times. This makes the disassembly process uncertain and reinforces the need for flexible planning and resource allocation.

The variability between battery types is summarized in Table 2.2. These sources of variability are important because they directly influence the task set, precedence relations, operation times, safety requirements, and suitable execution modes.

Table 2.2: Sources of variability in end-of-life EV battery packs.

Variability source	Examples	Impact on disassembly
Cell format and chemistry	Cylindrical, prismatic or pouch cells; LFP, NMC, NCA and other chemistries.	Influences handling, safety precautions, material value and possible recovery route.
Pack architecture	Cell-module-pack, cell-to-pack, structural battery concepts.	Changes the depth of disassembly and the accessibility of modules or cells.
Joining and fastening methods	Screws, clips, welds, adhesives, sealants and structural bonding.	Affects tool selection, processing time and risk of component damage.
Thermal management design	Cooling plates, liquid channels, hoses, thermal pads or thermal adhesives.	May create additional removal tasks and access constraints.
End-of-life condition	Aging, deformation, accident damage, corrosion or unknown history.	Increases uncertainty, safety risk and the need for adaptive decision-making.

For the present work, this variability is not a secondary detail. It is the reason why the problem is considered as a multi-type battery disassembly problem. Each battery type can have its own task set, processing times, resource requirements, and precedence relations. A disassembly line designed for such a context must therefore be able to handle heterogeneous products while maintaining a feasible workload distribution across stations. This point prepares the next sections, where battery disassembly operations and human-robot collaborative approaches are introduced.

2.3 End-of-Life Battery Disassembly

End-of-life battery disassembly can be understood as the set of operations required to open a battery pack, access its internal components, separate selected parts, and prepare them for the appropriate recovery route. In contrast with general product disassembly, EV battery disassembly must deal with high-voltage components, residual energy, possible degradation, and a strong diversity of pack architectures. Therefore, it cannot be treated only as the reverse of assembly. It must be planned as a controlled process that combines technical feasibility, safety, component preservation, and recovery objectives.

In the context of this thesis, disassembly is considered from an industrial point of view. The objective is not only to describe how a battery pack can be opened, but also to understand how disassembly tasks can be represented, ordered, assigned to stations, and performed by available resources. This is important because a structured modelling approach requires tasks, precedence relations, stations, human resources, robotic resources, and possible execution modes.

2.3.1 Definition and Role of Disassembly

Disassembly is commonly defined as the process of separating a product into subassemblies, components, or materials. For end-of-life EV batteries, this definition must be extended because disassembly also supports decision-making. By opening and separating the battery pack, the recovery system obtains access to components whose condition, safety, and value can be evaluated. Disassembly is therefore both a physical operation and an information-generating step.

Several recovery strategies depend on disassembly. If the objective is second-life use, disassembly may be needed to extract modules and test them individually. If the objective is remanufacturing, disassembly is necessary to identify defective elements, remove them, and preserve usable components. If the objective is recycling, disassembly can improve sorting quality, reduce safety risks, and separate components that require different treatment routes. Baazouzi et al. [4] emphasize that disassembly is required before applying circular economy strategies to electric vehicle batteries, because components must be accessed before they can be reused, remanufactured, or recycled.

The role of disassembly also depends on the desired level of recovery. A shallow disassembly may be sufficient when the objective is to remove external covers or disconnect auxiliary components. A deeper disassembly may be required to extract modules, separate cells, or prepare active materials for recycling. The deeper the disassembly level, the higher the need for detailed product information, specific tools, safety precautions, and time. This creates a trade-off between the value recovered and the effort required to obtain it.

From an operational perspective, disassembly is constrained by product architecture. Components cannot be removed in any order. Covers, connectors, cooling elements, fasteners, and modules are linked by physical, electrical, and safety dependencies. These dependencies create precedence relations between tasks. For example, a module cannot be removed before the cover is opened, the relevant electrical connections are secured, and the mechanical fixing elements are released. These precedence relations are a central element in disassembly planning and later in the mathematical formulation of the problem.

2.3.2 Disassembly Levels

EV battery disassembly can be performed at different levels depending on the recovery objective and the technical condition of the battery pack. At the lowest level, the complete battery pack may be kept intact when the objective is direct reuse or second-life evaluation. At a higher level, pack disassembly allows external components, covers, connectors, cooling elements, and modules to be accessed. Module-level disassembly goes deeper by separating modules and internal module components. Cell-level disassembly is more delicate because cells may be welded, glued, compressed, or strongly integrated inside the module. Finally, the deepest level concerns material recovery, where the objective is no longer to preserve the product structure but to recover raw materials for recycling.

The choice of disassembly level depends on the expected recovery route. Pack-level intervention may be sufficient when the battery can be reused as a complete unit or when only diagnosis and external preparation are required. Module-level disassembly is often relevant for second-life applications and remanufacturing, because modules may be tested and reused independently. Cell-level and material-level treatment are more relevant when detailed sorting, repair, or material recovery is required. However, deeper disassembly generally requires more operations, more time, more safety precautions, and more detailed product information.

Figure 2.2 summarizes the main levels of EV battery disassembly and shows how the depth of disassembly increases from complete pack preservation to material recovery.

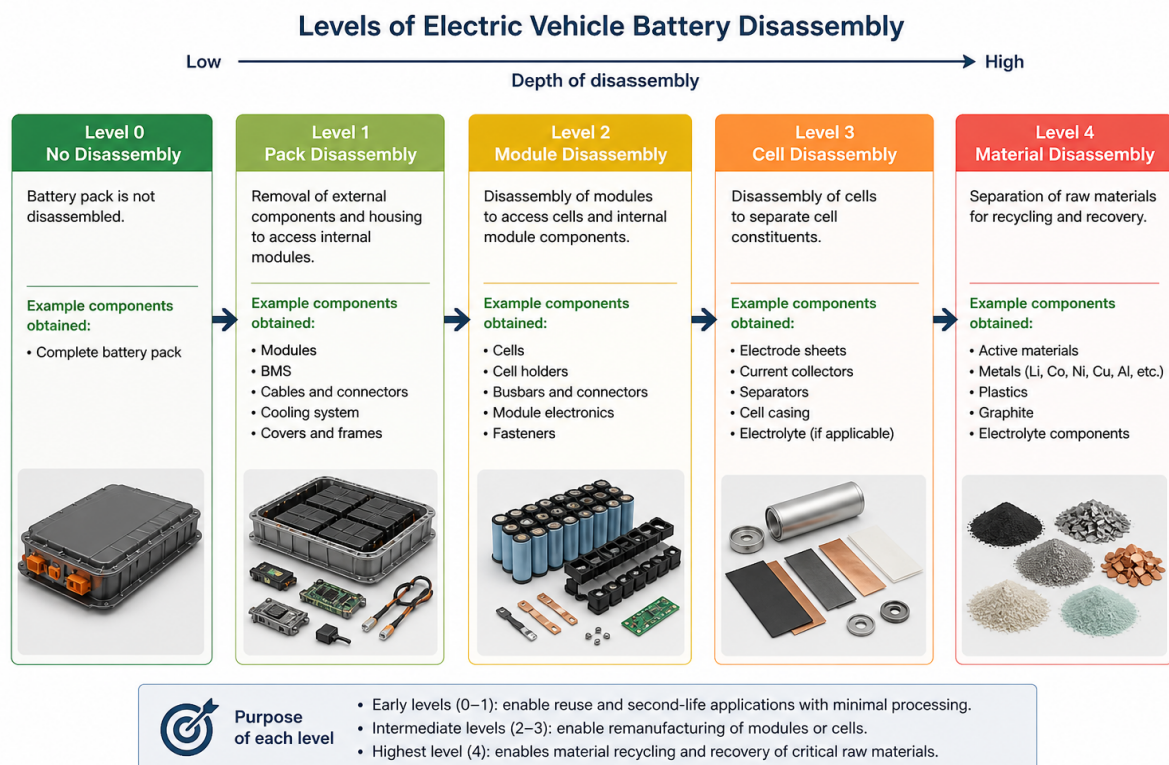


Figure 2.2: Levels of electric vehicle battery disassembly.

As shown in Figure 2.2, lower disassembly levels preserve the battery pack or modules for reuse and second-life applications, while intermediate levels support refurbishment and remanufacturing. Deeper levels, especially cell and material recovery levels, require

more detailed operations and are generally associated with recycling and the recovery of critical raw materials.

Wu et al. [51] studied cell-level disassembly of waste power battery modules in a human-machine hybrid mode. Their work is useful for this thesis because it shows that deeper disassembly levels require structured task representation, precedence constraints, and an allocation of operations between human and machine resources. They also highlight the importance of AND/OR relationships in the disassembly process, which is consistent with the need to represent alternative or conditional predecessors in disassembly planning.

This level-based view is important because a disassembly line may not always need to reach the same depth for all battery types. Some packs may be treated only at pack or module level, while others may require deeper operations. In a multi-type context, this means that each battery type can generate its own set of tasks, durations, safety requirements, and precedence relations.

2.3.3 Typical Disassembly Tasks

Although battery designs differ between manufacturers, several task families are commonly found in end-of-life battery disassembly. The process usually starts with identification and safety preparation. The battery pack must be recognized, inspected, and handled according to its condition. Information such as battery type, voltage level, chemistry, damage state, and available documentation can influence the rest of the process.

After the initial preparation, the pack can be opened. This may involve removing external covers, protection plates, seals, screws, bolts, clips, or adhesive joints. Once the internal structure is accessible, electrical and thermal subsystems must be treated carefully. High-voltage connections, busbars, fuses, contactors, wiring harnesses, sensors, and cooling components may need to be disconnected or removed before modules can be extracted.

The extraction of modules is usually one of the most important steps. Modules can be heavy, fragile, and connected to several other components. Their removal may require lifting devices, specific tools, or robotic assistance. After extraction, modules can be sorted, tested, stored, or transferred to another recovery process. If deeper treatment is required, module-level or cell-level disassembly can continue with operations such as removing module covers, separating cell holders, cutting welds, or detaching cells.

Rettenmeier et al. [43] analyze battery disassembly from a process-oriented perspective and show that disassembly technologies must be adapted to the diversity of traction battery designs. Their work also underlines that battery disassembly is essential for both component reuse and high-quality material recovery. This confirms that disassembly tasks should be represented not only as physical actions, but also as operations that influence the quality and value of downstream recovery.

Table 2.3 presents a simplified generic flow of end-of-life EV battery disassembly. It does not represent a fixed industrial sequence. It is used to show how task families can be organized from initial preparation to component routing.

Table 2.3: Generic flow of end-of-life EV battery disassembly tasks. Author’s elaboration based on [4, 43, 47].

Task family	Purpose	Examples of operations
Identification and condition check	Recognize the battery type and evaluate its visible condition.	Model identification, visual inspection, damage check, documentation review.
Safety preparation	Reduce electrical, thermal, chemical, and mechanical risks before opening.	Isolation, discharge verification, securing the working area, selecting protective tools.
Pack opening	Access internal components protected by the casing and covers.	Removing covers, screws, seals, protection plates, and external barriers.
Electrical and thermal disconnection	Separate internal interfaces before extracting modules.	Disconnecting busbars, cables, connectors, sensors, cooling hoses, or cooling plates.
Module extraction	Remove modules while preserving their integrity when possible.	Releasing fasteners, lifting modules, transferring modules to testing or storage.
Testing, sorting and routing	Direct components toward the appropriate recovery route.	Sorting modules, checking condition, routing to reuse, remanufacturing, or recycling.

For modelling purposes, each task family can be decomposed into elementary tasks. For example, pack opening may include several screw-removal operations, seal cutting, cover lifting, and inspection. Module extraction may include connector removal, busbar disconnection, cooling interface handling, unscrewing, lifting, and transfer. The level of detail depends on the objective of the model and the available data.

In this thesis, the disassembly process is represented by a set of tasks for each battery type. These tasks are subject to precedence relations and must be assigned to stations and execution modes. Some tasks may be performed only by a human operator, some only by a robot, some only through human–robot collaboration, and some may be performed by either a human or a robot. This representation allows the physical reality of battery disassembly to be translated into a structured optimization problem that can support line organization and resource allocation.

2.4 Disassembly Approaches

The disassembly of end-of-life EV batteries can be performed using different approaches depending on the level of automation, the product condition, the available equipment, the expected recovery route, and the safety requirements. In the literature, three main approaches are generally distinguished: manual disassembly, automated or robotised disassembly, and human–robot collaborative disassembly. These approaches should not be viewed as completely independent solutions. In practice, a recovery facility may combine them according to the task type, the battery model, and the available resources.

The choice of a disassembly approach is particularly important for end-of-life batteries because the product is both valuable and hazardous. Some operations require adaptability, observation, and human judgment. Other operations are repetitive, physically demanding, or risky, which makes robotic assistance attractive. A fully automated line may be efficient for standardized products, but end-of-life EV batteries are often heterogeneous and uncertain. This is why human–robot collaboration has become an interesting compromise between the flexibility of manual disassembly and the repeatability of robotic systems.

2.4.1 Manual Disassembly

Manual disassembly is still widely used for end-of-life EV batteries. In this approach, human operators perform most of the operations, including inspection, opening, unscrewing, connector removal, cable handling, module extraction, sorting, and decision-making. The main advantage of manual disassembly is flexibility. A trained operator can adapt to different pack designs, recognize unexpected situations, and modify the procedure when the battery is damaged or when product information is incomplete.

This flexibility is important because end-of-life batteries may arrive in very different states. Some battery packs are simply aged after normal vehicle use, while others may be mechanically damaged, corroded, swollen, partially dismantled, or affected by an accident. In such situations, human perception and judgment remain difficult to replace. Manual disassembly can also be easier to implement in small-scale facilities because it requires lower initial investment than a fully automated system.

However, manual disassembly has major limitations. First, it can expose operators to high-voltage risks, chemical hazards, sharp edges, heavy loads, and possible thermal events. Second, it can be time-consuming and difficult to standardize, especially when several battery models are treated on the same line. Third, repetitive operations such as unscrewing many fasteners, lifting modules, or removing covers may create ergonomic constraints. These limitations reduce productivity and make manual disassembly less suitable for large-scale recovery without assistance or process organization.

From a modelling perspective, manual disassembly corresponds to tasks that are performed by human resources. These tasks may be human-only when they require visual interpretation, flexible handling, or decision-making. They may also be normal tasks when they can be executed either by a human or by another resource. This distinction is important for the problem studied later, where each task is assigned to a station and an execution mode.

2.4.2 Automated and Robotised Disassembly

Automated and robotised disassembly aims to reduce human exposure to hazards and improve repeatability, productivity, and process control. Robots can be useful for operations such as unscrewing, cutting, lifting, holding heavy components, moving modules, or performing repetitive actions. In battery disassembly, robotised systems are attractive because they can support operations in dangerous zones and reduce the physical workload imposed on human operators [47, 28].

Nevertheless, complete automation remains difficult for end-of-life EV batteries. Unlike new products in assembly, end-of-life batteries are not always clean, standardized, or fully documented. Their condition may be uncertain, and their internal structure may vary significantly between manufacturers. A robot may need precise information about

the position of screws, connectors, covers, busbars, and modules. If this information is missing or if the battery is deformed, the task becomes more difficult.

Another challenge is manipulation. Battery components are not always rigid, regular, or easy to grasp. Flexible cables, hoses, thermal pads, sealants, adhesives, clips, and damaged parts can require force control, perception, and adaptation. Robots can perform some of these tasks, but the required sensing, tool changing, and decision-making increase system complexity and cost. For this reason, robotised disassembly is often more feasible for repetitive or well-defined operations than for the complete treatment of all battery types.

Robotised disassembly can therefore be considered as a partial solution rather than a universal replacement for human operators. It is useful when the task is dangerous, repetitive, heavy, or geometrically well defined. Examples include screw removal with a robotic tool, lifting assistance, cutting operations, or repetitive manipulation of modules. However, human supervision or intervention is often still necessary when the battery condition is uncertain or when the process requires interpretation.

2.4.3 Human–Robot Collaborative Disassembly

Human–robot collaborative disassembly combines human flexibility with robotic assistance. In this approach, humans and robots contribute to the same disassembly process, either sequentially or in a shared workspace. The human operator can handle tasks requiring judgment, perception, adaptation, and fine manipulation, while the robot can support tasks that are repetitive, physically demanding, precise, or hazardous. This makes human–robot collaboration particularly relevant for end-of-life EV batteries, where product variability and safety constraints are both significant.

Recent studies show the increasing interest in human–robot collaboration for battery disassembly. Wu et al. [51] proposed a human-machine hybrid mode for cell-level disassembly of waste power battery modules, where harmful and complex parts are assigned to different resources. Chu and Chen [9] developed a human–robot collaboration model for end-of-life power batteries by considering the disassembly sequence, the internal battery procedure, and the assignment strategy between humans and robots. Gao et al. [17] addressed human–robot collaborative disassembly of retired EV batteries using a partially observable multi-agent reinforcement learning approach. These works confirm that HRC is not only a technological option, but also an optimization and planning problem.

In a collaborative disassembly line, the main difficulty is to decide how tasks should be distributed between humans, robots, and collaborative execution. Some operations may be better assigned to humans, for example visual inspection, handling of flexible wiring, interpretation of damage, or adaptation to unexpected pack conditions. Some operations may be better assigned to robots, such as repetitive unscrewing, lifting, holding, or operations in hazardous zones. Other tasks may require simultaneous human–robot collaboration, such as holding a heavy cover while a human disconnects a component, or guiding a part while the robot provides lifting assistance.

This task distribution must respect safety and coordination constraints. A collaborative robot may be designed to work near humans, but the process must still prevent collisions, unsafe contact, tool interference, and uncontrolled movement of battery components. The work area, task timing, resource availability, and safety distances must be organized. Therefore, HRC disassembly is not only a matter of having a robot and a human in the same station. It requires a structured allocation of tasks and a feasible schedule of operations.

The HRC approach is closely related to the problem considered in this thesis. The following chapters distinguish several task categories: human-only tasks, robot-only tasks, collaborative tasks, and normal tasks that can be performed either by a human or by a robot. This classification makes it possible to represent the practical differences between disassembly operations and to decide which execution mode is selected for each task.

2.4.4 Comparison of Disassembly Approaches

The three approaches differ in flexibility, safety, investment, productivity, and suitability for heterogeneous battery types. Table 2.4 summarizes the main characteristics of manual, robotised, and human–robot collaborative disassembly.

Table 2.4: Comparison of disassembly approaches for end-of-life EV batteries. Author’s elaboration based on [47, 51, 9, 17].

Approach	Main advantages	Main limitations	Suitable tasks
Manual disassembly	High flexibility; human perception and judgment; ability to adapt to damaged or unknown batteries.	Safety exposure; ergonomic constraints; low repeatability; difficult standardization for large volumes.	Inspection, cable handling, damage evaluation, delicate manipulation, decision-based operations.
Robotised disassembly	High repeatability; reduced human exposure; useful for heavy, repetitive or hazardous operations.	Requires accurate product information; limited adaptability; high investment; difficult with damaged or variable packs.	Unscrewing, lifting, cutting, holding, repetitive manipulation, standardized operations.
Human–robot collaborative disassembly	Combines human adaptability with robotic assistance; can improve safety, flexibility and workload distribution.	Requires task allocation, coordination, safety management and human–robot interaction design.	Mixed operations involving human judgment and robotic support, such as assisted lifting, guided removal, or shared handling.

The comparison shows that no single approach is sufficient for all end-of-life EV battery disassembly situations. Manual disassembly is flexible but exposes operators to risks and may lack productivity. Robotised disassembly can improve repeatability and safety, but it is difficult to apply to highly variable products without detailed information and advanced perception. Human–robot collaboration appears as a promising intermediate solution because it can distribute tasks according to the strengths of each resource.

2.5 Planning and Scheduling of Battery Disassembly Operations

After identifying the structure of an end-of-life EV battery and the possible disassembly approaches, the next question is how the disassembly process should be organized. In an industrial context, it is not sufficient to know that a battery can be opened or that modules can be removed. The process must be transformed into a set of tasks, ordered according to technical and safety constraints, assigned to workstations, and executed by available resources within a feasible time structure.

This is the role of disassembly planning and scheduling. Disassembly planning mainly concerns the logical organization of tasks: which components must be removed, which operations are required, and which precedence relations must be respected. Scheduling and line balancing focus on the operational organization of these tasks over time and across stations. They determine how tasks are distributed between workstations, operators, robots, and collaborative resources while respecting cycle time, resource availability, and safety constraints.

In the case of end-of-life EV batteries, planning and scheduling are particularly difficult because the product is variable, hazardous, and multi-level. A disassembly line may receive different battery types, each with its own structure, number of tasks, processing times, recovery objective, and precedence graph. This means that the problem is not only a classical disassembly problem, but also a multi-type line organization problem with human–robot resource allocation.

2.5.1 Disassembly Sequence Planning

Disassembly sequence planning consists of determining the order in which disassembly tasks should be performed. In battery disassembly, this order is constrained by physical accessibility, safety requirements, and technological dependencies between components. For example, a module cannot be extracted before the pack is opened and its electrical and mechanical connections are released. Similarly, some high-voltage elements may need to be isolated before other operations can be safely executed.

A useful way to represent these dependencies is through a precedence graph. In such a graph, nodes represent disassembly tasks and arcs represent precedence relations. A precedence relation indicates that one task must be completed before another can start. This representation is widely used in assembly and disassembly line balancing because it makes the logical structure of the product explicit and allows the feasibility of task sequences to be verified.

For end-of-life batteries, precedence relations can be simple or conditional. Some predecessors are mandatory: the task must always be performed before the next one. Other predecessors may be alternative or optional, depending on the disassembly route, the battery condition, or the selected recovery level. This explains why some studies use AND/OR graphs to represent disassembly processes. Guo et al. [22] adopt an AND/OR graph to describe product disassembly in a human–robot collaborative line with stochastic operation times. This type of representation is useful when the disassembly process contains alternative paths or when several recovery options are possible.

In the context of this thesis, precedence relations are important because each battery type may have its own disassembly structure. A pack with bolted modules may require a different sequence from a pack with welded or strongly bonded components. A battery designed with a conventional cell–module–pack architecture may also differ from a more

integrated cell-to-pack design. Therefore, the disassembly sequence should not be considered as universal. It must be defined for each battery type according to its architecture and recovery objective.

Sequence planning also has a direct impact on safety. A technically feasible sequence may still be unacceptable if it exposes operators or robots to high-voltage risks, unstable components, chemical hazards, or heavy parts without proper preparation. As a result, safety constraints should be integrated into the planning logic. The sequence must not only allow components to be accessed, but also ensure that dangerous operations are performed under controlled conditions.

2.5.2 Task Allocation and Resource Constraints

Once the disassembly tasks and precedence relations are defined, the next decision concerns task allocation. Each task must be assigned to a workstation and executed by a suitable resource. In a human–robot collaborative disassembly context, the resource can be a human operator, a robot, or a simultaneous human–robot collaboration. This creates a richer allocation problem than in purely manual or purely robotic disassembly lines.

Task allocation depends first on task feasibility. Some operations may be human-only because they require visual interpretation, delicate manipulation, or adaptation to unexpected product conditions. Some operations may be robot-only because they are hazardous, repetitive, or require stable tool motion. Other operations may require collaboration, for example when a robot holds or lifts a heavy component while the human performs a precise disconnection or inspection. Finally, some tasks may be flexible and can be assigned either to a human or to a robot, depending on cost, time, workload, or resource availability.

This classification is directly related to the modelling perspective adopted in this work. Disassembly tasks may be divided into human-only tasks, robot-only tasks, collaborative tasks, and normal tasks executable by either a human or a robot. This classification allows a formulation to represent practical limitations of resources while still keeping flexibility in the allocation decision.

Resource constraints are also essential. A station can only perform a task if the required resource is available there. A human-only task requires a human operator at the station. A robot-only task requires a robot. A collaborative task requires both resources at the same station and during the same time interval. This condition is important because collaborative tasks are not simply tasks that can be performed by either resource; they require synchronized execution.

Line balancing introduces another constraint. The workload assigned to each station must remain compatible with the cycle time. If one station receives too many long tasks, it becomes a bottleneck and slows down the entire line. If other stations receive too little work, resources remain idle. Therefore, the allocation of tasks must balance the load between stations while respecting precedence and resource constraints.

2.5.3 Multi-Type Battery Disassembly Lines

In real recovery systems, a disassembly line may not process a single standardized battery pack. It may have to treat several types of end-of-life EV batteries. Each battery type can have its own task list, processing times, precedence relations, module layout, safety requirements, and recovery target. This creates a multi-type disassembly line problem.

The multi-type aspect has several consequences. First, workload balancing becomes more difficult because the time required at each station may change from one battery type to another. A station that is well balanced for one battery type may become overloaded for another. Second, the resource requirements may change. A task performed by a robot for one battery type may require human intervention for another because of accessibility, damage, or design differences. Third, the order of tasks may not be identical across products, which means that the line must be flexible enough to handle different precedence structures.

This situation is close to the multiple-product disassembly line balancing problems studied in recent literature. Qin et al. [42] address a multiple product hybrid disassembly line balancing problem with human–robot collaboration. Their work is relevant because it considers several products and human–robot task execution in the same general line balancing framework. Ehm [11] also considers scheduling and process planning with flexible disassembly modes and recovery levels for multiple product types, showing that product-dependent disassembly sequences and recovery decisions increase the complexity of the problem.

In the present thesis, the multi-type context is represented by considering several battery types, each one associated with a set of disassembly tasks. The product mix can be described by proportions that indicate how frequently each battery type appears in the system. This is important because the line should not be optimized only for one battery type, but for the expected mix of end-of-life batteries. As a result, station workloads, resource allocation, and cost evaluation must consider all battery types together.

The line organization problem can therefore be summarized as follows: given several battery types, their tasks, their precedence relations, their processing times in different execution modes, and the available human and robotic resources, determine how tasks should be assigned to stations and execution modes while respecting cycle time, precedence, resource availability, and non-overlap constraints. This description provides the conceptual basis for the modelling choices developed in the next chapter.

2.5.4 From Scheduling to Line Balancing

Disassembly scheduling and disassembly line balancing are closely related but not identical. Scheduling focuses on the timing of tasks: when each task starts and finishes, and how tasks are ordered on shared resources. Line balancing focuses on the distribution of tasks across stations so that workload is controlled and the line can operate efficiently. In a human–robot collaborative line, both aspects must be considered together.

The cycle time is a central parameter in line balancing. It represents the maximum workload that can be assigned to a station during one production cycle. If the total duration of tasks assigned to a station exceeds the cycle time, the station becomes infeasible. If the cycle time is too large, the line may use fewer stations but with lower utilization. If it is too small, more stations or more resources may be required. Therefore, the cycle time directly influences the number of opened stations, the distribution of tasks, and the cost of the line.

In addition to station workload, scheduling must prevent resource conflicts. If two tasks are assigned to the same station and use the same human operator, they cannot be executed at the same time. The same logic applies to tasks using the same robot. A collaborative task uses both human and robot resources simultaneously, which makes synchronization necessary. These constraints are especially important when start and finish times are considered for disassembly tasks.

Table 2.5 summarizes the main decisions and constraints involved in planning, scheduling, and line balancing for end-of-life EV battery disassembly.

Table 2.5: Main planning, scheduling and line balancing elements for end-of-life EV battery disassembly.

Element	Main decision or role	Relevance for this thesis
Task definition	Decompose each battery type into elementary disassembly tasks.	Defines the operations that must be assigned to stations and resources.
Precedence relations	Specify which tasks must be completed before others can start.	Ensures technical feasibility, accessibility and safety of the sequence.
Station assignment	Decide at which station each task is performed.	Determines the physical organization of the disassembly line.
Execution mode	Select human, robot or collaborative execution when feasible.	Represents the human–robot collaboration structure of the line.
Cycle time	Limit the workload assigned to each opened station.	Provides the line balancing constraint and prevents station overload.
Resource scheduling	Prevent overlapping tasks on the same human or robotic resource.	Ensures temporal feasibility of the obtained task allocation.

The planning and scheduling concepts introduced in this section provide the basis for understanding the considered problem. The next section uses these elements to clarify the main challenges of multi-type battery disassembly with human–robot collaboration and to justify the need for structured modelling approaches.

2.6 Challenges of Multi-Type Human–Robot Battery Disassembly

The previous sections showed that end-of-life EV battery disassembly involves product structure, task precedence, safety constraints, and resource allocation. When the process concerns only one battery model, these elements can already be difficult to manage. The difficulty increases significantly when several battery types must be treated on the same line and when human and robotic resources are used together. In this context, the disassembly system must remain flexible enough to adapt to product variability, while being organized enough to maintain safety, productivity, and cost control.

The first challenge is product heterogeneity. End-of-life battery packs differ in chemistry, cell format, module layout, casing design, joining methods, cooling architecture, and internal accessibility. These differences affect the number of tasks, the task durations, the required tools, and the order in which operations can be performed. A disassembly sequence that is suitable for one battery type may not be feasible for another. This makes

multi-type battery disassembly more complex than a single-product disassembly process [43, 47].

The second challenge is the uncertainty associated with end-of-life condition. A battery pack may be normally aged, partially damaged, corroded, deformed, or affected by previous thermal, electrical, or mechanical stress. Even when two batteries belong to the same model, their condition may differ because they have not followed the same usage history. This uncertainty can influence safety checks, access operations, handling time, and the decision to continue or stop disassembly at a given level. As a result, disassembly systems must be able to respond to variability not only between product types, but also between individual batteries of the same type.

The third challenge concerns safety. End-of-life batteries may still contain residual energy and may expose workers and equipment to high-voltage risks, short circuits, chemical leakage, fire, thermal runaway, or mechanical hazards. Safety constraints can modify the order of tasks, impose waiting or inspection steps, restrict access to certain areas, and require specific resources or tools. For this reason, safety is not an external condition added after planning. It is part of the disassembly organization itself [28, 33].

Another important challenge is the variability of processing times. Some tasks have relatively stable durations, such as removing standardized screws when their positions are known. Other tasks are more uncertain, especially when they depend on human judgment, battery condition, accessibility, operator skill, fatigue, or unexpected damage. This point is particularly important in human-involved disassembly. Human execution times are not always deterministic, and their variability may affect station workload, resource availability, and line balance. Recent works on human–robot collaborative disassembly consider this issue by introducing stochastic operation times or adaptive decision-making approaches [22, 17].

Human–robot collaboration adds another level of complexity. The objective is not simply to replace humans by robots, but to distribute tasks according to the strengths and limitations of each resource. Humans are valuable for perception, interpretation, adaptation, and delicate handling. Robots are useful for repetitive, heavy, precise, or hazardous tasks. Collaborative tasks may require both resources at the same time, which creates synchronization requirements. Therefore, a human–robot disassembly line must manage compatibility between tasks and resources, avoid resource conflicts, and ensure safe interaction in shared workspaces [9, 51].

The final challenge is line organization. In a multi-type disassembly line, the system must assign tasks to stations, balance workloads, and coordinate resources while respecting precedence relations and safety requirements. If a station receives too much work, it becomes a bottleneck. If human or robotic resources are not well distributed, some resources may remain idle while others are overloaded. If collaborative tasks are not correctly synchronized, the process may suffer from delays or unsafe interactions. These issues show that battery disassembly is not only a technical dismantling problem, but also an industrial organization and optimization problem.

Table 2.6 summarizes the main challenges of multi-type human–robot battery disassembly and their operational implications.

Table 2.6: Main challenges in multi-type human–robot EV battery disassembly.

Challenge	Description	Operational implication
Product heterogeneity	Battery packs differ in chemistry, geometry, architecture, fastening methods and cooling systems.	Each battery type may require different tasks, tools, durations and precedence relations.
End-of-life condition	Batteries may be aged, damaged, corroded, deformed or affected by unknown usage histories.	The process must remain flexible and may require inspection, adaptation or route changes.
Safety constraints	High voltage, residual energy, chemical leakage, thermal events and mechanical hazards may occur.	Task order, resource assignment and handling procedures must respect safety requirements.
Processing time variability	Task durations may vary because of battery condition, operator behavior, accessibility and uncertainty.	Workload balance and scheduling may be affected, especially when human operations are involved.
Human–robot coordination	Some tasks are human-only, robot-only, flexible or collaborative.	The line must manage resource compatibility, synchronization and safe interaction.
Line balancing	Tasks must be distributed across stations while avoiding overload and idle time.	A structured organization is needed to maintain productivity and feasible station workloads.

These challenges explain why a structured approach is needed for the organization of end-of-life EV battery disassembly. The problem must consider the diversity of battery types, the constraints imposed by product architecture, the availability and suitability of human and robotic resources, and the variability of operation times. This broader view is important because different modelling assumptions may be considered depending on the objective of the study, for example deterministic processing times, stochastic human execution times, or adaptive decision-making under uncertainty. The next chapter will build on these concepts to formulate the considered problem and present the proposed modelling and resolution approach.

2.7 Conclusion

This chapter presented the main technical and organizational concepts related to the disassembly of end-of-life electric vehicle batteries. It first showed that an EV battery pack is a complex multi-level system composed of cells, modules, electrical connections, thermal management components, mechanical protection elements, sensors, and control units. This structure is important because the way components are assembled directly influences the accessibility, safety, and feasibility of disassembly operations.

The chapter also highlighted the variability of end-of-life battery packs. Battery types may differ in chemistry, cell format, pack architecture, joining methods, cooling systems, and level of structural integration. In addition, batteries reaching the end-of-life stage may have different degradation histories and physical conditions. Some packs may

be normally aged, while others may be damaged, corroded, deformed, or affected by uncertain operating conditions. This variability makes it difficult to design a single fixed disassembly procedure that can be applied efficiently to all battery types.

Battery disassembly was then introduced as a controlled process that aims to access, separate, and prepare components for the appropriate recovery route. The chapter distinguished several disassembly levels, from pack-level opening to module extraction and, when necessary, cell-level treatment. It also presented typical disassembly task families such as identification, safety preparation, pack opening, electrical disconnection, cooling interface handling, module extraction, testing, sorting, and routing toward reuse, remanufacturing, or recycling.

Different disassembly approaches were discussed. Manual disassembly offers flexibility and adaptability, especially when product information is incomplete or when the battery condition is uncertain. However, it exposes operators to safety risks and ergonomic constraints. Robotised disassembly can improve repeatability, reduce human exposure, and assist with heavy or repetitive operations, but it remains difficult to apply to highly variable and damaged products. Human–robot collaborative disassembly appears as a promising intermediate solution, because it combines human judgment and adaptability with robotic precision, assistance, and repeatability.

The chapter also introduced planning, scheduling, and line balancing concepts. Disassembly tasks must be organized according to precedence relations, safety constraints, station capacities, resource availability, and execution modes. In a multi-type context, each battery type may have its own task set, processing times, and precedence structure. This creates a complex organization problem, especially when human and robotic resources must be coordinated on the same line.

Finally, the chapter identified the main challenges of multi-type human–robot EV battery disassembly: product heterogeneity, uncertain end-of-life conditions, safety requirements, processing time variability, human–robot coordination, and workload balancing. These challenges show that battery disassembly is not only a technical dismantling process, but also an industrial organization problem. The following chapter will build on these concepts by reviewing the existing literature on disassembly planning, EV battery disassembly, human–robot collaboration, uncertainty, and multi-product disassembly lines. This review will make it possible to identify the main research gaps and to position the present work within the existing scientific literature.

LITERATURE REVIEW

3.1 Introduction

The previous chapters introduced the general context of circular economy and the role of disassembly in the end-of-life management of electric vehicle batteries. They showed that disassembly is not only a technical operation, but also a strategic activity that enables reuse, remanufacturing, repurposing and recycling. However, in the case of electric vehicle batteries, this operation remains difficult to organize because of the high variability of battery architectures, the presence of hazardous components, the lack of standardization, and the uncertainty related to the real condition of end-of-life products.

For this reason, the scientific literature has increasingly focused on the development of decision-support models for disassembly planning. These models aim to determine how a product should be disassembled, in which order the operations should be performed, which resources should be used, and how the workload should be distributed among workstations. In the broader field of remanufacturing and recycling, disassembly has been studied through several related problems, such as disassembly scheduling, selective disassembly planning, disassembly sequence planning, and disassembly line balancing. These problems generally involve precedence constraints, resource capacity constraints, task assignment decisions, and performance criteria related to time, cost, profit, energy or risk.

In the specific case of electric vehicle batteries, the problem becomes even more complex. Battery packs and modules contain electrical, mechanical and thermal components that must be removed in a safe and structured way. Some operations are dangerous because of high voltage or thermal risks, while others require flexibility and human judgment due to product degradation or design heterogeneity. Villagrossi and Dinon [47] showed that robotic systems can support battery pack disassembly, but that product variability still limits full automation. Rettenmeier et al. [43] analyzed disassembly technologies as a key element of the circular battery value chain. Kaarlela et al. [28] reviewed robotised battery disassembly and emphasized the need for flexible tooling and product information. Li et al. [33] also highlighted the role of artificial intelligence and human-robot collaboration in future end-of-life battery disassembly systems.

This chapter presents a review of the main research contributions related to disassembly planning and line balancing, with a progressive focus on end-of-life electric vehicle batteries. The review first discusses general disassembly and remanufacturing scheduling problems, then examines the specific challenges of battery disassembly. After that, it analyzes works on disassembly sequence planning, disassembly line balancing, human-robot collaboration, uncertainty modeling, and multi-product disassembly lines. Particular attention is given to studies that are close to the present research, especially those dealing with human and robotic resources, stochastic operation times, and several product types.

The purpose of this state of the art is not only to summarize existing approaches, but also to identify the remaining research gaps. The literature shows that many contributions address battery disassembly through sequence optimization, line balancing, or human-robot task allocation. Nevertheless, most works remain focused on a single battery type

and deterministic data. Moreover, although uncertainty, multi-product disassembly and human–robot collaboration have been studied separately, their simultaneous integration remains limited. This observation motivates the present research, which first develops a deterministic mono-objective optimization model for a multi-product human–robot collaborative disassembly line. Then, in order to better reflect the variability of real end-of-life battery disassembly operations, the deterministic formulation is extended into a stochastic scenario-based model, where uncertainty is introduced through human operation times.

3.2 General Disassembly and Remanufacturing Scheduling Problems

Before focusing on electric vehicle batteries, it is necessary to place the disassembly problem within the broader context of remanufacturing and end-of-life product recovery. In closed-loop supply chains, disassembly is generally the first operational step that makes it possible to recover components, materials, or subassemblies. Unlike classical manufacturing or assembly, where the product structure is usually known and controlled, disassembly deals with returned products whose condition may vary from one unit to another. This makes the planning problem more difficult, especially when only some parts have to be recovered or when several recovery options are possible.

In the literature, disassembly has been studied from different decision-making perspectives. Some works focus on disassembly sequence planning, where the main question is to determine the order in which components should be removed. Other works consider disassembly scheduling, where operations must be assigned to machines or workstations over time. A third stream addresses disassembly line balancing, where tasks are distributed among stations while respecting precedence relations and cycle time constraints. These problems share a common structure: they involve a product precedence graph, a set of tasks or operations, limited resources, and one or several performance criteria.

3.2.1 Disassembly as a Scheduling and Process Planning Problem

In remanufacturing systems, disassembly is rarely treated as an isolated operation. It is often integrated with downstream processes such as cleaning, inspection, reprocessing, and reassembly. For this reason, several authors have formulated integrated planning and scheduling models for remanufacturing systems. In these models, the system usually includes a disassembly stage, a reprocessing stage, and a reassembly stage. The main decisions concern the selection of process routes, the assignment of operations to machines, and the sequencing of products or components.

Early contributions already showed that end-of-life recovery processes can be modeled as scheduling problems. Cheng et al. proposed a scheduling model for refurbishing processes in recycling management, showing that the sequencing of returned products and the weighting of completion times can influence the performance of recovery operations [8]. Although this work does not focus on batteries, it is useful because it introduces the idea that disassembly and refurbishment are not only technical processes, but also scheduling problems that require optimization.

More recent works integrate process planning and scheduling decisions in remanufacturing environments. Zhang et al. [57] studied an integrated process planning and scheduling problem in a flexible job-shop-type remanufacturing system composed of disassembly, reprocessing and reassembly workshops. In this type of system, the model

must determine the assignment and sequence of products in disassembly and reassembly stages, while also selecting processing routes and machines for the reprocessing stage. Zhang et al. [58] extended this logic by considering energy-oriented integrated process planning and scheduling. Another work by Zhang et al. [59] addressed a flexible job-shop-type remanufacturing system where total energy consumption and total completion time are considered.

These studies show that the disassembly stage cannot be completely separated from the rest of the remanufacturing system when the objective is to organize the whole recovery process. However, they mainly focus on general remanufacturing systems and do not always consider the specific constraints of battery disassembly, such as electrical hazards, thermal risks, and the need for human–robot cooperation.

3.2.2 Selective, Partial, and Multi-Product Disassembly

Another important research direction concerns selective and partial disassembly. In many end-of-life products, it is not always economically or technically necessary to remove all components. Instead, the decision-maker may target only valuable, reusable, hazardous, or legally required parts. This leads to selective disassembly planning, where the model must decide which operations are necessary and which can be avoided.

Ehm considered a selective disassembly planning and scheduling problem for multiple products in a job-shop environment. The proposed problem integrates the selection of disassembly operations, the choice between destructive and non-destructive modes, and the scheduling of operations on machines. The model aims to minimize the makespan and environmental impact, while respecting precedence relations, machine capacities, recovery requirements and restrictions related to destructive operations [11]. This work is important because it shows that multi-product disassembly can be formulated in a unified scheduling framework, even when different products have different structures and recovery requirements.

Partial disassembly has also been studied in robotic or automated line configurations. In this case, only demanded parts and hazardous parts may be imposed as mandatory, while other components can be left inside the product if their recovery value is not sufficient. This idea is particularly relevant for industrial recovery systems, because complete disassembly may increase the processing time and cost without necessarily improving the economic result. Therefore, partial disassembly introduces a trade-off between recovery value and operational effort.

For the present research, this literature is useful for two reasons. First, it shows that disassembly planning can be formulated as a structured optimization problem with task selection, precedence constraints and resource assignment. Second, it confirms that the multi-product dimension is important in realistic end-of-life systems. Nevertheless, most multi-product studies remain general and are not specifically designed for electric vehicle batteries or for human–robot collaborative stations.

3.2.3 Exact, Heuristic and Learning-Based Solution Approaches

The problems described above are generally combinatorial and difficult to solve for large instances. Exact methods such as mixed-integer linear programming are useful because they provide a clear mathematical description of the problem and can obtain optimal solutions for small or medium instances. However, when the number of tasks, products, routes or resources increases, exact methods often become computationally expensive.

For this reason, many authors propose heuristic or metaheuristic methods. Zhang et al. [57] used an improved artificial bee colony algorithm for integrated remanufacturing process planning and scheduling. Zhang et al. [58] relied on an improved spider monkey optimization approach for an energy-aware formulation. Zhang et al. [59] proposed an improved grey wolf optimization method for flexible job-shop remanufacturing scheduling. Tian et al. [46] considered an energy-efficient remanufacturing scheduling problem with a lot-streaming production mode. These methods do not always guarantee optimality, but they are able to provide good-quality solutions within acceptable computational time.

Uncertainty and dynamic decision-making have also been progressively introduced in remanufacturing scheduling. Fu et al. studied a stochastic integrated disassembly–reprocessing–reassembly scheduling problem where processing times are modeled through probability distributions [16]. Yuan et al. considered fuzzy processing times in capacitated disassembly scheduling, which is useful when exact probability distributions are not available [55]. Han et al. proposed a deep reinforcement learning approach for dynamic disassembly scheduling, showing that learning-based methods can support decisions when product quantities, buffers or system states evolve over time [23].

These contributions confirm that heuristic, metaheuristic and learning-based approaches are well suited for complex disassembly and remanufacturing problems. This observation is directly related to the methodology adopted in the present work. The deterministic mathematical model provides a rigorous formulation of the multi-product human–robot collaborative disassembly line. However, because the problem combines task assignment, station opening, mode selection, precedence relations, and resource constraints, it is expected to become difficult to solve exactly when the number of products and tasks increases. Therefore, the development of a metaheuristic solution method can be considered as a relevant future extension for addressing larger instances.

3.3 Electric Vehicle Battery Disassembly: Specific Challenges and Research Trends

After introducing disassembly as a general decision-making problem in remanufacturing systems, it is important to focus on the particular case of electric vehicle batteries. The disassembly of end-of-life electric vehicle batteries cannot be considered as a classical product disassembly problem. Battery packs are complex electrochemical systems that include cells, modules, busbars, cooling systems, electronic control units, safety devices, covers, connectors and several types of mechanical fasteners. Their structure depends strongly on the manufacturer, the vehicle model and the battery generation. Therefore, the disassembly process must deal with a high level of product heterogeneity.

In addition to structural complexity, electric vehicle batteries raise important safety issues. Even at the end of their first life, they may still contain residual energy and present electrical, thermal and chemical risks. Operations such as removing high-voltage connectors, separating modules, handling damaged cells or accessing internal components must be performed carefully in order to avoid short circuits, thermal runaway or operator exposure to hazardous materials. Harper et al. emphasized that the recycling of lithium-ion batteries from electric vehicles requires careful upstream handling and disassembly before material recovery, because the design and composition of battery packs have a direct impact on the safety and efficiency of recycling routes [24]. Similarly, Mossali et al. highlighted that battery recycling opportunities depend not only on downstream met-

allurgical processes, but also on the ability to prepare and separate battery components efficiently before recycling [37].

3.3.1 Specificity of End-of-Life EV Battery Disassembly

The specificity of electric vehicle battery disassembly is mainly related to three aspects: product architecture, safety constraints, and end-of-life uncertainty. First, battery packs are not standardized. Different manufacturers use different cell formats, module arrangements, cooling systems, enclosure designs, connection technologies and fastening methods. Kampker et al. proposed a framework for classifying battery system architectures, showing that battery packs can vary considerably in their structural organization and integration level [29]. Belingardi and Scattina also discussed the integration of battery packs into the vehicle structure, which confirms that battery accessibility and disassembly depend on architectural and design choices made at the vehicle level [5].

Second, battery disassembly includes hazardous tasks that cannot be assigned only according to processing time or cost. Some operations require specific safety procedures and may be more suitable for robotic execution, while others require human flexibility and judgment. For example, removing high-voltage components, handling damaged modules, or operating near potentially unstable cells may expose workers to serious risks. This explains why recent studies increasingly consider the allocation of hazardous tasks to robots and complex tasks to humans, instead of relying only on manual disassembly.

Third, end-of-life batteries are not always received in the same condition. Their state may depend on their usage history, state of health, accident history, level of degradation, corrosion, deformation or previous maintenance operations. Consequently, the time needed to perform the same disassembly task may vary from one battery to another. This point is particularly important for the present work, since a deterministic model with fixed operation times can be useful as a first modeling step, but it does not fully represent the variability of real disassembly operations.

3.3.2 Manual, Automated, and Human–Robot Assisted Disassembly

Current industrial battery disassembly is still largely manual. Manual disassembly remains attractive because humans are flexible and able to adapt to product variability, unexpected defects and incomplete product information. However, manual operations expose workers to ergonomic and safety risks, especially when handling heavy modules, sharp components, damaged batteries or high-voltage elements. Moreover, manual disassembly can be time-consuming and difficult to standardize.

For these reasons, several authors have investigated automated and robotised disassembly solutions. Villagrossi and Dinon studied the use of robotics for electric vehicle battery pack disassembly in the context of sustainable remanufacturing. They showed that robotic systems can support operations that are repetitive, physically demanding or dangerous, but also underlined that full automation remains difficult because of product variability, uncertainty and the complexity of battery structures [47]. Kaarlela et al. also reviewed robotised disassembly of electric vehicle batteries and concluded that automation requires flexible perception, adaptable tooling, safe manipulation strategies and better product information [28].

Between fully manual and fully automated disassembly, human–robot collaboration appears as an intermediate and promising solution. In such systems, humans and robots do not replace each other completely. Instead, each resource is used according to its

strengths. Human operators can handle tasks requiring perception, reasoning and adaptation, while robots can perform dangerous, repetitive, heavy or highly controlled operations. Rettenmeier et al. described disassembly technologies for end-of-life automotive battery packs as a key element of the circular battery value chain, and emphasized that future disassembly systems must combine safety, flexibility and process efficiency [43]. This supports the idea that collaborative or hybrid configurations may be more realistic than fully automated systems in the short and medium term.

3.3.3 Main Research Directions in EV Battery Disassembly

The literature on electric vehicle battery disassembly can be organized around several research directions. A first group of studies focuses on the physical and technological aspects of disassembly. These works analyze battery structures, disassembly procedures, tools, fasteners, accessibility and safety requirements. Wu et al. [49] reviewed lithium-ion battery disassembly for recycling and emphasized the importance of safe and efficient upstream dismantling. Rettenmeier et al. [43] analyzed battery pack disassembly technologies from a process-oriented perspective. Kaarlela et al. [28] focused on robotised disassembly and the requirements for flexible automation. Neri et al. [38] also reviewed sustainable management of EV battery remanufacturing, showing that disassembly, diagnostics and recovery-route selection are closely connected.

A second group focuses on disassembly planning and optimization. These studies formulate the disassembly process as a sequence planning, scheduling or line balancing problem. The objective is to determine a feasible and efficient organization of tasks while respecting precedence relations. For instance, Baazouzi et al. optimized disassembly strategies for electric vehicle batteries by considering not only the sequence of component removal, but also the depth of disassembly and the circular economy strategy associated with each component [4]. This type of work shows that the best disassembly strategy does not only depend on technical feasibility, but also on economic value and recovery decisions.

A third group of studies investigates artificial intelligence and data-driven methods for battery disassembly. Ai et al. [1] reviewed the use of artificial intelligence in electric vehicle battery disassembly. Li et al. [33] reviewed AI-driven end-of-life electric vehicle battery disassembly and discussed applications such as state-of-health assessment, sequence planning, robotic perception, decision-making and human–robot collaboration. These approaches are promising because they can help deal with product heterogeneity and uncertain end-of-life conditions. However, they also require reliable data, detailed product information and robust models that can generalize across different battery designs.

Finally, a more recent stream of research focuses on human–robot collaborative disassembly line balancing. In this direction, the problem is no longer limited to finding a disassembly sequence. It also includes the assignment of tasks to humans, robots or collaborative modes, the opening or use of workstations, and the satisfaction of cycle time and precedence constraints. This evolution is directly related to the present research, where the disassembly of several types of batteries is modeled in a human–robot collaborative line. The deterministic version of the model provides a first structured representation of the system, while the stochastic extension is introduced later to account for the variability of human operation times.

3.4 Disassembly Sequence Planning for EV Batteries

Disassembly sequence planning is one of the most studied problems in the field of end-of-life electric vehicle battery recovery. Its purpose is to determine a feasible and efficient order for removing components while respecting technological and physical precedence constraints. In the case of battery packs and modules, this problem is particularly important because a wrong sequence may increase the disassembly time, reduce the value of recovered components, create unnecessary tool changes, or even increase safety risks. Therefore, before dealing with line balancing or resource allocation, many studies first focus on the construction of a valid and optimized disassembly sequence.

The disassembly sequence planning problem is generally modeled using graphs or matrices. Components or operations are represented as nodes, while precedence relations, contact relations or accessibility constraints are represented as arcs or matrix values. Once this representation is built, the optimization method searches for one or several feasible sequences according to a given objective. Depending on the study, the objective may be to reduce disassembly time, maximize recovery profit, reduce tool changes, minimize energy consumption, or remove hazardous parts as early as possible.

3.4.1 Sequence, Depth, and Circular Strategy Optimization

A relevant contribution in this direction was proposed by Baazouzi et al., who studied the optimization of disassembly strategies for electric vehicle batteries. Their work is different from classical sequence planning because it does not only determine the order of disassembly operations. It also integrates the depth of disassembly and the circular economy strategy associated with each component. In other words, the model decides whether the battery should be fully disassembled or whether the process should stop at a certain level, and it also determines whether each recovered component should be reused, remanufactured, repurposed or recycled [4].

This contribution is important because complete disassembly is not always the best option. In some cases, continuing the disassembly process may require more time and cost than the value recovered from the additional components. The optimal strategy therefore depends on the condition of the battery and the economic value of its components. This is particularly relevant for end-of-life batteries, where the state of modules, covers, cooling systems or electronic parts may vary significantly from one unit to another.

Techno-economic and environmental disassembly planning also follows this logic. Alfaro-Algaba and Ramirez studied the disassembly planning of lithium-ion electric vehicle battery packs for remanufacturing by considering both profitability and environmental impact [3]. This type of contribution shows that the decision to continue or stop disassembly should be linked to the value of recovered components, the cost of operations, and environmental consequences. However, these approaches generally remain focused on planning or strategy selection rather than on the detailed balancing of a multi-product collaborative line.

3.4.2 Graph-Based and Matrix-Based Precedence Representation

Most disassembly sequence planning studies rely on a structured representation of the product. This representation is necessary because battery components cannot be removed in any arbitrary order. For example, covers, screws, busbars, sensors or cooling elements

may block access to internal modules. As a result, precedence constraints are required to describe which operations must be performed before others.

Ke et al. proposed a disassembly sequence planning method for electric vehicle batteries based on a frame-subgroup structure combined with a genetic algorithm. The authors first construct an improved disassembly relation hybrid graph and a disassembly relation matrix to represent both precedence and connection relationships between components. Then, they identify a particular structure called frame-subgroup, where several components are connected to a central frame but are relatively independent from each other. This structure makes it possible to reduce the search space, since several components can be permuted without violating the disassembly logic [30].

The main advantage of this approach is that it simplifies the optimization process. By using Cantor expansion, the authors transform the permutation-based sequence problem into a positive integer representation. This allows the genetic algorithm to manipulate solutions more easily, with simpler encoding and decoding procedures [30]. However, the effectiveness of this method depends on the presence of a frame-subgroup structure in the product. Therefore, it is particularly useful for certain battery architectures, but it may be less general when the product structure does not contain this type of organization.

Other works also use graph-based representations to handle precedence, accessibility and tool-related constraints. Zhan et al. developed an environment-oriented disassembly planning approach for end-of-life vehicle batteries based on a hybrid graph and an improved Northern Goshawk Optimization algorithm [56]. Meng et al. proposed a priority-constraint-graph-based method for lithium battery pack disassembly sequence optimization, considering criteria such as turns, tool changes and sequence rationality [36]. These studies confirm that graph and matrix representations remain central in battery disassembly planning.

Graph-based and matrix-based representations are also useful because they provide a direct link between the physical structure of the battery and the mathematical optimization model. This idea is important for the present research, since the proposed model also relies on precedence information to guarantee feasible task assignment and sequencing. However, unlike pure sequence planning studies, the present work does not stop at finding an order of component removal. It also considers stations, human and robotic resources, execution modes, and line capacity constraints.

3.4.3 Risk-Aware and Environment-Oriented Sequence Planning

Because battery disassembly involves high-voltage components and potentially hazardous materials, several authors have introduced risk and environmental criteria into sequence planning. Zhan et al. minimized the hazard index and energy consumption for end-of-life vehicle batteries, showing that the best sequence is not necessarily the fastest one, but the one that better balances safety and energy performance [56]. Yang et al. proposed an integrated risk-aware smart disassembly planning approach for scrap electric vehicle batteries, considering recovery profit, energy consumption and risk in the same planning framework [53].

These contributions are important because they show that battery disassembly cannot be evaluated only by feasibility or processing time. A sequence that removes risky components early may be preferable even if it is not the shortest sequence. Similarly, reducing tool changes or unnecessary manipulations can improve operational safety and reduce energy use. Nevertheless, these works generally remain focused on sequence planning for one battery type, while the present research focuses on line balancing and

resource allocation for several battery types.

3.4.4 Knowledge-Based and AI-Based Sequence Planning

More recent studies have started to use artificial intelligence and knowledge-based representations to improve disassembly sequence planning. This evolution is motivated by the fact that battery disassembly involves heterogeneous information: components, tools, connection types, risks, operation times, accessibility relations and possible recovery options. Classical precedence matrices can represent the order constraints, but they may not capture all the semantic relations between battery elements.

Yin et al. proposed a sequential disassembly planning approach based on knowledge graph and graph isomorphism network for supporting power battery remanufacturing. Their framework combines TransH knowledge graph embedding, Graph Isomorphism Network and MOEA/D to learn complex relations between battery components, tools and disassembly operations [54]. The use of a knowledge graph allows the model to represent richer information than a simple precedence matrix, while the graph neural network helps to learn structural dependencies in the disassembly process.

This type of approach is promising because it can support more adaptive and information-rich disassembly planning. It may be especially useful when the same system must deal with different battery structures or when product information needs to be updated. However, such methods often require detailed data and a more complex computational framework. For this reason, they are still difficult to apply directly in a simple mathematical model intended to define a first optimization framework.

3.4.5 Limits of Sequence Planning Approaches

Although disassembly sequence planning is an essential research direction, it does not cover the whole decision problem faced in a disassembly line. A sequence gives the order in which operations should be performed, but it does not necessarily specify how tasks are assigned to stations, whether a task is performed by a human, a robot or both, or how the workload is balanced across the line. In other words, sequence planning is necessary, but not sufficient when the objective is to design or operate a complete disassembly line.

Another limitation is that many sequence planning studies focus on a single battery type. The case study usually concerns one specific battery pack or module, such as an Audi, Tesla, Volkswagen or another battery architecture. This allows a detailed analysis of the product, but it does not fully represent the situation of industrial treatment centers, where several battery types may arrive and need to be processed using the same resources.

A further limitation concerns the deterministic nature of many models. Operation times, costs, energy consumption and risks are often assumed to be known in advance. This assumption simplifies the optimization problem, but it does not fully reflect end-of-life battery disassembly, where the same operation may take different times depending on the condition of the battery, the accessibility of fasteners, corrosion, deformation or operator performance. This is one of the reasons why the present research first develops a deterministic model as a structured baseline, and then extends it into a stochastic version where uncertainty is introduced through human operation times.

3.5 Disassembly Line Balancing for EV Batteries

Disassembly sequence planning provides the order in which the components of a product should be removed. However, when the objective is to organize an industrial disassembly system, the sequence alone is not sufficient. The decision-maker must also determine how the tasks are distributed among workstations, which resources are assigned to each workstation, and how the workload is balanced along the line. This leads to the disassembly line balancing problem, which is a natural extension of classical assembly line balancing to end-of-life products.

In a disassembly line balancing problem, a set of disassembly tasks must be assigned to workstations while respecting precedence constraints and a given cycle time. The aim is usually to obtain an efficient line configuration by reducing idle times, limiting the number of workstations, improving workload balance, reducing cost, or increasing safety. In the context of electric vehicle batteries, this problem becomes more complex because some tasks are hazardous, some require human flexibility, and others may be suitable for robotic execution. Therefore, task assignment cannot be based only on processing time; it must also consider the nature of the operation and the compatibility between tasks and resources.

3.5.1 From Sequence Planning to Line Balancing

The transition from disassembly sequence planning to disassembly line balancing represents an important step toward practical implementation. While sequence planning determines a feasible order of operations, line balancing transforms this order into a production organization. It defines which tasks are performed at each station and ensures that the total workload assigned to a station does not exceed the cycle time. This is particularly important when the disassembly process is repeated for several batteries and must be organized as a line rather than as a single isolated operation.

For electric vehicle batteries, line balancing has been studied to improve the efficiency and safety of module or pack disassembly. Wu et al. proposed a cell-level disassembly line balancing model for waste power battery modules in a human-machine hybrid mode. In their work, tasks are classified according to their characteristics: hazardous tasks are assigned to robots, complex tasks are assigned to humans, and ordinary tasks can be assigned to either humans or robots [51]. This classification is important because it introduces a practical link between the physical nature of the disassembly task and the resource that should perform it.

Their model considers a line composed of manual and robotic workstations, and the balancing problem is solved using NSGA-II. Although the study focuses on a specific battery module, it shows that battery disassembly line balancing cannot be treated as a classical line balancing problem. The presence of hazards, task complexity and resource compatibility must be explicitly integrated into the decision process [51]. This idea is also relevant for the present work, where each task can be performed in a specific execution mode: human, robot, or human-robot collaboration.

3.5.2 Manual, Robotic, Hybrid and Collaborative Workstations

A key issue in battery disassembly line balancing is the choice of workstation type. In a purely manual line, all tasks are performed by human operators. This configuration offers flexibility, but it exposes workers to safety risks and may lead to high variability

in operation times. In a robotic line, tasks are performed by robots, which can improve safety for dangerous operations but may have difficulty dealing with product variability and unexpected conditions. Hybrid or collaborative configurations aim to combine the advantages of both resources.

Wu et al. introduced a human-machine hybrid mode where human and robotic workstations coexist in the same disassembly line [51]. This approach is useful because it avoids assigning all operations to one type of resource. Instead, each task is directed toward the most suitable resource according to its difficulty and hazard level. However, in this type of hybrid system, a task is generally assigned either to a human or to a robot, and the collaboration between the two resources is not always modeled as a simultaneous execution mode.

Human-robot collaborative disassembly goes further by considering that some operations may require the simultaneous intervention of a human and a robot. Chu and Chen proposed a human-robot collaboration disassembly planning model for end-of-life power batteries [9]. Zhang et al. also studied a multi-objective human-robot collaboration disassembly planning approach for retired power batteries based on entropy-weight fuzzy hierarchical analysis and a differential evolution algorithm [61]. These contributions show that human-robot cooperation can improve the feasibility and efficiency of battery disassembly when tasks are properly assigned.

More recently, Qin et al. studied a multiple product hybrid disassembly line balancing problem with human-robot collaboration [42]. This work is particularly relevant because it introduces the multi-product dimension into a human-robot collaborative disassembly line. The authors consider several product types and integrate task assignment, station assignment and resource decisions in the same framework. Their contribution confirms that the multi-product dimension is becoming increasingly important in disassembly line balancing, since real recovery facilities rarely process only one product type.

3.5.3 Line Configuration and Operational Performance

Some studies focus on the physical configuration of the dismantling line. Mao et al. optimized dismantling lines for used electric vehicle battery packs by comparing unilateral and symmetric bilateral line configurations [35]. Their model considers the number of workstations, idle time, risk and disassembly cost. This contribution is useful because it shows that the line layout itself can affect operational performance. However, the present research does not focus on comparing physical layouts. It focuses on the assignment of tasks, stations, resources and execution modes in a multi-product collaborative line.

Other line balancing works introduce remanufacturing demand, hazard characteristics, destructive operations or environmental constraints. Zhu et al. studied a multi-objective human-robot collaborative disassembly line balancing problem considering component remanufacturing demand and hazard characteristics [64]. These contributions confirm that realistic disassembly line balancing increasingly considers more than simple workload distribution. Nevertheless, adding many objectives or operational features can make the model more difficult to interpret and solve.

3.5.4 Cost-Oriented and Performance-Oriented Line Balancing Criteria

The objectives considered in disassembly line balancing vary from one study to another. Some authors focus on minimizing the number of workstations or reducing idle time in order to improve line efficiency. Others include cost, risk, energy consumption, profit

or environmental indicators. In battery disassembly, safety and cost are particularly important because the process involves hazardous operations and expensive resources.

In the model proposed by Wu et al. [51], several criteria are considered, including the number of workstations, workload balance, the number of human workers and disassembly cost. Zhan et al. [56] considered hazard and energy indicators in environment-oriented sequence planning. Mao et al. [35] included workstation number, idle time, risk and disassembly cost when comparing dismantling line configurations. Zhu et al. [63] considered stochastic and sequence-dependent effects in disassembly line balancing. This reflects the fact that a good disassembly line must be efficient, safe and economically acceptable at the same time. However, including many objectives may make the model more difficult to interpret and solve. In industrial applications, it may also be useful to aggregate the main economic components into a single objective function, especially when the purpose is to obtain a clear and operational decision.

The present work follows this cost-oriented perspective. Instead of formulating the problem as a multi-objective model, it uses a mono-objective economic formulation. The objective is to minimize a total cost that includes station opening costs and task execution costs. In the stochastic extension, an expected recourse cost is also added to penalize possible overloads of workstations under uncertain human operation times. This choice makes it possible to keep a clear optimization criterion while still representing important operational decisions.

3.6 Human–Robot Collaboration in Battery Disassembly

The disassembly of end-of-life electric vehicle batteries requires both flexibility and safety. Human operators are able to adapt to product variability, unexpected damage, missing information and complex manual operations. Robots, on the other hand, are more suitable for repetitive, heavy, precise or hazardous tasks. For this reason, human–robot collaboration has become an important research direction in battery disassembly. It offers an intermediate solution between fully manual disassembly, which exposes workers to risks, and full automation, which remains difficult because of the diversity and uncertainty of end-of-life battery packs.

Several studies emphasize that full automation of battery disassembly is still challenging. Battery packs differ in architecture, fastening methods, cooling systems, module arrangement and accessibility. In addition, the condition of end-of-life batteries may be uncertain, especially when batteries have been damaged, aged or exposed to harsh operating conditions. Villagrossi and Dinon showed that robotic systems are promising for sustainable battery remanufacturing, but they also pointed out that robotized disassembly must deal with product variability, perception issues and complex manipulation tasks [47]. Kaarlela et al. reached a similar conclusion in their review of robotised electric vehicle battery disassembly, noting that flexible automation requires adaptable tooling, safe control, and reliable information about the product structure [28].

Human–robot collaboration is therefore not only a technological choice, but also a modeling issue. The disassembly system must decide which tasks are performed by humans, which tasks are performed by robots, and which tasks require cooperation between the two resources. These decisions affect safety, workload balance, station configuration, cycle time feasibility and economic performance. In this context, the mathematical model must represent not only the precedence relations between tasks, but also the compatibility between each task and each execution mode.

3.6.1 From Human–Machine Hybrid Systems to Real Collaboration

In the literature, it is important to distinguish between human–machine hybrid systems and real human–robot collaboration. In a hybrid system, humans and robots may coexist in the same line, but each task is generally assigned to either a human or a robot. In this case, the two resources are used separately. In a collaborative system, some tasks can be performed jointly by a human and a robot, which means that both resources are required at the same time for the same operation.

Wu et al. proposed a human–machine hybrid disassembly line balancing model for waste power battery modules [51]. In their model, hazardous tasks are assigned to robots, complex tasks are assigned to humans, and ordinary tasks can be assigned to either type of workstation. This classification is useful because it reflects the practical differences between task categories. However, the model mainly represents a hybrid allocation logic, where tasks are distributed between human and robotic stations, rather than a fully collaborative execution mode.

Chu and Chen went further by studying human–robot collaboration disassembly planning for end-of-life power batteries [9]. Their work explicitly considers collaborative disassembly and shows how task allocation and sequencing can be organized when humans and robots are both involved in the process. Gao et al. proposed a partially observable deep reinforcement learning approach for multi-agent strategy optimization in human–robot collaborative battery disassembly [17]. These works show that HRC battery disassembly can be approached either through mathematical optimization or through learning-based decision-making.

3.6.2 Task Classification in HRC Disassembly

A central element in HRC disassembly models is the classification of tasks. In battery disassembly, not all operations have the same level of risk, complexity or automation potential. Some tasks are hazardous because they involve high-voltage components, unstable cells or dangerous materials. These tasks are often more suitable for robotic execution in order to reduce operator exposure. Other tasks are complex because they require perception, dexterity, adaptation or decision-making. These tasks may remain more appropriate for human operators. Finally, some tasks are ordinary or flexible and can be performed either by a human or by a robot, depending on the line configuration.

The classification proposed by Wu et al. is based on this logic, with hazardous tasks, complex tasks and ordinary tasks [51]. This classification makes the task assignment decision more realistic than a simple time-based allocation. It also shows that safety and task nature must be integrated into disassembly planning. In the same direction, Chu and Chen considered task categories compatible with human execution, robot execution or collaboration [9]. These categories help define the feasible execution modes of each task.

The present research follows this idea by classifying battery disassembly tasks into four groups: human-only tasks, robot-only tasks, collaborative human–robot tasks, and normal tasks that can be performed either by a human or by a robot. This classification makes it possible to represent both technological restrictions and operational flexibility. Human-only tasks correspond to operations that require human dexterity or judgment. Robot-only tasks correspond to operations that are dangerous or better suited to automated execution. Collaborative tasks require both resources simultaneously. Normal tasks remain flexible and can be assigned to the most suitable resource according to the optimization result.

This classification is particularly important in a mono-objective cost-oriented model. Since the model minimizes a global economic cost, it must still respect the feasible execu-

tion modes of each task. In other words, the cost minimization cannot assign a hazardous task to a human-only mode if the task is defined as robot-only, and it cannot assign a collaborative task to a station that does not contain both a human and a robot. Therefore, task classification is not only descriptive; it directly shapes the feasible solution space of the optimization model.

3.6.3 Synchronization and Resource Constraints in Collaborative Stations

When a task is performed in collaboration, the model must ensure that the human and the robot are available at the same station and during the same time interval. This creates a synchronization requirement that does not exist in purely manual or purely robotic tasks. A collaborative operation cannot start if only one of the two resources is available. It also blocks both resources during its execution. Therefore, collaborative tasks increase the complexity of the scheduling and line balancing problem.

In HRC disassembly planning, this synchronization is usually handled through resource constraints and non-overlapping constraints. If two tasks use the same human resource in the same station, they cannot overlap. The same rule applies to robotic resources. For collaborative tasks, both sets of constraints are activated at the same time, because the task uses both the human and the robot. Chu and Chen highlighted the importance of such constraints in human–robot collaborative battery disassembly planning [9]. Qin et al. also considered human–robot collaboration in a multiple product disassembly line balancing framework, where the availability of resources and the assignment of tasks to workstations are jointly considered [42].

These modeling aspects are directly related to the present work. The proposed deterministic model assigns each task to a station and to one execution mode. If the task is collaborative, the station must contain both a human and a robot. In addition, tasks sharing the same human or robotic resource in the same station cannot overlap. This ensures that the planning remains physically feasible. In the stochastic extension, the same first-stage assignment decisions are kept, but the execution times of human tasks vary according to scenarios. This makes the synchronization and resource feasibility even more important, because the human workload may change from one scenario to another.

3.6.4 Learning-Based HRC and Remaining Implementation Issues

Recent studies also explore reinforcement learning and multi-agent learning for disassembly systems. Guo et al. reviewed reinforcement learning applications for disassembly system optimization, including sequence planning, line balancing and human–robot collaboration [21]. Gao et al. modeled HRC battery disassembly as a partially observable multi-agent decision problem and used deep reinforcement learning to optimize collaborative strategies [17]. These works are promising because they can handle dynamic decisions and incomplete information.

However, learning-based methods often require a simulation environment, large amounts of training data and careful definition of states, actions and rewards. This can make them difficult to use as a first modeling framework when the goal is to clearly formulate the structure of the optimization problem. For this reason, the present research focuses first on mathematical modeling. The deterministic model defines the structural decisions, and the stochastic extension introduces uncertainty in human operation times.

A metaheuristic solution method can then be developed to solve larger instances without requiring a full learning environment.

3.7 Uncertainty in Disassembly Planning

Most disassembly planning and line balancing models are first formulated in a deterministic way. In these models, operation times, costs, resource requirements and precedence relations are assumed to be known in advance. This assumption is useful because it makes the problem easier to formulate and solve. It also provides a clear baseline for understanding the structure of the disassembly system. However, in real end-of-life product recovery, and especially in electric vehicle battery disassembly, several parameters are uncertain.

The deterministic assumption becomes particularly restrictive when dealing with used batteries. Two batteries of the same model may not require exactly the same disassembly time, because their condition depends on their usage history, degradation level, accident history, corrosion, deformation, residual charge, or the state of fasteners and connectors. Therefore, a deterministic model can provide an initial feasible organization of the line, but it may not fully represent the variability observed in practice. This is why uncertainty modeling has become an important research direction in disassembly planning.

3.7.1 Sources of Uncertainty in End-of-Life Battery Disassembly

The main source of uncertainty in battery disassembly is the condition of the returned product. Unlike new products in assembly systems, end-of-life batteries arrive after several years of use and may have experienced different operating conditions. Some batteries may be intact, while others may be damaged, corroded, deformed or partially degraded. These differences directly affect the difficulty of disassembly operations.

Operation times are therefore among the most uncertain parameters. For example, removing a cover, disconnecting a cable, unscrewing fasteners or extracting a module may take more time than expected if the component is blocked, damaged or difficult to access. Human operation times are especially variable because they depend not only on the product condition, but also on the operator's experience, fatigue, judgment and adaptation to unexpected situations. This variability is one of the reasons why manual disassembly remains flexible but difficult to standardize.

Uncertainty may also affect safety and resource assignment. A task that is normally simple may become risky if the battery is damaged or if a component is not accessible in the expected way. Similarly, a task initially planned for human execution may require robotic assistance if the risk level increases. Villagrossi and Dinon [47] pointed out that product variability remains a major barrier for robotized battery pack disassembly. Kaarlela et al. [28] also emphasized the need for adaptable tooling and reliable product information in robotised battery disassembly. Li et al. [33] highlighted that AI-driven disassembly still depends on reliable data and robust decision-making methods. These observations justify the need for models that can move beyond fixed deterministic parameters.

3.7.2 Fuzzy, Stochastic, and Scenario-Based Approaches

Several modeling approaches have been proposed in the literature to represent uncertainty in disassembly and remanufacturing systems. A first approach consists of using fuzzy

numbers. In this case, operation times are not represented by a single fixed value, but by an interval or a triangular fuzzy number. This allows the model to describe uncertain task durations when exact probability distributions are not available. Yuan et al. used fuzzy processing times in a capacitated multi-objective disassembly scheduling problem, showing that fuzzy modeling can be useful when disassembly durations are imprecise rather than exactly random [55].

A second approach is stochastic modeling. Here, uncertain parameters are represented by probability distributions. Operation times may follow normal, uniform or other distributions depending on the available data and assumptions. Fu et al. studied stochastic multi-objective integrated disassembly–reprocessing–reassembly scheduling with processing times following normal distributions [16]. This type of work is important because it shows that uncertainty should be considered not only in isolated disassembly tasks, but also in integrated remanufacturing systems.

A third approach is scenario-based optimization. Instead of solving the problem for one deterministic value of each parameter, several scenarios are generated. Each scenario represents one possible realization of uncertain operation times. The optimization model then searches for a solution that performs well over all scenarios, or in expectation. This approach is particularly useful when uncertainty affects the processing times but the main structural decisions, such as task assignment and station opening, must be made before the real condition of the product is fully known.

This scenario-based logic is consistent with the present research. The deterministic model is first used to define the basic structure of the multi-product human–robot collaborative disassembly line. Then, the stochastic extension introduces uncertainty in human operation times. The first-stage decisions, such as station opening, task assignment, execution mode and resource allocation, remain common to all scenarios. The second-stage variables, such as task starting times, finishing times and recourse variables, are scenario-dependent.

3.7.3 Stochastic Disassembly Line Balancing Models

In the context of human–robot collaborative disassembly, Guo et al. studied a disassembly line balancing problem with stochastic operation times and proposed a solution based on a multi-objective shuffled frog leaping algorithm [22]. Their work is important because it directly recognizes that operation times in HRC disassembly are not always deterministic. It also shows that stochastic task durations can significantly influence the balancing of the line and the quality of the obtained solutions.

Other stochastic disassembly line balancing studies consider uncertain task times, energy consumption or sequence-dependent effects. Zhu et al. proposed a stochastic sequence-dependent disassembly line balancing problem and solved it using a multi-objective adaptive large neighbourhood search algorithm [63]. Their work accounts for uncertain operation times and sequence-dependent effects, which makes the planning problem closer to real end-of-life conditions. Zhang et al. studied an energy-oriented stochastic disassembly line balancing problem where task times and energy consumption are random and the objective is to reduce total energy consumption [60]. Wu et al. proposed a hybrid evolutionary algorithm for a stochastic HRC disassembly line balancing problem considering carbon emission optimization [50]. These works support the idea that deterministic processing times are often insufficient for realistic disassembly line design.

The stochastic extension of the present work follows this idea, but with a mono-

objective economic formulation. Instead of treating the stochastic problem as a multi-objective optimization problem, the model minimizes a total expected cost. This cost includes station opening costs, task execution costs and an expected recourse cost associated with possible station overloads in the scenarios. In this way, the uncertainty is not ignored, but it is translated into an economic penalty.

The recourse mechanism is an important modeling choice. In the deterministic model, each opened station must respect the cycle time as a strict capacity constraint. In the stochastic version, the station load may exceed the cycle time in some scenarios, but only within a bounded margin and with a penalty cost. This makes the model less rigid and closer to real operational conditions. Instead of forcing the line to be feasible for the worst possible realization of all human times, the model allows limited deviations and penalizes them economically.

3.7.4 Limits of Existing Stochastic Approaches

Although uncertainty has been increasingly considered in disassembly planning, several limitations remain. First, many stochastic or fuzzy models are still developed for general products rather than for electric vehicle batteries. As a result, they do not always include battery-specific constraints such as hazardous operations, high-voltage components, or human-robot collaboration.

Second, stochastic models often focus on one product type. This limits their applicability in real recovery centers, where several battery types may be processed on the same line. Each battery type has its own tasks, precedence relations, durations and resource requirements. Therefore, combining uncertainty with a multi-product structure remains a relevant research direction.

Third, many existing studies use uncertainty mainly to evaluate or compare solutions, while the integration of uncertainty into the economic structure of the model is less frequent. In practical terms, uncertainty should not only be treated as a technical variation, but also as a cost-related issue. Delays, overloads, additional labor time or operational disruptions can all generate economic consequences.

For these reasons, the present work adopts a progressive modeling strategy. A deterministic mono-objective model is first developed in order to define the basic assignment, station opening and resource allocation decisions. Then, a stochastic scenario-based model is introduced to better represent the variability of human operation times. This extension keeps the same structural decisions across scenarios, while allowing scenario-dependent scheduling and bounded recourse on station loads. This approach makes it possible to preserve the clarity of the deterministic model while improving its realism.

3.8 Multi-Product Disassembly Lines

Most studies on electric vehicle battery disassembly focus on a single battery pack or a single battery module. This choice is understandable because each battery type has its own structure, components, fastening methods and precedence relations. Working on one product makes it possible to describe the disassembly process in detail and to build a specific graph or matrix of precedence constraints. However, in real recovery facilities, end-of-life batteries do not necessarily belong to the same model. A dismantling center may receive several battery types with different architectures, operation times and safety requirements. This industrial reality motivates the study of multi-product disassembly

lines.

A multi-product disassembly line is more complex than a single-product line because the model must handle several task sets and several precedence structures at the same time. Each product has its own disassembly graph, but the products may share the same stations, operators, robots and cycle time. Therefore, the optimization problem must determine how the tasks of different products are assigned to the available workstations while preserving the technological logic of each product. This makes the problem closer to a mixed or multi-model production environment, but with additional difficulties related to end-of-life uncertainty, product condition and safety constraints.

3.8.1 Motivation for Multi-Product Disassembly

The need for multi-product modeling is particularly clear in the case of electric vehicle batteries. Battery packs are not standardized across manufacturers. Their internal structure depends on the cell format, the module arrangement, the cooling system, the type of enclosure, the fastening technologies and the electrical connections. Kampker et al. showed that battery system architectures can be classified according to several structural and functional characteristics, which confirms the high diversity of battery pack designs [29]. This diversity directly affects disassembly planning because a task sequence defined for one battery type cannot be applied automatically to another one.

From an operational point of view, treating each battery type with a completely separate line would not always be economically feasible. It would require several dedicated infrastructures, each designed for a specific battery model. A more flexible approach consists of using the same line to process different battery types, while adapting the task assignment and execution modes according to each product. This is why multi-product disassembly planning is important for future battery recovery systems.

Multi-product disassembly also creates an important modeling challenge. If each battery type has a different number of tasks and different precedence relations, the model must keep the identity of each product. It is not possible to merge all tasks into a single generic sequence without losing the technological structure of each battery. Therefore, the product index becomes essential in the mathematical formulation. This idea is also adopted in the present research, where each battery type has its own task set, precedence matrix and operation times.

3.8.2 Multi-Product Modeling Approaches

In the broader disassembly literature, Ehm proposed a scheduling and process planning model for dismantling systems with flexible disassembly modes and recovery levels [11]. This type of work is useful because it shows how disassembly decisions can be formulated for systems where different products or recovery requirements must be considered. The model integrates the selection of disassembly operations, the choice of recovery level and the scheduling of tasks, which makes it relevant for studying more realistic end-of-life product recovery systems.

For electric vehicle batteries, Qin et al. studied a multiple product hybrid disassembly line balancing problem with human–robot collaboration [42]. Their work is one of the closest contributions to the present research because it explicitly combines a multi-product setting with human–robot resources. In such a framework, the line must process several products while deciding how tasks are distributed among stations and resources. This

confirms that the combination of multi-product disassembly and HRC is a recent and relevant research direction.

A common way to represent several products is to keep a separate precedence structure for each product. Each battery type is described by its own precedence matrix or graph. Then, the optimization model uses a product index to distinguish the tasks and constraints associated with each battery type. This approach avoids creating artificial precedence relations between tasks belonging to different products. In the present work, this modeling logic is adopted by defining a task set for each product and by formulating precedence constraints separately for each battery type.

The use of product proportions or product weights is also important in multi-product disassembly. In a real treatment center, all battery types may not arrive with the same frequency. Some types may represent a larger share of the incoming flow, while others may be less frequent. For this reason, a multi-product model can use product weights to represent the product mix. This allows the objective function to reflect the relative importance of each battery type in the overall system. In the present deterministic model, the execution cost of tasks is weighted by the proportion of each product type in the product mix.

3.8.3 Destructive Operations, Parallel Layouts and Industrial Extensions

Recent multi-product studies extend the classical disassembly line balancing problem by adding destructive operations, preventive maintenance, parallel layouts or environmental criteria. Zhang et al. studied reliability and efficiency optimization of multi-product disassembly lines with destructive operations and preventive maintenance [62]. Guo et al. proposed an industrial application of a human–robot collaborative parallel two-sided destructive disassembly line balancing problem in multi-product and multi-line layouts [20]. Liang et al. developed a multi-product disassembly line balancing optimization method aiming at high disassembly profit and low energy consumption with noise pollution constraints [34].

These works confirm that the multi-product dimension is increasingly considered in disassembly line balancing. They also show that realistic industrial systems may require additional features such as destructive modes, environmental constraints, maintenance planning or parallel line structures. However, most of these contributions are not specifically focused on electric vehicle batteries or do not integrate stochastic human operation times. They are therefore useful for understanding the broader evolution of multi-product disassembly, but they do not fully cover the positioning of the present thesis.

3.8.4 Multi-Product HRC and Remaining Limitations

Although the multi-product dimension is important, it is still less developed than single-product disassembly planning in the battery literature. Many studies optimize the disassembly of one battery pack or one module, such as a Tesla, Audi or Volkswagen battery. These studies are useful because they provide detailed product-level models, but their results are strongly linked to the selected case study. When the battery type changes, the precedence graph, task durations and feasible execution modes may also change.

The work of Qin et al. represents an important step toward multi-product human–robot disassembly line balancing [42]. However, the combination of multi-product modeling, human–robot collaboration and uncertainty remains limited in the literature. In

particular, many models still rely on deterministic task durations. This assumption simplifies the formulation, but it does not fully represent the variability of human disassembly operations in end-of-life battery treatment.

Another limitation concerns the objective structure. Existing studies often use several performance criteria such as number of stations, workload balance, cost, risk or energy. These criteria are relevant, but a multi-objective formulation may produce a set of compromise solutions that require an additional decision-making step. In contrast, the present work adopts a mono-objective economic formulation. This choice makes the decision criterion clearer by aggregating the main cost components into a single objective function. The deterministic version minimizes station opening and execution costs, while the stochastic version adds an expected recourse cost associated with station overloads under uncertain human operation times.

Therefore, multi-product disassembly lines represent a key research direction for realistic battery recovery systems. They make it possible to move from product-specific case studies toward a more general decision framework. The present research builds on this idea by considering several battery types in the same human-robot collaborative line. Each product keeps its own disassembly structure, but all products share the same potential stations and resources. This allows the model to represent a more flexible and industrially relevant disassembly system.

3.9 Synthesis of the Literature and Research Gap

The reviewed literature shows that disassembly planning for end-of-life electric vehicle batteries has become an active research topic. Existing studies address the problem from different angles, including disassembly sequence planning, disassembly line balancing, human-robot task allocation, robotic disassembly, stochastic modeling, risk-aware planning and energy-oriented optimization. These contributions provide a strong foundation for understanding how battery disassembly can be organized and optimized. However, they also show that several important dimensions are still rarely integrated within the same framework.

3.9.1 Main Trends Identified in the Literature

A first important trend is the use of structured product representations. Most studies rely on precedence graphs, hybrid disassembly graphs, priority matrices or relation matrices to represent the logical and physical constraints between components. Baazouzi et al. [4] used precedence relations to optimize disassembly strategy and disassembly depth. Ke et al. [30] used a hybrid graph and a relation matrix to represent battery component dependencies. Zhan et al. [56] relied on a hybrid disassembly graph for environment-oriented sequence planning. Yin et al. [54] introduced a knowledge graph and a graph neural network to represent richer relations between components, tools and operations. These works show that structured representations are essential for generating feasible disassembly plans.

A second trend concerns the increasing use of heuristic and metaheuristic methods. Battery disassembly planning problems are generally combinatorial and difficult to solve exactly when the number of tasks increases. Wu et al. [51] used NSGA-II for a cell-level battery module disassembly line balancing problem. Chu and Chen [9] proposed an optimization approach for HRC battery disassembly planning. Guo et al. [22] used

a multi-objective shuffled frog leaping algorithm for stochastic HRC disassembly line balancing. Zhu et al. [63] proposed a multi-objective adaptive large neighbourhood search algorithm for a stochastic sequence-dependent DLBP. Wu et al. [50] developed a hybrid evolutionary algorithm for a stochastic HRC disassembly line balancing problem. This observation is important for the present work, since the proposed mathematical model is expected to become difficult to solve exactly for larger multi-product instances. It also motivates, as a future research direction, the development of metaheuristic solution approaches.

A third trend is the growing interest in human-robot collaboration. Villagrossi and Dinon [47] showed that robotics can support battery pack disassembly but that full automation remains limited by variability. Kaarlela et al. [28] reached a similar conclusion in their review of robotised battery disassembly. Chu and Chen [9] explicitly modeled human-robot collaboration for end-of-life power batteries. Qin et al. [42] extended this direction to a multiple product hybrid disassembly line balancing problem with HRC. These works show that HRC is a realistic intermediate solution between fully manual and fully automated disassembly.

A fourth trend is the progressive consideration of uncertainty. Many early models assume deterministic operation times, costs and resource requirements. However, end-of-life battery disassembly is strongly affected by variability. Fu et al. [16] modeled stochastic processing times in an integrated remanufacturing scheduling problem. Yuan et al. [55] used fuzzy processing times when precise probability distributions were not available. Guo et al. [22] considered stochastic operation times in HRC disassembly line balancing. Zhu et al. [63] introduced stochastic and sequence-dependent effects in DLBP. Zhang et al. [60] studied stochastic task times and energy consumption in an energy-oriented DLBP. These works justify the transition from a deterministic formulation to a stochastic one when human operation times are uncertain.

A fifth trend is the expansion of performance criteria. Many articles consider time, cost, risk, energy, profit, environmental impact, remanufacturing demand or carbon emissions. This diversity shows that disassembly is a multi-dimensional problem. However, it also means that the decision-maker often needs to select one final solution among several compromises. The present thesis does not ignore this richness, but it chooses a mono-objective economic formulation in order to keep the model clear and operational.

3.9.2 Main Limitations

Despite these advances, several limitations remain. The first limitation is the predominance of single-product case studies. Most works focus on one specific battery pack or module, such as a Tesla, Audi or Volkswagen battery. This allows a detailed modeling of the selected product, but it does not fully represent industrial dismantling centers, where several battery types may be received and processed using the same resources. In practice, battery architectures vary significantly across manufacturers and vehicle models, which makes the multi-product dimension essential [29].

The second limitation is the frequent use of deterministic data. In many studies, operation times are assumed to be fixed and known in advance. This assumption is useful for building a first model, but it does not fully reflect the real variability of end-of-life batteries. Human disassembly times are especially uncertain because operators must adapt to the actual condition of each battery. Therefore, a deterministic model can be considered as a necessary baseline, but it should be extended when the objective is to better represent real operating conditions.

The third limitation concerns the integration of human–robot collaboration with other realistic dimensions. Several works study HRC battery disassembly, but they often remain focused on one product type or deterministic operation times. On the other hand, some works introduce multi-product or stochastic aspects, but without fully integrating collaborative human–robot execution modes. As a result, the combination of multi-product disassembly, human–robot collaboration and stochastic human operation times remains insufficiently explored.

The fourth limitation is related to the objective structure. Many studies formulate the problem as a multi-objective optimization problem, considering criteria such as time, risk, energy, number of stations or cost. These criteria are relevant, but they may lead to a set of Pareto solutions that require an additional selection step. In contrast, an economic mono-objective formulation can be useful when the aim is to provide a clear operational decision. By aggregating station opening costs, task execution costs and, in the stochastic case, recourse costs, the decision-maker obtains a single criterion that remains interpretable from an industrial point of view.

3.9.3 Positioning of the Present Research

Based on these observations, the present research is positioned at the intersection of multi-product disassembly line planning, human–robot collaborative task allocation and stochastic modeling of human operation times. The first step of the work consists in developing a deterministic mono-objective optimization model. This model defines the basic structure of the problem by assigning tasks of several battery types to stations and execution modes, while respecting precedence constraints, resource compatibility and cycle time limitations.

The deterministic model is useful because it provides a clear and rigorous formulation of the system. It allows the main decisions to be represented in a structured way: opening stations, assigning human and robotic resources, selecting execution modes, and organizing tasks under precedence constraints. However, this deterministic version is only a first approximation of the real disassembly process. Since end-of-life battery disassembly is affected by uncertain human operation times, the model is then extended to a stochastic scenario-based formulation.

In the stochastic extension, the structural decisions remain common to all scenarios, while scheduling decisions and station overload recourse variables become scenario-dependent. This makes it possible to account for the variability of human disassembly times without completely changing the structure of the deterministic model. The stochastic formulation also introduces a bounded recourse mechanism, allowing limited station overloads under uncertainty while penalizing them economically.

Therefore, the contribution of this work lies in the progressive construction of a mono-objective optimization framework for multi-product human–robot collaborative battery disassembly. The deterministic model provides the baseline, while the stochastic extension improves the representation of real operating conditions. The computational complexity of the problem also opens a perspective for future work based on metaheuristic solution methods.

3.10 Conclusion

This chapter reviewed the main research works related to disassembly planning and line balancing, with a particular focus on end-of-life electric vehicle batteries. The literature shows that battery disassembly is a complex decision-making problem due to the diversity of battery architectures, the presence of hazardous components, the need to respect precedence constraints, and the variability of end-of-life product conditions.

The reviewed studies show that several approaches have been proposed to address this complexity. Disassembly sequence planning methods focus on determining feasible and efficient removal orders. Disassembly line balancing models extend this logic by assigning tasks to workstations and respecting cycle time constraints. More recent works introduce human–robot collaboration in order to combine human flexibility with robotic safety and precision. Other studies consider uncertainty through stochastic or fuzzy models, recognizing that operation times may vary significantly in real disassembly operations. The literature also includes studies on risk-aware planning, energy-oriented optimization, artificial intelligence, reinforcement learning, destructive operations, preventive maintenance and advanced line configurations.

However, the literature also reveals several gaps. Most battery disassembly studies remain focused on a single product type, even though real dismantling centers may process several battery models. In addition, many models are deterministic, while the real disassembly process is affected by uncertain operation times, especially for human tasks. Finally, the integration of multi-product disassembly, human–robot collaboration and stochastic operation times remains limited.

For these reasons, the present research proposes a progressive modeling approach. First, a deterministic mono-objective model is developed for a multi-product human–robot collaborative disassembly line. This deterministic version provides the basic structure of the problem and defines the main assignment, station opening, resource and precedence decisions. Then, because fixed operation times do not fully represent the reality of end-of-life battery disassembly, the model is extended into a stochastic scenario-based formulation, where uncertainty is introduced through human operation times and handled by a bounded recourse mechanism.

The next chapter presents the mathematical formulation of the proposed problem. It first describes the deterministic model, including the sets, parameters, decision variables, objective function and constraints. Then, it introduces the stochastic extension based on scenario approximation, where human operation times vary across scenarios while the main structural decisions remain common to all scenarios.

PROBLEM FORMULATION AND MATHEMATICAL MODELLING

4.1 Introduction

The previous chapter showed that end-of-life electric vehicle battery disassembly is a complex planning problem. This complexity comes from the diversity of battery architectures, the presence of hazardous components, the need to respect technological precedence relations, and the difficulty of coordinating human and robotic resources. It also showed that many existing studies focus either on a single product, deterministic operation times, or a limited form of human–robot collaboration.

Based on these observations, this chapter presents the mathematical formulation adopted in this thesis. The problem is modeled as a multi-product human–robot collaborative disassembly line. Several battery types are considered, and each battery type is represented by its own set of tasks, operation times, execution modes and precedence relations. The line contains a maximum number of potential stations, but not all stations have to be opened in the final solution.

The chapter first describes the problem and the input data used to construct the model. Then, the deterministic formulation is presented. In this version, all operation times are assumed to be known and fixed. After that, the stochastic extension is introduced. In this second version, uncertainty is considered only on human operation times, while robot and collaborative operation times remain deterministic. The stochastic model uses a scenario-based approximation and includes a bounded recourse mechanism on station loads.

4.2 Problem Statement

The considered system is a disassembly line dedicated to the treatment of several types of end-of-life electric vehicle batteries. Each product $p \in P$ represents one battery type and is composed of a set of disassembly tasks I_p . Each task must be assigned to one station and executed according to one feasible execution mode. Three execution modes are considered: human mode, robot mode and collaborative human–robot mode.

The tasks are divided into four categories. The first category contains tasks that can only be executed by a human operator. These tasks usually require manual dexterity, perception or judgment. The second category contains tasks that can only be executed by a robot, mainly because of safety or handling constraints. The third category contains tasks that must be executed in collaboration between a human and a robot. The fourth category contains normal tasks, which can be executed either by a human or by a robot.

The disassembly line contains a maximum number m of potential stations. Each station may be opened or closed. If a station is opened, it must contain at least one resource: a human operator, a robot, or both. A station can contain at most one human operator and one robot. A collaborative task requires both resources simultaneously in the same station.

The technological feasibility of the disassembly process is represented by precedence

relations. Two types of precedences are considered. AND precedences are mandatory: if task i is an AND-predecessor of task j , then i must be completed before j when both are assigned to the same station, and i must not be placed after j in the physical order of stations. OR precedences are alternative: if task j has several OR-predecessors, at least one of them must be selected to satisfy the access condition of task j .

The objective is economic. In the deterministic model, the objective is to minimize the total cost composed of station opening costs and task execution costs. In the stochastic model, an additional expected recourse cost is added to penalize possible station overloads caused by uncertain human operation times.

4.3 Input Data and Parameter Definition

4.3.1 Data Sources and Construction Logic

The input data were built from several literature sources dealing with electric vehicle battery disassembly. Since these sources do not provide the same type of information, a common construction logic was used to obtain homogeneous parameters for all battery cases. The retained data include the list of tasks, the classification of tasks, the feasible execution modes, the operation times, the cost parameters and the precedence matrices.

Table 4.1 summarizes the main sources used to construct the battery data. The DOI information is kept in the bibliography, while the table focuses on the role of each source in the model.

Table 4.1: Main sources used for the construction of the battery data

Battery case	Source article	Data used in the model
Tesla Model 1	Zhang et al. [61]	Tasks, operation times in the three modes, energy values, task characteristics and precedence graph.
Tesla Model S	Chu and Chen [9]	Human and robot operation times, precedence graph and task classification adapted to the proposed model.
Guangqi Toyota LB7A-FX1	Yang et al. [53]	Operation times, energy values, cost information and precedence relations.
Red Flag	Mao et al. [35]	Operation times, cost and risk information, and precedence graph for the 26-task case.
Tesla module with 44 tasks	Wu et al. [52]	Task list, task categories, operation times and precedence relations for the 44-task Tesla module case.

Two additional references were used for energy-related cost parameters. When task-level energy consumption is available, the coefficient $c_2 = 0.2750$ is used following Nourmohammadi et al. [40]. When task-level energy consumption is not available, a generic robot energy cost per second is calculated from Nourmohammadi et al. [39] as:

$$\frac{1.8900}{12.0000} = 0.1575.$$

4.3.2 Summary of the Battery Cases

Five battery cases are used in the computational study. They differ in the number of tasks and in the available data. Table 4.2 gives a compact summary of the retained cases.

Table 4.2: Summary of the battery cases used in the model

Battery case	Tasks	Energy data	Main information retained
Tesla Model 1	22	Available	Three operation times, energy values, task classes and precedence matrix.
Tesla Model S	22	Not available	Human and robot times, calculated collaborative times, task classes and precedence matrix.
Guangqi Toyota LB7A-FX1	24	Available	Operation times converted into seconds, energy values, costs and precedence matrix.
Red Flag	26	Not available	Operation times, calculated robot and collaborative times, costs and precedence matrix.
Tesla module	44	Not available	Task categories, operation times, calculated costs and precedence matrix.

4.3.3 Illustrative Example: Tesla Model 1

Tesla Model 1 is used as an illustrative example because the source data reported by Zhang et al. [61] contain detailed information on tasks, operation times, energy values and precedence relations. The disassembly process contains 22 tasks. Table 4.3 gives the classification of the tasks according to the four categories used in the model.

Table 4.3: Task classification for Tesla Model 1

Task category	Tasks
Human-only tasks	10 – Insulation mats; 13 – Charging port connectors; 15 – BMS.
Robot-only tasks	7 – Battery modules; 14 – Battery harnesses; 16 – Battery system harnesses; 22 – Harmful battery packs.
Collaborative tasks	1 – Upper shell; 4 – High-pressure assembly upper shell; 6 – Fuses; 8 – Busbars; 12 – Cooling lines; 17 – Module PCBs; 20 – Electric cores; 21 – Coolants.
Normal tasks	2 – Upper shell screws; 3 – Acoustic foam; 5 – High-pressure assembly on shell screw; 9 – Metal spacers; 11 – Fiberboards; 18 – Fiberboard screws; 19 – High-voltage electrical fuses.

Table 4.4 presents the operation times and cost parameters retained for Tesla Model 1. The table is kept as one single table, but it is formatted with small spacing so that all columns remain readable.

Table 4.4: Operating times and cost parameters for Tesla Model 1

No.	Task	t^H	t^R	t^C	e^R	c^H	c^C
1	Upper shell	180.0000	90.0000	68.0000	1.2969	27.0000	11.1799
2	Upper shell screws	51.0000	29.0000	22.0000	0.1619	7.6500	3.4228
3	Acoustic foam	45.0000	27.0000	20.0000	0.2257	6.7500	3.1672
4	High-pressure assembly upper shell	30.0000	24.0000	18.0000	0.2759	4.5000	2.9069
5	High-pressure assembly on shell screw	45.0000	27.0000	20.0000	0.2161	6.7500	3.1601
6	Fuses	24.0000	15.0000	11.0000	0.1007	3.6000	1.7238
7	Battery modules	60.0000	36.0000	27.0000	0.3524	9.0000	4.3143
8	Busbars	45.0000	23.0000	17.0000	0.2543	6.7500	2.7379
9	Metal spacers	42.0000	30.0000	23.0000	0.3011	6.3000	3.6809
10	Insulation mats	18.0000	18.0000	14.0000	0.6970	2.7000	2.6421
11	Fiberboards	9.0000	9.0000	7.0000	0.0693	1.3500	1.1039
12	Cooling lines	33.0000	24.0000	18.0000	0.3175	4.9500	2.9381
13	Charging port connectors	21.0000	21.0000	16.0000	0.9731	3.1500	3.1414
14	Battery harnesses	24.0000	22.0000	17.0000	2.2663	3.6000	4.3013
15	BMS	12.0000	12.0000	9.0000	0.1406	1.8000	1.4554
16	Battery system harnesses	24.0000	24.0000	18.0000	0.3247	3.6000	2.9435
17	Module PCBs	24.0000	18.0000	14.0000	0.1792	3.6000	2.2394
18	Fiberboard screws	15.0000	15.0000	11.0000	0.1324	2.2500	1.7471
19	High-voltage electrical fuses	6.0000	6.0000	5.0000	0.0452	0.9000	0.7877
20	Electric cores	48.0000	48.0000	36.0000	0.3551	7.2000	5.6663
21	Coolants	36.0000	36.0000	27.0000	0.3584	5.4000	4.3188
22	Harmful battery packs	24.0000	20.0000	15.0000	1.0307	3.6000	3.0230

The precedence relations of Tesla Model 1 are represented by a precedence matrix. In this matrix, a value of 0 means that no precedence relation exists between two tasks, a value of 1 represents an AND-type precedence relation, and a value of 2 represents an OR-type precedence relation. The matrix is shown in Figure 4.1.

Matrice de precedence	i/j	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
	1	0	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0
	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	3	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
	5	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
	7	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0
	8	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	9	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
	18	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
	19	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	21	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
	22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 4.1: Precedence matrix for Tesla Model 1

4.3.4 Generalization to the Other Battery Types

The same construction logic is applied to the other battery types. For each product, the task list and precedence structure are kept product-specific. The operation times are either

taken directly from the source article or calculated using the same rules as those adopted in the data file. When the three execution times are not directly available, the reference time is considered as the human time, the robot time is estimated as $0.7500t_{pi}^H$, and the collaborative time is calculated as:

$$t_{pi}^C = 0.6000t_{pi}^R + 0.2000t_{pi}^H.$$

Human costs are calculated with a unit human cost equal to 0.1500. When task-level energy values are available, the robot energy cost is calculated using $c_2 = 0.2750$. When these values are not available, the generic coefficient 0.1575 is used.

4.4 Deterministic Mathematical Model

This section formulates the deterministic version of the proposed multi-product human–robot collaborative disassembly line balancing problem. In this formulation, the processing times are considered known and fixed. The model simultaneously determines the line configuration, the assignment of disassembly tasks to workstations, the allocation of human and robotic resources, the selection of feasible execution modes, and the satisfaction of product-specific precedence relations.

The formulation is developed as a mono-objective economic optimization model. Its objective function minimizes the total cost associated with opened workstations and selected task execution modes. The temporal variables are introduced to guarantee the feasibility of the resulting schedule, particularly with respect to intra-station precedence relations and non-overlap of operations sharing the same human or robotic resource. They are not used to minimize completion time directly. Consequently, the Gantt charts presented in the results chapter are obtained through a post-processing compaction step that preserves the optimized line configuration.

4.4.1 Sets and Indices

Table 4.5: Sets and indices of the deterministic model

Symbol	Definition
$P = \{1, \dots, P \}$	Set of products, where each product corresponds to one battery type.
$K = \{1, \dots, m\}$	Set of potential workstations in the line.
I_p	Set of disassembly tasks of product p .
I_p^H	Set of tasks of product p that can only be executed by a human operator.
I_p^R	Set of tasks of product p that can only be executed by a robot.
I_p^C	Set of tasks of product p that can only be executed in human–robot collaboration.
I_p^N	Set of normal tasks of product p , executable either by a human operator or by a robot.
Ω	Global set of operations, defined as $\Omega = \{(p, i) \mid p \in P, i \in I_p\}$.
Q	Set of unordered pairs of operations, defined using an arbitrary total order $\triangleleft$: $Q = \{(a, b) \in \Omega^2 \mid a \triangleleft b\}$.

For each product p , the task subsets are assumed to be mutually disjoint and collectively exhaustive:

$$I_p = I_p^H \cup I_p^R \cup I_p^C \cup I_p^N, \quad \forall p \in P. \quad (4.1)$$

The order $\triangleleft$ used to construct Q does not represent a technological precedence relation. It is only introduced to define each pair of operations once in the non-overlap constraints.

4.4.2 Parameters

Table 4.6: Parameters of the deterministic model

Symbol	Definition
m	Maximum number of potential workstations.
N^H	Maximum number of available human operators.
N^R	Maximum number of available robots.
λ_p	Proportion of product p in the product mix, with $\sum_{p \in P} \lambda_p = 1$.
f_k	Fixed opening cost of station k .
CT	Cycle time used as the maximum admissible load of an opened station.
$CT_{\min}^{sto}$	Reference processing-time value obtained from the stochastic scenario set and used to calibrate the common cycle time.
t_{pi}^H	Processing time of task i of product p in human mode.
t_{pi}^R	Processing time of task i of product p in robot mode.
t_{pi}^C	Processing time of task i of product p in collaborative mode.
c_{pi}^H	Execution cost of task i of product p in human mode.
e_{pi}^R	Energy-related execution cost of task i of product p in robot mode.
c_{pi}^C	Execution cost of task i of product p in collaborative mode.
M^T	Big-M parameter used in temporal constraints.
M^K	Big-M parameter used only for physical station-order constraints.

In the computational experiments, the deterministic and stochastic formulations are evaluated with the same cycle-time value. Therefore, the cycle time is not calibrated separately from the nominal deterministic processing times. It is fixed according to the stochastic reference value obtained after scenario generation:

$$CT = 2 CT_{\min}^{sto}. \quad (4.2)$$

The value of $CT_{\min}^{sto}$ is defined in the stochastic formulation as the maximum individual processing time observed across all generated human-time scenarios and the deterministic robot and collaborative processing times. Using the same cycle time in both formulations ensures that the deterministic and stochastic results are compared under a common line-capacity reference.

For each product p , the precedence structure is represented by a matrix:

$$S^p = [s_{ij}^p], \quad i, j \in I_p, \quad (4.3)$$

where:

$$s_{ij}^p \in \{0, 1, 2\}. \quad (4.4)$$

The value $s_{ij}^p = 0$ indicates the absence of a direct precedence relation between tasks i and j . The value $s_{ij}^p = 1$ indicates that task i is a mandatory AND-predecessor of task j . The

value $s_{ij}^p = 2$ indicates that task i is a possible OR-predecessor of task j . The corresponding predecessor sets are defined as:

$$P_{pj}^{AND} = \{i \in I_p \mid s_{ij}^p = 1\}, \quad \forall p \in P, \forall j \in I_p, \quad (4.5)$$

$$P_{pj}^{OR} = \{i \in I_p \mid s_{ij}^p = 2\}, \quad \forall p \in P, \forall j \in I_p. \quad (4.6)$$

Two different Big-M parameters are used in the formulation. The first one is associated with temporal constraints:

$$M^T = \sum_{p \in P} \sum_{i \in I_p} \max \{t_{pi}^H, t_{pi}^R, t_{pi}^C\}. \quad (4.7)$$

The second one is associated only with the physical order of stations:

$$M^K = m. \quad (4.8)$$

Using two separate constants avoids applying an unnecessarily large temporal constant to station-index constraints.

4.4.3 Decision Variables

The assignment variables determine both the station and the execution mode selected for each task. For every $p \in P$, $i \in I_p$ and $k \in K$:

$$x_{pik}^H = \begin{cases} 1, & \text{if task } i \text{ of product } p \text{ is assigned to station } k \text{ and executed in human mode,} \\ 0, & \text{otherwise,} \end{cases} \quad (4.9)$$

$$x_{pik}^R = \begin{cases} 1, & \text{if task } i \text{ of product } p \text{ is assigned to station } k \text{ and executed in robot mode,} \\ 0, & \text{otherwise,} \end{cases} \quad (4.10)$$

$$x_{pik}^C = \begin{cases} 1, & \text{if task } i \text{ of product } p \text{ is assigned to station } k \text{ and executed in collaborative mode,} \\ 0, & \text{otherwise.} \end{cases} \quad (4.11)$$

The station and resource variables are defined for each $k \in K$ as follows:

$$u_k = \begin{cases} 1, & \text{if station } k \text{ is opened,} \\ 0, & \text{otherwise,} \end{cases} \quad (4.12)$$

$$y_k^H = \begin{cases} 1, & \text{if a human operator is assigned to station } k, \\ 0, & \text{otherwise,} \end{cases} \quad (4.13)$$

$$y_k^R = \begin{cases} 1, & \text{if a robot is assigned to station } k, \\ 0, & \text{otherwise.} \end{cases} \quad (4.14)$$

For each OR-precedence relation, the variable below indicates whether a possible predecessor is selected:

$$z_{pij} = \begin{cases} 1, & \text{if OR-predecessor } i \text{ is selected to satisfy task } j \text{ for product } p, \\ 0, & \text{otherwise,} \end{cases} \quad \forall p \in P, \forall j \in I_p, \forall i \in P_{pj}^{OR} \quad (4.15)$$

The temporal variables $S_{pi} \geq 0$ and $F_{pi} \geq 0$ denote the start and finish dates of task i of product p .

The variable $T_p \geq 0$ is an auxiliary makespan indicator for product p . It is not part of the objective function but is useful for interpreting the final schedule.

For every pair $(a, b) \in Q$, the variables w_{ab}^H and w_{ab}^R define the relative order of the two operations when they share the same human or robotic resource. For each station $k \in K$, the binary variable δ_{ab}^k indicates whether operations a and b are assigned to the same station k .

4.4.4 Objective Function

The deterministic model minimizes the total economic cost of the line:

$$\min Z_C = \sum_{k \in K} f_k u_k + \sum_{p \in P} \lambda_p \sum_{i \in I_p} \sum_{k \in K} (c_{pi}^H x_{pik}^H + e_{pi}^R x_{pik}^R + c_{pi}^C x_{pik}^C). \quad (4.16)$$

The first term represents the fixed cost of opened stations. The second term represents the weighted execution cost of all disassembly tasks according to the product mix. Since the model is mono-objective and cost-oriented, the temporal variables are used to ensure feasibility rather than to minimize the completion time directly.

4.4.5 Constraints

The deterministic formulation is structured around six groups of constraints: task assignment, station and resource configuration, temporal definition, precedence relations, station-load feasibility, resource non-overlap, and variable domains.

Task assignment according to execution category

This first group defines the admissible execution modes associated with each task category. Human-only tasks must be assigned once in human mode, whereas robot and collaborative assignments are excluded:

$$\sum_{k \in K} x_{pik}^H = 1, \quad \forall p \in P, \forall i \in I_p^H, \quad (4.17)$$

$$x_{pik}^R = 0, \quad \forall p \in P, \forall i \in I_p^H, \forall k \in K, \quad (4.18)$$

$$x_{pik}^C = 0, \quad \forall p \in P, \forall i \in I_p^H, \forall k \in K. \quad (4.19)$$

Similarly, robot-only tasks must be assigned exactly once in robot mode:

$$\sum_{k \in K} x_{pik}^R = 1, \quad \forall p \in P, \forall i \in I_p^R, \quad (4.20)$$

$$x_{pik}^H = 0, \quad \forall p \in P, \forall i \in I_p^R, \forall k \in K, \quad (4.21)$$

$$x_{pik}^C = 0, \quad \forall p \in P, \forall i \in I_p^R, \forall k \in K. \quad (4.22)$$

Tasks classified as collaborative are restricted to the human-robot collaborative mode:

$$\sum_{k \in K} x_{pik}^C = 1, \quad \forall p \in P, \forall i \in I_p^C, \quad (4.23)$$

$$x_{pik}^H = 0, \quad \forall p \in P, \forall i \in I_p^C, \forall k \in K, \quad (4.24)$$

$$x_{pik}^R = 0, \quad \forall p \in P, \forall i \in I_p^C, \forall k \in K. \quad (4.25)$$

Normal tasks preserve allocation flexibility and must be assigned either to the human mode or to the robot mode:

$$\sum_{k \in K} (x_{pik}^H + x_{pik}^R) = 1, \quad \forall p \in P, \forall i \in I_p^N, \quad (4.26)$$

$$x_{pik}^C = 0, \quad \forall p \in P, \forall i \in I_p^N, \forall k \in K. \quad (4.27)$$

Resource availability and station configuration

The number of installed human and robotic resources is bounded by the available resource capacities:

$$\sum_{k \in K} y_k^H \leq N^H, \quad (4.28)$$

$$\sum_{k \in K} y_k^R \leq N^R. \quad (4.29)$$

Resource installation is linked to station opening. A resource may only be installed in an opened station, and each opened station must contain at least one resource:

$$y_k^H \leq u_k, \quad \forall k \in K, \quad (4.30)$$

$$y_k^R \leq u_k, \quad \forall k \in K, \quad (4.31)$$

$$u_k \leq y_k^H + y_k^R, \quad \forall k \in K. \quad (4.32)$$

The following condition enforces a contiguous station-opening structure:

$$u_k \geq u_{k+1}, \quad \forall k = 1, \dots, m-1. \quad (4.33)$$

This convention eliminates symmetric solutions in which downstream stations are opened while upstream stations remain unused.

Task assignments must be compatible with the resources installed at the selected station:

$$x_{pik}^H \leq y_k^H, \quad x_{pik}^R \leq y_k^R, \quad (4.34)$$

$$x_{pik}^C \leq y_k^H, \quad x_{pik}^C \leq y_k^R, \quad \forall p \in P, \forall i \in I_p, \forall k \in K. \quad (4.35)$$

Moreover, no task can be assigned to a closed station:

$$x_{pik}^H \leq u_k, \quad x_{pik}^R \leq u_k, \quad x_{pik}^C \leq u_k, \quad \forall p \in P, \forall i \in I_p, \forall k \in K. \quad (4.36)$$

Temporal definition and physical station index

The finish date of each task is obtained from its start date and from the processing time corresponding to the selected execution mode:

$$F_{pi} = S_{pi} + \sum_{k \in K} (t_{pi}^H x_{pik}^H + t_{pi}^R x_{pik}^R + t_{pi}^C x_{pik}^C), \quad \forall p \in P, \forall i \in I_p. \quad (4.37)$$

For notational convenience, the following aggregate assignment variable is introduced:

$$X_{pik} = x_{pik}^H + x_{pik}^R + x_{pik}^C, \quad \forall p \in P, \forall i \in I_p, \forall k \in K. \quad (4.38)$$

Thus, X_{pik} identifies whether task i of product p is assigned to station k . The station index associated with each task is then expressed as:

$$A_{pi} = \sum_{k \in K} k(x_{pik}^H + x_{pik}^R + x_{pik}^C), \quad \forall p \in P, \forall i \in I_p. \quad (4.39)$$

The value A_{pi} supports the modelling of the physical order of stations along the disassembly line.

Precedence constraints

For each mandatory AND-precedence relation $i \rightarrow j$, the predecessor must not be assigned to a station located after the successor:

$$A_{pi} \leq A_{pj}, \quad \forall p \in P, \forall j \in I_p, \forall i \in P_{pj}^{AND}. \quad (4.40)$$

When the two tasks are assigned to the same station, their temporal order is enforced as follows:

$$S_{pj} \geq F_{pi} - M^T(2 - X_{pik} - X_{pjk}), \quad \forall p \in P, \forall j \in I_p, \forall i \in P_{pj}^{AND}, \forall k \in K. \quad (4.41)$$

If both tasks are processed at station k , the constraint imposes $S_{pj} \geq F_{pi}$. Otherwise, the Big-M term deactivates the intra-station timing relation, while the station-order constraint preserves the technological order along the line.

For each task having OR-predecessors, at least one admissible predecessor must be selected:

$$\sum_{i \in P_{pj}^{OR}} z_{pij} \geq 1, \quad \forall p \in P, \forall j \in I_p : P_{pj}^{OR} \neq \emptyset. \quad (4.42)$$

The physical station-order condition associated with an OR-predecessor is activated only when this predecessor is selected:

$$A_{pi} \leq A_{pj} + M^K(1 - z_{pij}), \quad \forall p \in P, \forall j \in I_p, \forall i \in P_{pj}^{OR}. \quad (4.43)$$

The corresponding temporal precedence is imposed when the selected OR-predecessor and the successor are assigned to the same station:

$$S_{pj} \geq F_{pi} - M^T[(1 - z_{pij}) + (2 - X_{pik} - X_{pjk})], \quad \forall p \in P, \forall j \in I_p, \forall i \in P_{pj}^{OR}, \forall k \in K. \quad (4.44)$$

Makespan indicator and station load

The auxiliary makespan indicator of product p is defined by:

$$T_p \geq F_{pi}, \quad \forall p \in P, \forall i \in I_p. \quad (4.45)$$

This variable is retained for interpretation and visualization purposes; it does not enter the deterministic objective function.

The total processing load assigned to station k is defined as:

$$L_k = \sum_{p \in P} \sum_{i \in I_p} (t_{pi}^H x_{pik}^H + t_{pi}^R x_{pik}^R + t_{pi}^C x_{pik}^C), \quad \forall k \in K. \quad (4.46)$$

The deterministic station-capacity constraint is then written as:

$$L_k \leq CTu_k, \quad \forall k \in K. \quad (4.47)$$

Accordingly, the workload assigned to an opened station must remain within the calibrated cycle time.

Coexistence and resource non-overlap constraints

For any operation $a = (p, i)$, define:

$$X_{ak} = x_{pik}^H + x_{pik}^R + x_{pik}^C, \quad (4.48)$$

$$H_{ak} = x_{pik}^H + x_{pik}^C, \quad (4.49)$$

$$R_{ak} = x_{pik}^R + x_{pik}^C. \quad (4.50)$$

Here, X_{ak} identifies the station assignment of operation a , while H_{ak} and R_{ak} indicate whether this operation requires the human or robotic resource at station k .

For every pair of operations and every station, the following linear relations define whether the two operations are assigned to the same station:

$$\delta_{ab}^k \leq X_{ak}, \quad (4.51)$$

$$\delta_{ab}^k \leq X_{bk}, \quad (4.52)$$

$$\delta_{ab}^k \geq X_{ak} + X_{bk} - 1. \quad (4.53)$$

For two generic operations $a = (p, i)$ and $b = (q, j)$, let $S_a = S_{pi}$, $F_a = F_{pi}$, $S_b = S_{qj}$ and $F_b = F_{qj}$. If the two operations are assigned to the same station and both require the human resource, one of them must be scheduled before the other:

$$S_b \geq F_a - M^T \left[(1 - w_{ab}^H) + (1 - \delta_{ab}^k) + (1 - H_{ak}) + (1 - H_{bk}) \right], \quad (4.54)$$

$$S_a \geq F_b - M^T \left[w_{ab}^H + (1 - \delta_{ab}^k) + (1 - H_{ak}) + (1 - H_{bk}) \right], \quad (4.55)$$

$$\forall (a, b) \in Q, \forall k \in K.$$

The same non-overlap structure is applied to the robotic resource:

$$S_b \geq F_a - M^T \left[(1 - w_{ab}^R) + (1 - \delta_{ab}^k) + (1 - R_{ak}) + (1 - R_{bk}) \right], \quad (4.56)$$

$$S_a \geq F_b - M^T \left[w_{ab}^R + (1 - \delta_{ab}^k) + (1 - R_{ak}) + (1 - R_{bk}) \right], \quad (4.57)$$

$$\forall (a, b) \in Q, \forall k \in K.$$

Because a collaborative task simultaneously occupies the human and the robot over the interval $[S_{pi}, F_{pi}]$, both human and robotic non-overlap constraints are active for such operations whenever they share a station with other tasks.

Domain constraints

$$x_{pik}^H, x_{pik}^R, x_{pik}^C \in \{0, 1\}, \quad \forall p \in P, \forall i \in I_p, \forall k \in K, \quad (4.58)$$

$$u_k, y_k^H, y_k^R \in \{0, 1\}, \quad \forall k \in K, \quad (4.59)$$

$$z_{pij} \in \{0, 1\}, \quad \forall p \in P, \forall j \in I_p, \forall i \in P_{pj}^{OR}, \quad (4.60)$$

$$w_{ab}^H, w_{ab}^R \in \{0, 1\}, \quad \forall (a, b) \in Q, \quad (4.61)$$

$$\delta_{ab}^k \in \{0, 1\}, \quad \forall (a, b) \in Q, \forall k \in K, \quad (4.62)$$

$$S_{pi}, F_{pi}, T_p \geq 0, \quad \forall p \in P, \forall i \in I_p. \quad (4.63)$$

4.5 Stochastic Mathematical Model

The deterministic formulation provides a structured representation of the line under fixed processing times. Nevertheless, end-of-life battery disassembly is affected by operational variability, especially when human operators perform tasks on products whose condition, accessibility and degradation level are not perfectly known in advance. Human operation times may therefore change from one battery to another, even when the same nominal task is considered.

To account for this variability, the deterministic formulation is extended into a scenario-based stochastic model. The structural decisions of the line are taken before the realization of uncertainty and remain identical across all scenarios. These decisions include station opening, task assignment, execution-mode selection, resource allocation, OR-predecessor selection and same-station identification. The scenario-dependent decisions concern the temporal organization of operations, the ordering of tasks on shared resources, the resulting station loads and the recourse variables used to represent possible overloads. Uncertainty is introduced only through human processing times, while robotic and collaborative processing times are kept deterministic.

4.5.1 Additional Sets and Parameters

Let $S = \{1, \dots, N_s\}$ denote the set of scenarios. The probability or weight of scenario s is denoted by ω_s and satisfies:

$$\sum_{s \in S} \omega_s = 1. \quad (4.64)$$

When all scenarios are equiprobable, the weight of each scenario is:

$$\omega_s = \frac{1}{N_s}, \quad \forall s \in S. \quad (4.65)$$

Table 4.7: Additional parameters of the stochastic model

Symbol	Definition
$S = \{1, \dots, N_s\}$	Set of scenarios.
ω_s	Weight associated with scenario s .
$t_{pi}^{H,s}$	Human processing time of task i of product p in scenario s .
t_{pi}^R	Deterministic robot processing time of task i of product p .
t_{pi}^C	Deterministic collaborative processing time of task i of product p .
$CT_{\min}^{sto}$	Reference processing-time value used to calibrate the common cycle time of both formulations.
ρ_k	Unit recourse cost associated with station k .
η	Maximum allowed recourse ratio for an opened station. In the numerical experiments, $\eta = 0.1500$.

Since human task durations are scenario-dependent, the stochastic reference duration is defined as the largest individual processing time observed over all generated scenarios, products, tasks and execution modes:

$$CT_{\min}^{sto} = \max_{s \in S, p \in P, i \in I_p} \{t_{pi}^{H,s}, t_{pi}^R, t_{pi}^C\}. \quad (4.66)$$

The common cycle time adopted in both the deterministic and stochastic formulations is then calibrated as:

$$CT = 2 CT_{\min}^{sto}. \quad (4.67)$$

This value is obtained after scenario generation by identifying the maximum individual processing time among the sampled human durations and the deterministic robot and collaborative durations. The same calibrated cycle time is then imposed in the deterministic and stochastic experiments of the same instance, so that the effect of uncertainty is evaluated under a common line-capacity reference.

The temporal Big-M parameter is also adapted to the scenario-dependent human times:

$$M^T = \sum_{p \in P} \sum_{i \in I_p} \max_{s \in S} \{t_{pi}^{H,s}, t_{pi}^R, t_{pi}^C\}. \quad (4.68)$$

The station-order Big-M remains:

$$M^K = m. \quad (4.69)$$

4.5.2 Scenario Generation

The scenarios are generated using Latin Hypercube Sampling. For each nominal human processing time, the uncertain duration is represented by a normal distribution:

$$T_{pi}^H \sim \mathcal{N}(\mu_{pi}^H, (\sigma_{pi}^H)^2). \quad (4.70)$$

The mean is equal to the nominal human processing time:

$$\mu_{pi}^H = t_{pi}^H. \quad (4.71)$$

The standard deviation is defined by a constant coefficient of variation ρ :

$$\sigma_{pi}^H = \rho t_{pi}^H. \quad (4.72)$$

In the computational experiments, the coefficient of variation is set to:

$$\rho = 0.2500. \quad (4.73)$$

For each task (p, i) , the interval $[0, 1]$ is divided into N_s sub-intervals:

$$I_r = \left[\frac{r-1}{N_s}, \frac{r}{N_s} \right], \quad r = 1, \dots, N_s. \quad (4.74)$$

A random value $u_{pi,r}$ is drawn from each sub-interval and then assigned to scenarios. The corresponding standard normal value is obtained through the inverse cumulative distribution function:

$$z_{pi,s} = \Phi^{-1}(u_{pi,s}). \quad (4.75)$$

The generated human time before truncation is:

$$\tilde{t}_{pi}^{H,s} = t_{pi}^H(1 + \rho z_{pi,s}). \quad (4.76)$$

To avoid negative or unrealistically small processing times, the generated value is bounded from below:

$$t_{pi}^{H,s} = \max \{0.0500 t_{pi}^H, \tilde{t}_{pi}^{H,s}\}. \quad (4.77)$$

Equivalently:

$$t_{pi}^{H,s} = \max \{0.0500 t_{pi}^H, t_{pi}^H(1 + \rho z_{pi,s})\}. \quad (4.78)$$

4.5.3 Decision Variables

The first-stage variables are independent of the scenario and represent the structural configuration of the disassembly line:

$$x_{pik}^H, x_{pik}^R, x_{pik}^C, u_k, y_k^H, y_k^R, z_{pij}, \delta_{ab}^k.$$

The second-stage variables are scenario-dependent. For each $s \in S, p \in P$ and $i \in I_p, S_{pi}^s \geq 0$ and $F_{pi}^s \geq 0$ denote the start and finish dates of task i of product p under scenario s . The variable $T_p^s \geq 0$ is the corresponding product-level makespan indicator.

For each pair $(a, b) \in Q$, the binary variables $w_{ab}^{H,s}$ and $w_{ab}^{R,s}$ define the relative order of the two operations on the human and robot resources under scenario s . Finally, for each station k and scenario s , the continuous variable $r_k^s \geq 0$ measures the overload absorbed through recourse.

4.5.4 Objective Function

The stochastic formulation minimizes the expected total economic cost:

$$\min Z = \sum_{k \in K} f_k u_k + \sum_{p \in P} \lambda_p \sum_{i \in I_p} \sum_{k \in K} (c_{pi}^H x_{pik}^H + e_{pi}^R x_{pik}^R + c_{pi}^C x_{pik}^C) + \sum_{s \in S} \omega_s \sum_{k \in K} \rho_k r_k^s. \quad (4.79)$$

The first term corresponds to station opening costs, the second term to the execution costs induced by the selected modes, and the third term to the expected cost of recourse. Through this last component, scenario-dependent overloads are incorporated into the economic assessment of the line while preserving a common structural configuration across all scenarios.

4.5.5 Constraints

The stochastic formulation retains the first-stage structural constraints of the deterministic model for task assignment, station opening, resource availability, station contiguity, task-resource compatibility and OR-predecessor selection. These constraints are imposed before the realization of uncertainty and therefore do not include a scenario index. The following equations define the scenario-dependent part of the model.

Finish time definition by scenario

For each task and each scenario, the finish date is determined by the selected execution mode and the processing time realized in that scenario:

$$F_{pi}^s = S_{pi}^s + \sum_{k \in K} (t_{pi}^{H,s} x_{pik}^H + t_{pi}^{R,s} x_{pik}^R + t_{pi}^C x_{pik}^C), \quad \forall p \in P, \forall i \in I_p, \forall s \in S. \quad (4.80)$$

The station index remains scenario-independent because task assignments are first-stage decisions:

$$A_{pi} = \sum_{k \in K} k (x_{pik}^H + x_{pik}^R + x_{pik}^C), \quad \forall p \in P, \forall i \in I_p. \quad (4.81)$$

As in the deterministic formulation, the aggregate assignment variable is defined as:

$$X_{pik} = x_{pik}^H + x_{pik}^R + x_{pik}^C, \quad \forall p \in P, \forall i \in I_p, \forall k \in K. \quad (4.82)$$

Scenario-dependent precedence constraints

For each AND-precedence relation, intra-station temporal feasibility must be satisfied in every scenario:

$$S_{pj}^s \geq F_{pi}^s - M^T (2 - X_{pik} - X_{pjk}), \quad \forall p \in P, \forall j \in I_p, \forall i \in P_{pj}^{AND}, \forall k \in K, \forall s \in S. \quad (4.83)$$

The physical order of stations is scenario-independent:

$$A_{pi} \leq A_{pj}, \quad \forall p \in P, \forall j \in I_p, \forall i \in P_{pj}^{AND}. \quad (4.84)$$

For OR-precedence relations, the selection of at least one admissible predecessor remains a first-stage requirement:

$$\sum_{i \in P_{pj}^{OR}} z_{pij} \geq 1, \quad \forall p \in P, \forall j \in I_p : P_{pj}^{OR} \neq \emptyset. \quad (4.85)$$

When an OR-predecessor is selected, its temporal relation with the successor is enforced in every scenario whenever both tasks are assigned to the same station:

$$S_{pj}^s \geq F_{pi}^s - M^T [(1 - z_{pij}) + (2 - X_{pik} - X_{pjk})], \quad (4.86)$$

$$\forall p \in P, \forall j \in I_p, \forall i \in P_{pj}^{OR}, \forall k \in K, \forall s \in S. \quad (4.87)$$

The selected OR-predecessor must also respect the physical order of stations:

$$A_{pi} \leq A_{pj} + M^K (1 - z_{pij}), \quad \forall p \in P, \forall j \in I_p, \forall i \in P_{pj}^{OR}. \quad (4.88)$$

Makespan indicator, station load and recourse

The makespan indicator is defined for every product and every scenario:

$$T_p^s \geq F_{pi}^s, \quad \forall p \in P, \forall i \in I_p, \forall s \in S. \quad (4.89)$$

This variable is retained for analysis and visualization and is not directly minimized in the objective function.

The load of station k under scenario s is defined as:

$$L_k^s = \sum_{p \in P} \sum_{i \in I_p} (t_{pi}^{H,s} x_{pi}^H + t_{pi}^R x_{pi}^R + t_{pi}^C x_{pi}^C), \quad \forall k \in K, \forall s \in S. \quad (4.90)$$

Unlike in the deterministic formulation, station-capacity feasibility is expressed with a bounded recourse variable:

$$L_k^s \leq CT u_k + r_k^s, \quad \forall k \in K, \forall s \in S. \quad (4.91)$$

To preserve operational realism, the admissible overload is limited to a fixed proportion of the cycle time:

$$r_k^s \leq \eta CT u_k, \quad \forall k \in K, \forall s \in S. \quad (4.92)$$

In the numerical experiments, $\eta = 0.1500$, which limits the admissible overload to 15% of the cycle time for each opened station.

Scenario-dependent resource non-overlap constraints

For a generic operation $a = (p, i)$, define:

$$X_{ak} = x_{pik}^H + x_{pik}^R + x_{pik}^C, \quad (4.93)$$

$$H_{ak} = x_{pik}^H + x_{pik}^C, \quad (4.94)$$

$$R_{ak} = x_{pik}^R + x_{pik}^C. \quad (4.95)$$

The same-station identification constraints are retained from the deterministic formulation:

$$\delta_{ab}^k \leq X_{ak}, \quad (4.96)$$

$$\delta_{ab}^k \leq X_{bk}, \quad (4.97)$$

$$\delta_{ab}^k \geq X_{ak} + X_{bk} - 1, \quad \forall (a, b) \in Q, \forall k \in K. \quad (4.98)$$

For $a = (p, i)$ and $b = (q, j)$, human-resource non-overlap is imposed in every scenario:

$$S_{qj}^s \geq F_{pi}^s - M^T \left[(1 - w_{ab}^{H,s}) + (1 - \delta_{ab}^k) + (1 - H_{ak}) + (1 - H_{bk}) \right], \quad (4.99)$$

$$S_{pi}^s \geq F_{qj}^s - M^T \left[w_{ab}^{H,s} + (1 - \delta_{ab}^k) + (1 - H_{ak}) + (1 - H_{bk}) \right], \quad (4.100)$$

$$\forall (a, b) \in Q, \forall k \in K, \forall s \in S.$$

The corresponding robot-resource non-overlap constraints are:

$$S_{qj}^s \geq F_{pi}^s - M^T \left[(1 - w_{ab}^{R,s}) + (1 - \delta_{ab}^k) + (1 - R_{ak}) + (1 - R_{bk}) \right], \quad (4.101)$$

$$S_{pi}^s \geq F_{qj}^s - M^T \left[w_{ab}^{R,s} + (1 - \delta_{ab}^k) + (1 - R_{ak}) + (1 - R_{bk}) \right], \quad (4.102)$$

$$\forall (a, b) \in Q, \forall k \in K, \forall s \in S.$$

If two operations are assigned to the same station and require the same resource, the formulation imposes a feasible order between them in every scenario. Collaborative operations activate both human and robot non-overlap relations because both resources are occupied over the same interval $[S_{pi}^s, F_{pi}^s]$.

Domain constraints

$$x_{pik}^H, x_{pik}^R, x_{pik}^C \in \{0, 1\}, \quad \forall p \in P, \forall i \in I_p, \forall k \in K, \quad (4.103)$$

$$u_k, y_k^H, y_k^R \in \{0, 1\}, \quad \forall k \in K, \quad (4.104)$$

$$z_{pij} \in \{0, 1\}, \quad \forall p \in P, \forall j \in I_p, \forall i \in P_{pj}^{OR}, \quad (4.105)$$

$$\delta_{ab}^k \in \{0, 1\}, \quad \forall (a, b) \in Q, \forall k \in K, \quad (4.106)$$

$$w_{ab}^{H,s}, w_{ab}^{R,s} \in \{0, 1\}, \quad \forall (a, b) \in Q, \forall s \in S, \quad (4.107)$$

$$S_{pi}^s, F_{pi}^s, T_p^s \geq 0, \quad \forall p \in P, \forall i \in I_p, \forall s \in S, \quad (4.108)$$

$$r_k^s \geq 0, \quad \forall k \in K, \forall s \in S. \quad (4.109)$$

4.5.6 Post-Processing of the Compacted Schedule

The objective function minimizes economic cost rather than makespan. Consequently, the start and finish dates returned by the solver may include temporal slack, particularly in the presence of Big-M constraints. A compaction procedure is therefore applied after optimization to produce clearer Gantt charts.

This post-processing step does not modify the optimized first-stage solution: opened stations, task assignments, execution modes, resource allocation, selected OR-predecessors and resource-ordering variables remain unchanged. It only recalculates compact display dates that remain consistent with the precedence and resource-ordering structure of the optimized solution.

For each scenario, the compaction graph contains the AND precedences whose two tasks are assigned to the same station, the selected OR precedences whose two tasks are assigned to the same station, and the ordering arcs derived from $w^{H,s}$ and $w^{R,s}$ for operations sharing the same resource in the same station. Precedences between tasks located in different stations are represented by the physical station order and are not added as temporal arcs in the compacted graph.

For each operation v , let $Pred^s(v)$ denote its set of predecessors in the compacted graph of scenario s , and let d_v^s be its selected duration in that scenario. The compacted display start date is:

$$\widetilde{S}_v^s = \max_{u \in Pred^s(v)} \widetilde{F}_u^s. \quad (4.110)$$

If $Pred^s(v) = \emptyset$, then:

$$\widetilde{S}_v^s = 0. \quad (4.111)$$

The compacted display finish date is:

$$\widetilde{F}_v^s = \widetilde{S}_v^s + d_v^s. \quad (4.112)$$

This operation is only a visualization step and does not transform the cost-minimization model into a time-minimization model.

4.6 Conclusion

This chapter presented the problem formulation and mathematical models used in this thesis. The considered system is a multi-product human–robot collaborative disassembly line for end-of-life electric vehicle batteries. Each product has its own tasks, task categories, operation times and precedence matrix, while all products share the same potential stations and resources.

The chapter first described the data construction logic and illustrated it with Tesla Model 1. The task categories, operation times, costs and precedence matrix were presented in a compact way.

The deterministic mathematical model was then formulated as a mono-objective MILP. It determines the opened stations, task assignments, execution modes, resource allocation, OR-predecessor selection and temporal ordering of tasks. Its objective minimizes the economic cost composed of station opening and execution costs, while the constraints ensure task feasibility, AND/OR precedence satisfaction, station-load compliance and non-overlap of human and robotic resources.

Finally, the stochastic extension was introduced. In this version, uncertainty affects only human operation times, which are generated using Latin Hypercube Sampling. The

first-stage decisions remain common to all scenarios, while start times, finish times, resource orders, station loads and recourse variables become scenario-dependent. The recourse mechanism allows bounded station overloads and penalizes them economically, which makes it possible to evaluate the robustness of the line configuration under uncertain human task durations.

The next chapter uses these deterministic and stochastic formulations to present the computational experiments, analyze the obtained solutions and compare the behavior of the two models.

COMPUTATIONAL RESULTS AND DISCUSSION

5.1 Introduction

The previous chapter presented the mathematical formulation of the proposed multi-product human–robot collaborative disassembly line balancing problem. Two formulations were developed. The first one is a deterministic model, in which all operation times are assumed to be known and fixed. The second one is a stochastic scenario-based model, in which uncertainty is introduced through human operation times while the main structural decisions remain common to all scenarios.

The objective of this chapter is to evaluate the behavior of these two formulations through computational experiments. The analysis focuses on the feasibility of the obtained solutions, the opening of workstations, the allocation of human and robotic resources, the assignment of tasks to execution modes, the distribution of station loads, and the impact of uncertain human operation times on the final line configuration.

The computational experiments are carried out on several instances built from the battery data described in Chapter 4. The exact mixed-integer linear programming models are solved for small and medium-size instances, namely the one-battery, two-battery and three-battery cases. These instances make it possible to analyze the structure of the solutions and to compare the deterministic and stochastic formulations under controlled conditions.

For larger instances involving four and five battery types, the exact models become computationally difficult to solve. The increase in the number of products leads to a significant growth in the number of tasks, assignment variables, precedence relations, station-resource coupling constraints and non-overlap constraints. As a result, the MILP formulation becomes too large to provide exploitable exact results within a reasonable computational time. These cases are therefore used to highlight the computational limits of the exact modeling approach.

The chapter is organized as follows. Section 5.2 presents the experimental design, including the implementation environment, the test instances, and the main parameter settings. Section 5.3 reports and analyzes the results obtained with the deterministic formulation. Section 5.4 introduces the scenario generation settings and presents the stochastic results, with particular attention to station-load variability and recourse variables under uncertain human task durations. Section 5.5 compares the deterministic and stochastic solutions. Section 5.6 provides a graphical interpretation of the solutions using Gantt charts. Finally, Section 5.7 discusses the computational limitations of the exact models before concluding the chapter.

5.2 Experimental Design

This section presents the experimental framework used to evaluate the deterministic and stochastic formulations proposed in Chapter 4. The computational experiments were designed to analyze the behavior of the models on progressively larger multi-product

instances. The aim is not only to report the numerical results, but also to understand how the number of battery types affects the line configuration, resource allocation, station loads, and computational complexity.

5.2.1 Implementation Environment

The deterministic and stochastic mathematical models were implemented in Python and solved using Gurobi Optimizer, version 10. The experiments were conducted on a MacBook Pro Retina 13-inch, Early 2015, running macOS version 11.6.7.

A time limit was imposed in order to control the computational effort required by the exact MILP formulations. For the deterministic model, the maximum resolution time was fixed at two hours. For the stochastic model, which includes scenario-dependent variables and constraints, the maximum resolution time was fixed at five hours.

These time limits were selected because the stochastic formulation is significantly larger than the deterministic one. In particular, the stochastic model introduces scenario-dependent starting times, finishing times, resource-ordering variables, station loads, and recourse variables. Therefore, a larger computational time was allowed for the stochastic model in order to give the solver a more reasonable opportunity to explore the solution space.

Table 5.1: Computational environment

Element	Description
Programming language	Python
Solver	Gurobi Optimizer
Solver version	10
Computer	MacBook Pro Retina 13-inch, Early 2015
Operating system	macOS 11.6.7
Time limit – deterministic model	2 hours
Time limit – stochastic model	5 hours

5.2.2 Test Instances

The computational study considers three exact MILP test instances. These instances are constructed by progressively increasing the number of battery types included in the same disassembly line. The first instance includes only Tesla Model 1. The second instance combines Tesla Model 1 and Tesla Model S. The third instance combines Tesla Model 1, Tesla Model S, and Guangqi Toyota LB7A-FX1.

This progressive construction makes it possible to evaluate how the model behaves when the number of products increases. Each battery type has its own task set, precedence matrix, task classification, operation times and cost parameters. However, all products share the same set of potential workstations and the same resource availability limits.

Additional instances involving four and five battery types were also considered during the experimental work. However, these larger cases could not be solved effectively using the exact MILP formulations within the adopted computational limits. The increase in the number of products leads to a rapid growth in the number of binary variables,

Table 5.2: Test instances considered in the exact MILP experiments

Instance	Battery types included	Number of battery types
1-battery instance	Tesla Model 1	1
2-battery instance	Tesla Model 1 and Tesla Model S	2
3-battery instance	Tesla Model 1, Tesla Model S and Guangqi Toyota LB7A-FX1	3

precedence constraints, resource non-overlap constraints, and station assignment combinations. Therefore, the numerical analysis in this chapter focuses on the one-battery, two-battery and three-battery instances, for which exploitable exact results were obtained.

5.2.3 Parameter Settings

For the one-battery, two-battery and three-battery instances, the same upper bounds were used for the line configuration parameters. The maximum number of potential stations was fixed at 20. The maximum number of available human operators was also fixed at 20, and the maximum number of available robots was fixed at 20.

These values do not mean that all stations, humans or robots are necessarily used in the final solution. They only define the maximum available capacity of the system. The optimization model decides which stations should be opened and which resources should be assigned according to the cost minimization objective and the feasibility constraints.

Table 5.3: Main line configuration parameters

Parameter	Value
Maximum number of potential stations	20
Maximum number of human operators	20
Maximum number of robots	20

The same cycle-time value is used for the deterministic and stochastic experiments of a given instance. This value is calibrated from the stochastic reference duration obtained after scenario generation, as defined in Chapter 4. This choice ensures that both formulations are compared under the same line-capacity reference.

5.3 Deterministic Model Results

This section presents the results obtained with the deterministic formulation. In this model, all operation times are considered fixed and known in advance. The objective is to minimize the total economic cost, composed of station opening costs and task execution costs, while respecting precedence constraints, station capacity, execution-mode compatibility, and resource non-overlap constraints.

The deterministic model was solved for three instances: one battery, two batteries and three batteries. For all these instances, the solver returned an optimal solution. The main numerical results are summarized in Table 5.4.

The results show that the number of opened stations increases with the number of battery types considered in the instance. The one-battery instance requires only one station, while the two-battery and three-battery instances require three and five stations, respectively. In all cases, the opened stations are equipped with both a human operator and

Table 5.4: Summary of deterministic results

Instance	Status	Objective	Station cost	Task cost	Opened stations	CT (s)	Max utilization (%)
1 battery	Optimal	5046.4869	5000.0000	46.4869	1	505.7250	99.8600
2 batteries	Optimal	15087.0287	15000.0000	87.0287	3	519.2654	97.6400
3 batteries	Optimal	29971.6941	25000.0000	4971.6941	5	852.6178	96.2300

a robot. This confirms that the optimal line configuration relies on hybrid human–robot stations in order to satisfy the execution requirements of human, robotic and collaborative tasks.

5.3.1 One-Battery Instance

The first deterministic instance considers only Tesla Model 1. This instance contains 22 disassembly tasks. The optimization model opens one workstation, equipped with both a human operator and a robot. The total objective value is equal to 5046.4869, including 5000.0000 as station opening cost and 46.4869 as task execution cost.

The cycle time is equal to 505.7250 seconds. The load of the opened station is 505.0000 seconds, corresponding to a utilization rate of 99.8600%. Therefore, the station is almost fully used while remaining feasible with respect to the cycle time constraint.

Table 5.5: Deterministic station load for the one-battery instance

Station	Configuration	Load (s)	CT (s)	Utilization (%)
1	H+R	505.0000	505.7250	99.8600

The solution assigns all tasks to the same workstation. This result is feasible because the total workload remains slightly below the cycle time. The station contains both types of resources, which allows the model to execute human-only, robot-only and collaborative tasks in the same station. In terms of execution modes, 3 tasks are performed by the human, 11 tasks by the robot, and 8 tasks in collaborative mode.

Table 5.6: Execution-mode distribution for the one-battery deterministic solution

Mode	Number of tasks	Share (%)
Human	3	13.6364
Robot	11	50.0000
Collaborative	8	36.3636

The product makespan after compacted scheduling is equal to 465.0000 seconds. This value is lower than the station load because some tasks can be executed in parallel when they use different resources within the same station. This confirms the importance of representing human and robot resources separately in the scheduling constraints.

5.3.2 Two-Battery Instance

The second deterministic instance considers two battery types: Tesla Model 1 and Tesla Model S. The total number of tasks is 44, with 22 tasks for each battery. The optimal solution opens three workstations, each equipped with one human operator and one

robot. The total objective value is 15087.0287, composed of 15000.0000 as station opening cost and 87.0287 as task execution cost.

The cycle time is equal to 519.2654 seconds. The station loads are reported in Table 5.7. All opened stations respect the cycle time constraint. Station 2 is the bottleneck station, with a load of 507.0000 seconds and a utilization rate of 97.6400%.

Table 5.7: Deterministic station loads for the two-battery instance

Station	Configuration	Load (s)	CT (s)	Utilization (%)
1	H+R	305.2000	519.2654	58.7800
2	H+R	507.0000	519.2654	97.6400
3	H+R	315.2000	519.2654	60.7000

The results show that the model distributes the tasks of the two products over three stations. Station 2 is highly loaded, while Stations 1 and 3 have lower utilization rates. This difference is mainly explained by the need to respect precedence relations and execution-mode compatibility. The model does not only balance total processing time; it must also ensure that tasks are assigned to feasible stations and that human and robotic resources do not overlap when they are required by several tasks.

In this solution, 8 tasks are executed in human mode, 22 tasks in robot mode and 14 tasks in collaborative mode. This distribution confirms that robotic execution remains dominant in terms of number of assigned tasks, while collaborative execution is also used frequently for tasks requiring simultaneous human and robot intervention.

Table 5.8: Execution-mode distribution for the two-battery deterministic solution

Mode	Number of tasks	Share (%)
Human	8	18.1818
Robot	22	50.0000
Collaborative	14	31.8182

The compacted makespan values are 432.0000 seconds for Tesla Model 1 and 316.0000 seconds for Tesla Model S. These values indicate that the model can schedule the operations of each product within the opened stations while preserving precedence feasibility and resource availability.

5.3.3 Three-Battery Instance

The third deterministic instance considers three battery types: Tesla Model 1, Tesla Model S and Guangqi Toyota LB7A-FX1. The instance contains 68 tasks in total. The optimal solution opens five workstations, each equipped with a human operator and a robot. The total objective value is 29971.6941, composed of 25000.0000 as station opening cost and 4971.6941 as task execution cost.

The cycle time is equal to 852.6178 seconds. The station loads are shown in Table 5.9. All stations satisfy the cycle time constraint. The highest load is observed at Station 1, with 820.5000 seconds and a utilization rate of 96.2300%. Stations 2 and 5 are also highly utilized, with utilization rates of 91.8600% and 92.9900%, respectively.

Compared with the one-battery and two-battery cases, the three-battery instance produces a more distributed line configuration. This is expected because the addition of

Table 5.9: Deterministic station loads for the three-battery instance

Station	Configuration	Load (s)	CT (s)	Utilization (%)
1	H+R	820.5000	852.6178	96.2300
2	H+R	783.2000	852.6178	91.8600
3	H+R	642.9000	852.6178	75.4000
4	H+R	693.4500	852.6178	81.3300
5	H+R	792.8500	852.6178	92.9900

Guangqi Toyota LB7A-FX1 increases the number of tasks, the total workload and the number of precedence relations to be respected. The station utilization values show that the model uses the opened stations efficiently while preserving feasibility.

The task execution cost increases significantly in this instance. This increase is mainly related to the inclusion of the Guangqi Toyota LB7A-FX1 battery, whose task costs are higher than those of the two Tesla cases. The weighted cost of this product is 4913.6750, while the weighted costs of Tesla Model 1 and Tesla Model S are 15.4956 and 42.5235, respectively. Therefore, the third product strongly influences the total task cost.

The execution-mode distribution is also different from the previous instances. In total, 19 tasks are executed in human mode, 30 tasks in robot mode and 19 tasks in collaborative mode. This shows that the third instance requires a more balanced use of the three execution modes, especially because the added battery contains several human and robot tasks with significant processing times.

Table 5.10: Execution-mode distribution for the three-battery deterministic solution

Mode	Number of tasks	Share (%)
Human	19	27.9412
Robot	30	44.1176
Collaborative	19	27.9412

The compacted makespan values are 820.5000 seconds for Tesla Model 1, 765.2000 seconds for Tesla Model S, and 638.8500 seconds for Guangqi Toyota LB7A-FX1. The high makespan values are consistent with the larger cycle time and the increased number of operations considered in the three-battery instance.

5.3.4 Synthesis of Deterministic Results

The deterministic results show that the proposed MILP formulation is able to generate feasible and optimal line configurations for the one-battery, two-battery and three-battery instances. In all cases, the cycle time constraints are respected, the opened stations are equipped with both human and robotic resources, and the task assignments satisfy the execution-mode restrictions.

The number of opened stations increases progressively from one station for the one-battery instance to three stations for the two-battery instance and five stations for the three-battery instance. This evolution is consistent with the increasing number of tasks and with the additional precedence and resource constraints introduced by each new battery type.

Table 5.11: Synthesis of deterministic line configurations

Instance	Tasks	Opened stations	Human stations	Robot stations	Bottleneck station	Bottleneck load (s)
1 battery	22	1	1	1	Station 1	505.0000
2 batteries	44	3	3	3	Station 2	507.0000
3 batteries	68	5	5	5	Station 1	820.5000

A first observation is that the station opening cost is the dominant component of the objective function in the one-battery and two-battery instances. In the three-battery instance, the task execution cost becomes more significant because the Guangqi Toyota LB7A-FX1 battery has higher task costs. This illustrates that the economic structure of the solution depends not only on the number of opened stations, but also on the cost characteristics of the products included in the instance.

A second observation concerns the utilization of human and robotic resources. Since all opened stations are configured as H+R stations, the model favors flexible stations capable of processing human, robot and collaborative tasks. This choice reduces the risk of incompatibility between task categories and station resources, while making it possible to schedule collaborative operations within the same station.

Finally, the deterministic results provide a useful baseline for comparison with the stochastic formulation. The deterministic model gives an optimized line configuration under fixed operation times. However, it does not directly evaluate the effect of human time variability. This effect is analyzed in the following section through the stochastic scenario-based model.

5.4 Stochastic Model Results

This section presents the results obtained with the stochastic scenario-based formulation. In this model, uncertainty is introduced through human operation times, while robot and collaborative operation times remain deterministic. The structural decisions, including station opening, task assignment, execution mode selection, resource allocation and OR-predecessor selection, are common to all scenarios. In contrast, starting times, finishing times, station loads and recourse variables are scenario-dependent.

5.4.1 Scenario Generation Settings

For the stochastic model, uncertainty is introduced only through human operation times. Robot operation times and collaborative operation times are considered deterministic. This choice reflects the assumption that human operations are more sensitive to product condition, accessibility difficulties, component degradation and operator adaptation.

The stochastic formulation was tested using five scenarios. These scenarios were generated using Latin Hypercube Sampling. For each human operation time, the nominal deterministic value was used as the mean of a normal distribution. The coefficient of variation was fixed at 0.2500, and a lower bound equal to 5% of the nominal human time was imposed in order to avoid unrealistic negative or extremely small values.

The use of five scenarios provides a first approximation of the variability of human operation times while keeping the stochastic MILP computationally tractable. Since each additional scenario increases the number of second-stage variables and constraints, the number of scenarios must remain compatible with the resolution capacity of the exact model.

Table 5.12: Scenario generation settings

Element	Setting
Uncertain parameter	Human operation time
Number of scenarios	5
Sampling method	Latin Hypercube Sampling
Probability distribution	Normal distribution
Mean value	Nominal human operation time
Coefficient of variation	0.2500
Minimum bound	$0.0500 t_{pi}^H$
Robot operation times	Deterministic
Collaborative operation times	Deterministic

Based on these scenarios, the stochastic model was solved for the same three instances as the deterministic model: one battery, two batteries and three batteries. Five scenarios were used in each case. The main numerical results are summarized in Table 5.13.

Table 5.13: Summary of stochastic results

Instance	Status	Objective	Station cost	Task cost	Expected recourse cost	Opened stations	CT (s)	Max load (s)
1 battery	Optimal	5460.5824	5000.0000	48.6224	411.9600	1	505.7250	513.1696
2 batteries	Optimal	15087.0287	15000.0000	87.0287	0.0000	3	519.2654	437.8510
3 batteries	Optimal	29971.6941	25000.0000	4971.6941	0.0000	5	852.6178	850.9407

The results show that the stochastic model provides optimal solutions for the three considered instances. The number of opened stations is equal to one for the one-battery instance, three for the two-battery instance, and five for the three-battery instance. In all cases, the opened stations are equipped with both a human operator and a robot, which allows the line to execute human, robotic and collaborative tasks.

The main difference between the three stochastic instances concerns the recourse cost. In the one-battery case, the expected recourse cost is positive and equal to 411.9600. This means that some scenarios generate a station load slightly higher than the common cycle time. In contrast, the two-battery and three-battery instances have a zero expected recourse cost. Therefore, the line configurations obtained for these two instances are able to absorb the generated human-time variability without exceeding the cycle time in any scenario.

5.4.2 One-Battery Instance

The first stochastic instance considers Tesla Model 1 only. The model opens one workstation, equipped with one human operator and one robot. The objective value is equal to 5460.5824. This value is composed of 5000.0000 as station opening cost, 48.6224 as weighted task execution cost, and 411.9600 as expected recourse cost.

The cycle time is equal to 505.7250 seconds. Since only one station is opened, all tasks are assigned to the same station. The station load varies from one scenario to another

because human operation times are stochastic. Table 5.14 reports the station load and recourse values for the five scenarios.

Table 5.14: Scenario-dependent station loads for the one-battery stochastic instance

Scenario	Load (s)	CT (s)	Recourse (s)
1	502.7994	505.7250	0.0000
2	508.5794	505.7250	2.8544
3	503.9160	505.7250	0.0000
4	498.3959	505.7250	0.0000
5	513.1696	505.7250	7.4446

The results show that Scenarios 2 and 5 generate a station load above the cycle time. The corresponding overloads are equal to 2.8544 seconds and 7.4446 seconds, respectively. These values remain below the maximum allowed recourse, which is equal to 75.8588 seconds. Therefore, the solution remains feasible under the bounded recourse mechanism.

The positive recourse cost is explained by the compact configuration of the solution. Since only one station is opened, the line has limited flexibility to absorb increases in human operation times. When the generated human times are slightly higher, the total station load may exceed the cycle time. The recourse variable captures this effect and converts it into an economic penalty.

In terms of execution modes, 5 tasks are assigned to human mode, 9 tasks to robot mode and 8 tasks to collaborative mode. Compared with the deterministic solution, the stochastic model assigns more tasks to human mode and fewer tasks to robot mode for this instance. This change slightly increases the execution cost and also contributes to the presence of recourse in some scenarios.

Table 5.15: Execution-mode distribution for the one-battery stochastic solution

Mode	Number of tasks	Share (%)
Human	5	22.7273
Robot	9	40.9091
Collaborative	8	36.3636

The compacted makespan varies between scenarios because human task durations change. The compacted makespan values range from 442.9667 seconds to 455.6030 seconds. This confirms that the stochastic model does not only modify station loads, but also affects the detailed scheduling behavior of the line.

5.4.3 Two-Battery Instance

The second stochastic instance considers Tesla Model 1 and Tesla Model S. The optimal solution opens three workstations, each equipped with one human operator and one robot. The total objective value is equal to 15087.0287. This value is composed of 15000.0000 as station opening cost, 87.0287 as weighted task execution cost, and 0.0000 as expected recourse cost.

The absence of recourse cost means that the station loads remain below the cycle time in all scenarios. The cycle time is equal to 519.2654 seconds, while the maximum station

load observed over all scenarios is 437.8510 seconds. Table 5.16 reports the minimum, mean and maximum load of each opened station across the five scenarios.

Table 5.16: Scenario-dependent station load ranges for the two-battery stochastic instance

Station	Type	Min load (s)	Mean load (s)	Max load (s)
1	H+R	426.8506	432.9277	437.8510
2	H+R	291.2137	299.5509	313.9044
3	H+R	381.3231	396.8250	408.3867

The station loads show that Station 1 is the most loaded station in this stochastic solution. However, its maximum load remains far below the cycle time. This indicates that the three-station configuration provides enough capacity to absorb the generated variability in human operation times.

Table 5.17 summarizes the maximum station load and the mean open-station load for each scenario.

Table 5.17: Scenario summary for the two-battery stochastic instance

Scenario	Total recourse (s)	Max station load (s)	Mean open-station load (s)
1	0.0000	426.8506	373.7849
2	0.0000	431.8597	377.5263
3	0.0000	434.9702	383.7494
4	0.0000	433.1072	368.9541
5	0.0000	437.8510	378.1581

The execution-mode distribution is identical to the deterministic solution for this instance. A total of 8 tasks are executed in human mode, 22 tasks in robot mode and 14 tasks in collaborative mode. This indicates that, for the two-battery case, the introduction of uncertainty does not change the selected execution-mode structure.

Table 5.18: Execution-mode distribution for the two-battery stochastic solution

Mode	Number of tasks	Share (%)
Human	8	18.1818
Robot	22	50.0000
Collaborative	14	31.8182

Overall, the two-battery stochastic solution is stable with respect to the generated scenarios. The opened stations and resources are sufficient to maintain all scenario-dependent station loads below the cycle time, without using any recourse.

5.4.4 Three-Battery Instance

The third stochastic instance includes Tesla Model 1, Tesla Model S and Guangqi Toyota LB7A-FX1. The model opens five workstations, all equipped with one human operator and one robot. The objective value is equal to 29971.6941, composed of 25000.0000 as station opening cost, 4971.6941 as weighted task execution cost and 0.0000 as expected recourse cost.

The cycle time is equal to 852.6178 seconds. The maximum station load observed across all scenarios is 850.9407 seconds. This value is very close to the cycle time, but it remains feasible without recourse. Therefore, the stochastic solution is tight but does not violate the station capacity constraints.

Table 5.19: Scenario-dependent station load ranges for the three-battery stochastic instance

Station	Type	Min load (s)	Mean load (s)	Max load (s)
1	H+R	590.1710	616.5712	660.5887
2	H+R	610.9649	681.5231	850.4589
3	H+R	761.9357	808.1082	850.9407
4	H+R	802.4874	822.3554	842.5825
5	H+R	777.6515	809.6734	843.7893

The station load distribution shows that Stations 3, 4 and 5 are highly utilized. Station 3 reaches the highest load, with 850.9407 seconds in one scenario. This value is only slightly below the cycle time. The result indicates that the five-station configuration is efficiently used and that the stochastic variability is absorbed without requiring any recourse.

Table 5.20 presents the scenario-level load indicators. Although the total recourse remains equal to zero in all scenarios, the maximum station loads vary significantly from one scenario to another.

Table 5.20: Scenario summary for the three-battery stochastic instance

Scenario	Total recourse (s)	Max station load (s)	Mean open-station load (s)
1	0.0000	843.7893	746.5076
2	0.0000	835.9536	744.4218
3	0.0000	850.4589	791.8170
4	0.0000	802.4874	714.5413
5	0.0000	850.9407	740.9435

The execution-mode distribution is also the same as in the deterministic three-battery solution. In total, 19 tasks are assigned to human mode, 30 tasks to robot mode and 19 tasks to collaborative mode. This shows that, for this instance, the consideration of uncertain human operation times does not change the selected execution modes, but it affects the scenario-dependent station loads and schedules.

Table 5.21: Execution-mode distribution for the three-battery stochastic solution

Mode	Number of tasks	Share (%)
Human	19	27.9412
Robot	30	44.1176
Collaborative	19	27.9412

The three-battery stochastic instance is therefore the most constrained case among the instances solved exactly. The model opens five stations and uses them intensively. However, the absence of recourse indicates that the selected configuration remains feasible across the five generated scenarios.

5.4.5 Synthesis of Stochastic Results

The stochastic results confirm that the proposed scenario-based formulation can be solved exactly for the one-battery, two-battery and three-battery instances. The structural line configurations remain compact: one station is opened for the one-battery case, three stations for the two-battery case and five stations for the three-battery case. All opened stations are configured as H+R stations, which provides the necessary flexibility to execute human, robotic and collaborative tasks.

Table 5.22: Synthesis of stochastic line configurations

Instance	Tasks	Opened stations	Human stations	Robot stations	Expected recourse cost	Maximum recourse (s)
1 battery	22	1	1	1	411.9600	7.4446
2 batteries	44	3	3	3	0.0000	0.0000
3 batteries	68	5	5	5	0.0000	0.0000

The main role of the stochastic formulation is visible through the scenario-dependent load analysis. For the one-battery instance, the single-station configuration is sensitive to variations in human operation times, which leads to limited recourse in two scenarios. For the two-battery and three-battery instances, the opened stations provide sufficient capacity to absorb the generated variability without exceeding the cycle time.

These results show that the stochastic model does not necessarily produce a different structural configuration in every instance. However, it provides additional information that the deterministic model cannot capture directly, especially regarding scenario-dependent station loads and the possible need for recourse. This information is important for evaluating the robustness of a line configuration under uncertain human task durations.

5.5 Comparison Between Deterministic and Stochastic Results

This section compares the deterministic and stochastic formulations for the one-battery, two-battery and three-battery instances. The objective is to analyze whether the introduction of uncertain human operation times modifies the economic cost, the number of opened stations, the resource allocation, the station loads and the robustness of the obtained solutions.

The deterministic model provides a reference solution based on fixed operation times. In contrast, the stochastic model evaluates the line configuration under several possible realizations of human task durations. Therefore, the comparison is not limited to the objective value. It also considers the recourse cost and the scenario-dependent station loads, which provide additional information about the behavior of the line under uncertainty.

5.5.1 Comparison of Cost Components

Table 5.23 compares the main cost components of the deterministic and stochastic solutions.

For the one-battery instance, the stochastic objective value is higher than the deterministic objective value. This difference is mainly explained by the expected recourse cost. In this case, the line contains only one opened station, and all tasks are assigned to this

Table 5.23: Comparison of deterministic and stochastic cost components

Instance	Det. objective	Stoch. objective	Det. task cost	Stoch. task cost	Expected recourse cost	Difference
1 battery	5046.4869	5460.5824	46.4869	48.6224	411.9600	414.0955
2 batteries	15087.0287	15087.0287	87.0287	87.0287	0.0000	0.0000
3 batteries	29971.6941	29971.6941	4971.6941	4971.6941	0.0000	0.0000

station. Therefore, when the human operation times increase in some scenarios, the total station load can exceed the cycle time. The stochastic model captures this effect through the recourse variable and penalizes it in the objective function.

For the two-battery and three-battery instances, the deterministic and stochastic objective values are identical. In both cases, the expected recourse cost is equal to zero. This means that the selected line configurations are able to absorb the generated variability in human operation times without exceeding the cycle time in the considered scenarios. Therefore, the stochastic formulation does not increase the total cost for these instances.

This result does not mean that the stochastic formulation is unnecessary. Even when the objective value remains unchanged, the stochastic model provides additional information about the behavior of the solution under uncertain human task durations. In particular, it makes it possible to verify whether station loads remain feasible across scenarios and whether recourse is required.

5.5.2 Comparison of Station Opening and Resource Allocation

Table 5.24 compares the number of opened stations and the resources used in the deterministic and stochastic solutions.

Table 5.24: Comparison of station opening and resource allocation

Instance	Det. stations	Stoch. stations	Det. humans	Stoch. humans	Det. robots	Stoch. robots
1 battery	1	1	1	1	1	1
2 batteries	3	3	3	3	3	3
3 batteries	5	5	5	5	5	5

The comparison shows that the stochastic model does not change the number of opened stations for the three solved instances. The one-battery instance requires one station, the two-battery instance requires three stations, and the three-battery instance requires five stations in both formulations.

The same observation applies to resource allocation. In all cases, each opened station is equipped with both a human operator and a robot. This result is consistent with the nature of the disassembly tasks. Since the instances include human-only tasks, robot-only tasks and collaborative tasks, the model tends to open hybrid stations containing both resources. This configuration provides the flexibility needed to satisfy the execution-mode restrictions and to perform collaborative operations.

Although the number of stations and resources remains unchanged, the stochastic model still gives a more detailed evaluation of the solution. It shows whether the same structural configuration remains feasible when human operation times vary across scenarios.

5.5.3 Comparison of Station Loads and Recourse

The most important difference between the deterministic and stochastic formulations appears in the analysis of station loads. In the deterministic model, each station load is calculated using fixed operation times. In the stochastic model, station loads are scenario-dependent because human task durations vary from one scenario to another.

Table 5.25 compares the maximum station load observed in the deterministic and stochastic formulations.

Table 5.25: Comparison of maximum station loads and recourse

Instance	CT (s)	Max det. load (s)	Max stoch. load (s)	Maximum recourse (s)	Expected recourse cost
1 battery	505.7250	505.0000	513.1696	7.4446	411.9600
2 batteries	519.2654	507.0000	437.8510	0.0000	0.0000
3 batteries	852.6178	820.5000	850.9407	0.0000	0.0000

For the one-battery instance, the deterministic maximum station load is 505.0000 seconds, which is slightly below the cycle time of 505.7250 seconds. However, in the stochastic model, the maximum scenario-dependent load reaches 513.1696 seconds. This value exceeds the cycle time, which explains the activation of the recourse variable. The maximum overload is equal to 7.4446 seconds. This overload remains limited and below the allowed recourse bound, but it shows that the deterministic solution is very tight and sensitive to human time variability.

For the two-battery instance, the stochastic model does not require any recourse. The maximum stochastic station load is 437.8510 seconds, which remains clearly below the cycle time of 519.2654 seconds. This indicates that the three-station configuration has enough available capacity to absorb the generated variability in human operation times.

For the three-battery instance, the stochastic maximum load is 850.9407 seconds, which is very close to the cycle time of 852.6178 seconds. However, no recourse is required. This means that the stochastic solution is feasible in all scenarios, but the line operates close to its capacity limit. Therefore, the three-battery instance is more constrained than the two-battery instance, even though the expected recourse cost remains equal to zero.

5.5.4 Discussion on the Impact of Human Time Uncertainty

The comparison between the deterministic and stochastic formulations shows that the impact of uncertainty depends on the structure and capacity of the line configuration.

In the one-battery instance, the line is extremely compact because only one station is opened. This configuration is economically attractive, but it leaves little capacity margin. As a result, small increases in human operation times can lead to a station overload in some scenarios. The stochastic model identifies this risk and translates it into an expected recourse cost. Such information cannot be captured by the deterministic formulation alone.

In the two-battery instance, the line is distributed over three stations. The additional stations provide more capacity margin, and the generated variability in human task durations does not lead to any overload. In this case, the stochastic model confirms that the line configuration remains feasible across the considered scenarios.

In the three-battery instance, the line is distributed over five stations. The stochastic maximum load remains below the cycle time, but it is very close to it. This indicates that the configuration is feasible but tight. The stochastic analysis therefore provides a

more detailed evaluation of the available capacity margins, showing that the line remains feasible while some stations operate close to their capacity limit.

Overall, the stochastic formulation does not necessarily change the structural solution in every instance. However, it provides a more detailed evaluation of the robustness of the line configuration. The deterministic model identifies an optimal configuration under fixed data, while the stochastic model evaluates how this configuration behaves when human operation times vary. This is particularly important in end-of-life battery disassembly, where human tasks may be affected by product degradation, accessibility difficulties and unexpected component conditions.

These findings support the use of the deterministic formulation as a baseline model, complemented by the stochastic formulation for evaluating robustness under uncertain human operation times. The deterministic formulation remains useful for building and understanding the line configuration, while the stochastic formulation provides complementary information on load variability, recourse activation and robustness under uncertain human operation times.

5.6 Graphical Analysis

This section provides a graphical interpretation of the solutions obtained with the deterministic and stochastic formulations. The analysis is based on Gantt charts generated from the compacted schedules. These charts illustrate the temporal organization of tasks, the utilization of human and robotic resources, and the synchronization of collaborative operations within the opened stations.

The Gantt charts are used only as a post-processing representation and do not modify the optimization results. They improve the readability of the schedules obtained from the MILP solutions. As explained in Chapter 4, the compacted schedule preserves the station openings, task assignments, execution modes, resource allocations and precedence relations obtained by the optimization model. As explained in Chapter 4, the compacted schedule preserves the station openings, task assignments, execution modes, resource allocations and precedence relations obtained by the optimization model.

5.6.1 Interpretation of Deterministic Gantt Charts

Figures 5.1, 5.2 and 5.3 present the deterministic Gantt charts for the one-battery, two-battery and three-battery instances, respectively.

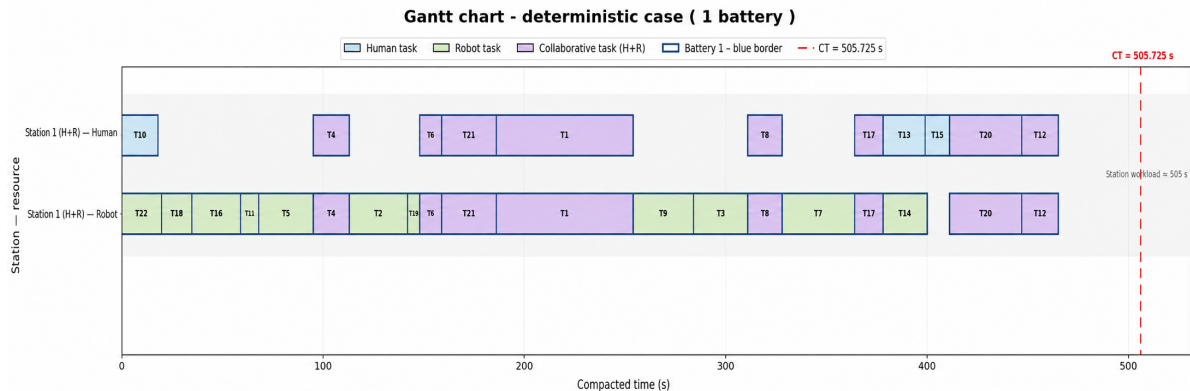


Figure 5.1: Deterministic Gantt chart for the one-battery instance

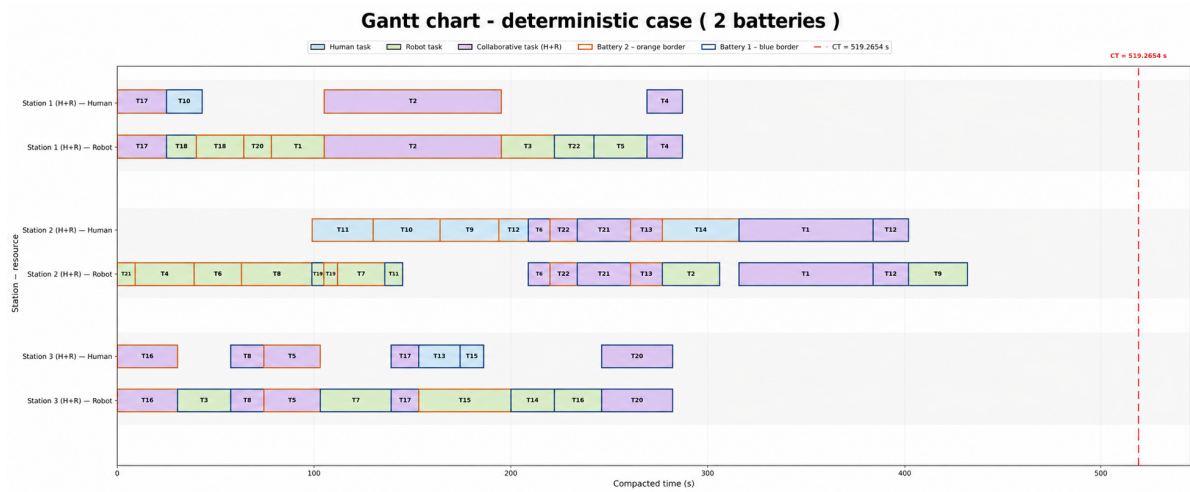


Figure 5.2: Deterministic Gantt chart for the two-battery instance

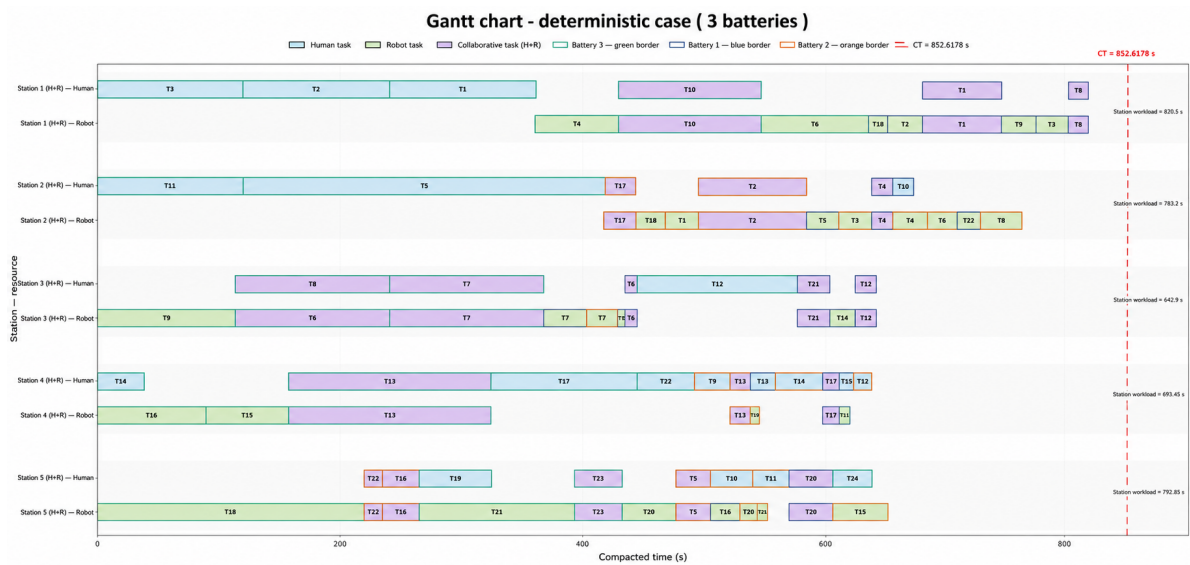


Figure 5.3: Deterministic Gantt chart for the three-battery instance

For the one-battery instance, all tasks are assigned to a single opened station. The Gantt chart shows how the human and robotic resources are used within the same station. Some operations are performed by only one resource, while collaborative tasks occupy both the human and the robot during the same time interval. This representation confirms that the model does not simply accumulate task durations, but also schedules operations according to resource availability and non-overlap constraints.

For the two-battery instance, the tasks are distributed over three opened stations. The Gantt chart illustrates the transition from a compact single-station configuration to a more distributed line configuration. The tasks of the two products are assigned while respecting their own precedence relations. The chart also shows that the opened stations are configured as hybrid human–robot stations, which allows both products to be processed using the same resource structure.

For the three-battery instance, the Gantt chart becomes denser because the number of tasks and precedence relations increases. The five opened stations are used to distribute the workload of Tesla Model 1, Tesla Model S and Guangqi Toyota LB7A-FX1. The visual result confirms that the deterministic model remains feasible for this instance, but also shows the increasing complexity of the schedule when several battery types are processed on the same line.

5.6.2 Interpretation of Stochastic Gantt Charts

Figures 5.4, 5.5 and 5.6 present the stochastic Gantt charts generated for Scenario 1 of each solved instance. Since the stochastic model generates one schedule for each scenario, Scenario 1 is selected only for graphical illustration. The complete scenario-dependent behavior is discussed through the numerical station-load and recourse tables.

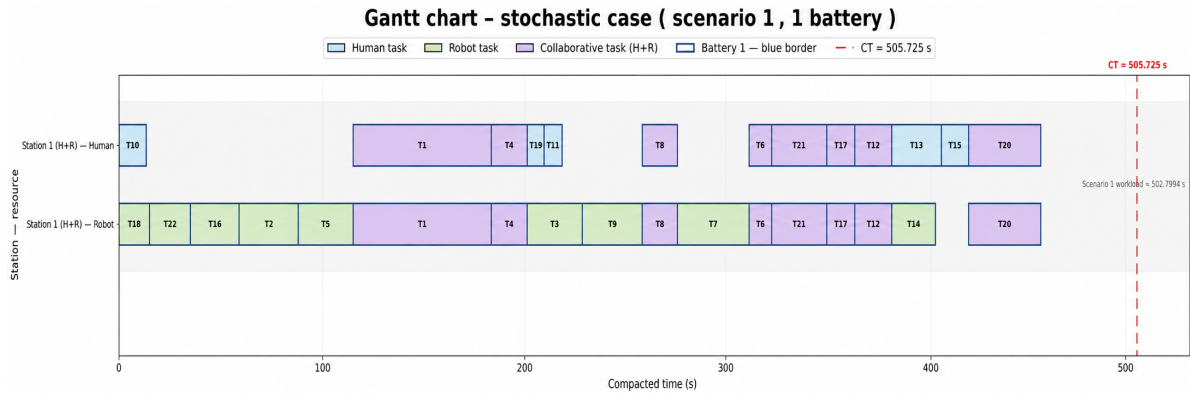


Figure 5.4: Stochastic Gantt chart for the one-battery instance, Scenario 1

The stochastic Gantt charts have the same structural interpretation as the deterministic ones. However, the task durations associated with human execution may change from one scenario to another. Therefore, the same line configuration can lead to different schedules depending on the realization of uncertain human operation times.

In the one-battery instance, Scenario 1 is used as a representative stochastic schedule. The Gantt chart illustrates how the same structural line configuration is scheduled when human task durations are generated from the stochastic scenario set. The detailed numerical analysis of the scenario loads, presented earlier in Table 5.14, shows that the recourse is activated only in some scenarios. Therefore, the figure is used for visual interpretation, while the complete scenario-dependent behavior is analyzed through the load and recourse tables.

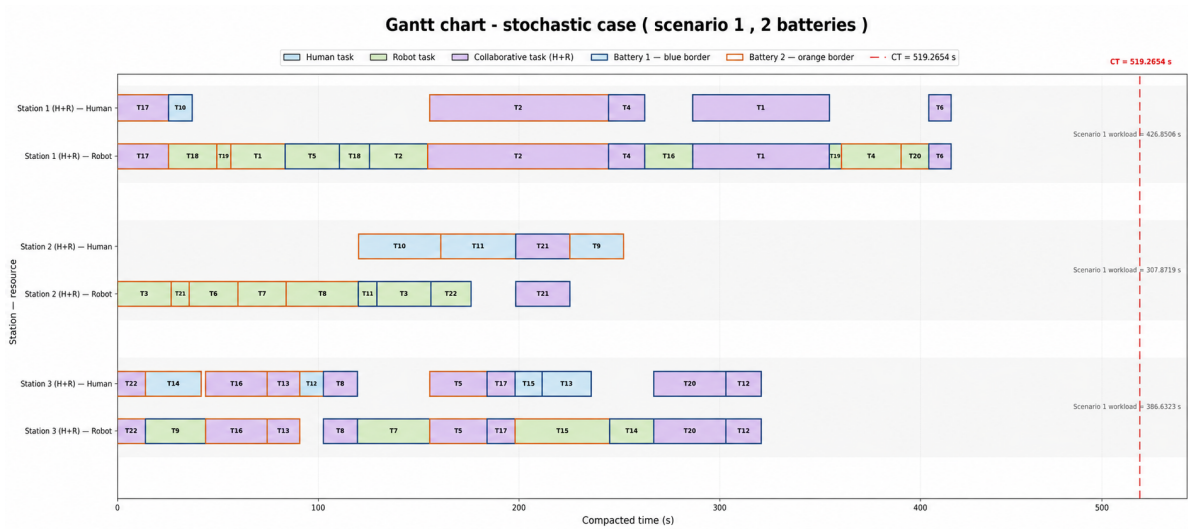


Figure 5.5: Stochastic Gantt chart for the two-battery instance, Scenario 1

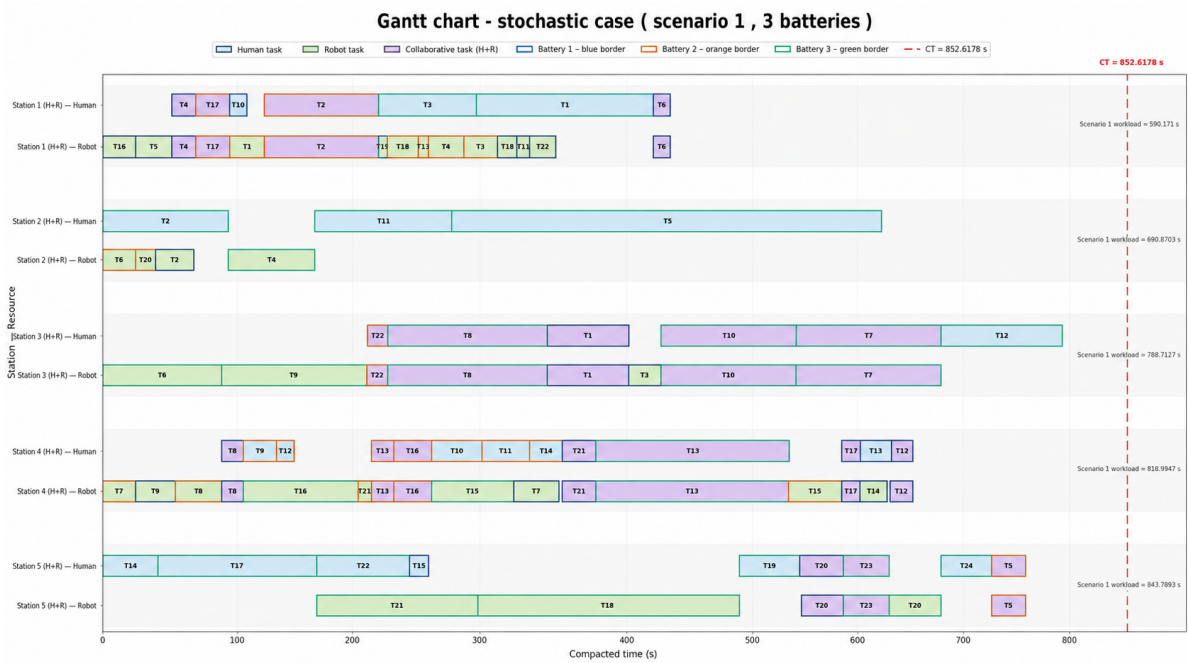


Figure 5.6: Stochastic Gantt chart for the three-battery instance, Scenario 1

In the two-battery instance, the stochastic Gantt chart confirms that the three-station configuration provides enough capacity to absorb human-time variability. Even when human durations change across scenarios, the station loads remain below the cycle time and no recourse is required.

In the three-battery instance, the stochastic Gantt chart shows a dense schedule distributed over five opened stations. The scenario-dependent station loads remain feasible, but some stations operate close to the cycle time. This confirms the numerical analysis presented earlier: the solution does not require recourse, but the available capacity margin is limited.

5.6.3 General Observations from the Gantt Charts

The Gantt charts provide several useful observations. First, they confirm the role of hybrid human–robot stations in the obtained solutions. Since the opened stations contain both resources, they can handle human-only, robot-only and collaborative tasks. This structure is particularly important for battery disassembly, where task categories impose different execution requirements.

Second, the charts show the importance of collaborative tasks. A collaborative task occupies both the human and the robot during the same operation. Therefore, it must be scheduled while respecting the availability of both resources. This confirms the need to model human and robot non-overlap constraints separately.

Third, the charts illustrate the effect of increasing the number of battery types. The one-battery instance produces a compact schedule, while the two-battery and three-battery instances require more stations and more complex task coordination. This visual complexity is consistent with the numerical increase in the number of tasks, precedence relations and binary assignment decisions.

Finally, the stochastic Gantt charts highlight the role of scenario-dependent scheduling. Even when the structural decisions remain identical to the deterministic solution, the actual timing of operations may vary from one scenario to another. This confirms the usefulness of the stochastic formulation as a complementary evaluation tool for analyzing the robustness of the line under uncertain human operation times.

5.7 Computational Limits of the Exact Models

The previous sections showed that the deterministic and stochastic MILP formulations can provide exploitable exact results for the one-battery, two-battery and three-battery instances. These results make it possible to analyze the behavior of the proposed models, compare deterministic and stochastic formulations, and evaluate the effect of uncertain human operation times on station loads and recourse variables.

However, the computational experiments also revealed the limits of the exact approach when the number of battery types increases. In particular, instances involving four and five battery types could not be solved effectively within the adopted computational time limits. For these larger instances, the size of the mathematical model increases significantly due to the simultaneous growth of the number of tasks, assignment variables, precedence relations, station-resource coupling constraints and non-overlap constraints.

The increase in problem size is mainly explained by the multi-product structure of the model. Each additional battery type introduces a new set of tasks, a new precedence matrix, new operation times, new execution-mode restrictions, and additional task as-

signment decisions. Since the same line must process all products, the model must jointly decide how all tasks are assigned to the available stations and resources while preserving the specific precedence structure of each battery.

A second source of complexity comes from the human–robot collaborative structure. For each task, the model must decide whether the task is assigned to a human, a robot or a collaborative mode, depending on its category. Moreover, each opened station may contain a human resource, a robotic resource, or both. These decisions create additional binary variables and coupling constraints between tasks, stations and resources.

A third important source of complexity is related to the non-overlap constraints. The model must prevent two operations from using the same human resource or the same robot resource at the same station at the same time. To formulate these constraints, the set of unordered operation pairs is introduced. As the number of tasks increases, the number of operation pairs grows rapidly. Therefore, the number of sequencing and coexistence variables also increases strongly with the size of the instance.

This effect becomes even more important in the stochastic formulation. In the stochastic model, the first-stage decisions remain common to all scenarios, but the scheduling variables, finishing times, resource-ordering variables, station loads and recourse variables become scenario-dependent. Consequently, increasing the number of scenarios multiplies part of the model size. Even with only five scenarios, the stochastic formulation becomes much larger than the deterministic one.

Table 5.26 summarizes the computational status of the tested instances.

Table 5.26: Computational status of the exact MILP models

Instance	Battery types	Total tasks	Exact result	Comment
1-battery instance	1	22	Obtained	Solved exactly by both deterministic and stochastic models.
2-battery instance	2	44	Obtained	Solved exactly by both deterministic and stochastic models.
3-battery instance	3	68	Obtained	Solved exactly, but the model becomes larger and more constrained.
4-battery instance	4	94	Not obtained	The MILP becomes too large to provide exploitable exact results.
5-battery instance	5	138	Not obtained	The exact formulation becomes computationally too heavy.

The results show that the exact formulation is suitable for small and medium-size instances, but its computational difficulty increases rapidly when the number of products increases. This observation is consistent with the combinatorial nature of the problem. The model combines several difficult decisions: station opening, task assignment, execution-mode selection, resource allocation, precedence satisfaction and resource sequencing.

It is important to emphasize that the absence of exact results for the four-battery and five-battery cases does not invalidate the proposed model. On the contrary, it highlights the computational complexity of the considered problem. The mathematical formulation remains useful because it provides a rigorous representation of the disassembly line and makes it possible to solve smaller instances optimally. It also allows the structure of the problem to be clearly understood.

Nevertheless, for larger industrial instances, relying only on an exact MILP solver may not be sufficient. The computational burden becomes particularly important when several battery types must be processed simultaneously and when uncertainty is introduced through scenario-dependent human operation times. Therefore, the exact approach is more appropriate for validation, analysis and benchmarking on limited-size instances, while larger instances would require alternative solution strategies in future work.

In the context of this thesis, the computational results obtained for one, two and three battery types are sufficient to analyze the behavior of the proposed deterministic and stochastic models. They show how the line configuration evolves with the number

of products, how human and robotic resources are allocated, and how the stochastic formulation provides additional information through scenario-dependent station loads and recourse variables. The larger instances highlight the practical difficulty of scaling exact formulations to more complex multi-product disassembly systems.

5.8 Conclusion

This chapter presented the computational results obtained with the deterministic and stochastic formulations proposed in Chapter 4. The objective was to evaluate the behavior of the models on several multi-product battery disassembly instances and to analyze the effect of uncertain human operation times on the final line configuration.

The experiments were carried out on three exact MILP instances involving one, two and three battery types. The deterministic model was first used as a baseline formulation with fixed operation times. The results showed that the model is able to generate feasible and optimal configurations for these instances. The number of opened stations increased progressively with the number of battery types, from one station for the one-battery instance to three stations for the two-battery instance and five stations for the three-battery instance. In all cases, the opened stations were equipped with both human and robotic resources, confirming the importance of hybrid human-robot workstations for handling human-only, robot-only and collaborative tasks.

The stochastic model was then applied to the same instances using five scenarios for human operation times. The stochastic formulation enriched the analysis by capturing scenario-dependent variations in station loads and by identifying the possible need for recourse under uncertain human operation times. In particular, it makes it possible to evaluate the sensitivity of the line configuration to variations in human task durations, to analyze scenario-dependent station loads, and to identify whether recourse is required.

For the one-battery instance, the stochastic model generated a positive expected recourse cost. This result indicates that the compact one-station configuration is sensitive to human time variability. Although the deterministic station load remains slightly below the cycle time, some stochastic scenarios lead to a limited overload. This overload remains bounded and feasible, but it shows that the deterministic solution may be tight when human operation times vary.

For the two-battery and three-battery instances, the stochastic model did not require any recourse. The opened station configurations were able to absorb the generated human-time variability while remaining within the cycle time. However, the three-battery instance operated close to the cycle time in some scenarios, which indicates that the solution is feasible but more constrained. This highlights the relevance of the stochastic formulation as an evaluation framework, even when the structural configuration and the total objective value remain unchanged.

The comparison between deterministic and stochastic results showed that the stochastic model does not necessarily lead to a different structural solution for every instance. However, it enriches the analysis by providing information about the robustness of the line configuration under uncertain human operation times. The deterministic model remains useful as a clear and structured baseline, while the stochastic model gives a more realistic view of possible operational deviations.

The graphical analysis based on Gantt charts also confirmed the feasibility of the obtained schedules. The charts illustrated the use of human and robotic resources inside the opened stations, the synchronization of collaborative tasks, and the increasing complexity

of the schedules when the number of battery types increases. They also showed the relevance of the compacted schedule as a post-processing step for improving the readability of the MILP solutions without modifying the optimized decisions.

Finally, the experiments highlighted the computational limits of the exact MILP approach. While the one-battery, two-battery and three-battery instances could be solved exactly, the four-battery and five-battery instances became too large to provide exploitable results within the adopted computational limits. This difficulty is mainly due to the rapid increase in the number of tasks, binary assignment variables, precedence constraints, resource non-overlap constraints and scenario-dependent variables in the stochastic formulation.

Overall, the results demonstrate that the proposed deterministic and stochastic formulations provide a rigorous basis for analyzing multi-product human–robot collaborative disassembly lines for end-of-life electric vehicle batteries. The results show the relevance of considering several battery types, execution modes, station resources, precedence relations and uncertainty in human operation times. These findings provide the basis for the general conclusion, where the main contributions, limitations and possible future research directions of the thesis are discussed.

GENERAL CONCLUSION

This thesis addressed the problem of organizing the disassembly of several types of end-of-life electric vehicle batteries in a human–robot collaborative disassembly line. The work was motivated by the growing importance of electric vehicle batteries in the circular economy and by the need to recover their remaining value through reuse, refurbishment, remanufacturing, repurposing and recycling. Since this value is not directly accessible, battery disassembly was considered as a key operational step for accessing, separating and preparing components for the appropriate recovery route.

The first part of the thesis established the general context of the study. The circular economy was presented as a framework for preserving product, component and material value. In the case of electric vehicle batteries, this perspective is particularly relevant because batteries contain valuable materials and components, but also involve safety risks and technical complexity. The study showed that end-of-life battery recovery is not only an environmental objective, but also an industrial organization problem that requires safe, structured and efficient operations.

The second part of the thesis focused on the disassembly of end-of-life electric vehicle batteries. It showed that battery packs are complex multi-level systems composed of cells, modules, electrical connections, cooling systems, electronic boards, casing parts, fasteners, sensors and protection elements. Their disassembly is constrained by product architecture, component accessibility, technological precedence relations and safety requirements. The thesis also highlighted the importance of product variability, since battery packs differ between manufacturers, vehicle models, chemistries, structures and end-of-life conditions.

Human–robot collaboration was identified as a relevant approach for this context. Manual disassembly offers flexibility and adaptability, but it exposes operators to ergonomic and safety risks. Robotic disassembly can improve repeatability and reduce human exposure, but full automation remains difficult because of the heterogeneity and uncertainty of end-of-life products. Human–robot collaborative disassembly therefore appears as an intermediate and promising solution, since it combines human judgment and adaptability with robotic assistance, precision and safety support.

The literature review confirmed that several research directions have been developed for battery disassembly, including disassembly sequence planning, disassembly line balancing, human–robot task allocation, stochastic modelling, risk-aware planning and multi-product disassembly. However, the review also revealed that many studies remain focused on a single product type or on deterministic data. The simultaneous integration of multi-product disassembly, human–robot collaboration and uncertain human operation times remains limited. This observation justified the modelling choices adopted in this thesis.

Main Contribution and Added Value

The main added value of this thesis lies in the development of a structured optimization framework for a multi-type human–robot collaborative disassembly line dedicated to end-of-life electric vehicle batteries. Unlike approaches that focus on a single battery model, the proposed formulation considers several battery types processed on the same line. Each battery type keeps its own task set, precedence relations, operation times, task

categories and execution constraints. This modelling choice better reflects the context of future recovery facilities, where different battery architectures may need to be processed using shared stations and shared resources.

Another contribution concerns the explicit modelling of human, robotic and collaborative execution modes. The proposed formulation distinguishes human-only tasks, robot-only tasks, collaborative tasks and normal tasks that can be executed either by a human or by a robot. This classification makes it possible to represent both technological restrictions and operational flexibility. It also allows the model to decide not only where a task should be performed, but also how it should be performed and which resources should be installed at each station.

A further contribution is the integration of precedence relations, station assignment, resource allocation, cycle-time feasibility and non-overlap constraints in the same mathematical framework. The model goes beyond task-to-station assignment by jointly enforcing the technological logic of the disassembly process, resource availability at opened stations, and non-overlap constraints for human and robotic resources. This provides a rigorous representation of the operational constraints of a collaborative disassembly line.

The deterministic mixed-integer linear programming model constitutes the first level of the proposed contribution. It defines a clear and rigorous baseline for the considered problem under fixed operation times. This formulation makes it possible to analyze the structure of the line, the number of opened stations, the allocation of human and robotic resources, the selection of execution modes and the distribution of workloads.

The stochastic scenario-based formulation extends this contribution by incorporating uncertainty in human operation times. In this extension, uncertainty is introduced through human operation times, while robot and collaborative operation times remain deterministic. The main structural decisions remain common to all scenarios, whereas scheduling variables, station loads and recourse variables become scenario-dependent. This modelling choice reflects the fact that human execution times may vary according to battery condition, accessibility, degradation, operator adaptation or unexpected difficulties during disassembly.

The introduction of a bounded recourse mechanism is also an important element of the proposed approach. Instead of forcing the line to be feasible for every possible variation in human operation times, the stochastic model allows limited station overloads under uncertainty and penalizes them economically. This makes the model more flexible and closer to practical operating conditions, where small deviations may occur but should remain controlled.

The computational results confirmed the relevance of the proposed framework. The deterministic model generated feasible and optimal configurations for the one-battery, two-battery and three-battery instances. The number of opened stations increased with the number of battery types, showing that the model reacts logically to the growth of workload and precedence complexity. The stochastic model provided additional information about station-load variability and recourse activation. In particular, it showed that the one-battery configuration is sensitive to human-time variability, while the two-battery and three-battery configurations were able to absorb the considered uncertainty without recourse.

The graphical analysis based on Gantt charts also contributed to the interpretation of the results. It showed how human and robotic resources are used inside the opened stations, how collaborative tasks require simultaneous resource availability, and how the schedules become more complex when the number of battery types increases. These visualizations confirmed the feasibility of the optimized solutions and made the temporal

organization of the line easier to understand.

Overall, the value added by this work is not limited to obtaining numerical results. The thesis proposes a complete modelling logic that connects circular economy objectives, battery disassembly requirements, human–robot collaboration, multi-product line balancing and uncertainty modelling. It therefore provides a basis for understanding how end-of-life battery disassembly can be organized as an industrial optimization problem rather than as a set of isolated manual operations.

Limitations and Perspectives

Despite these contributions, several limitations should be acknowledged. First, the input data were constructed from literature sources. Although this approach made it possible to build homogeneous test instances, the data may not fully represent all the constraints of a real industrial dismantling facility. In practice, additional information would be required about operator skills, available tools, station layouts, safety distances, handling devices, battery diagnosis and detailed product condition.

Second, uncertainty was introduced only through human operation times. This assumption is justified because human tasks are strongly affected by accessibility, degradation, damage and operator adaptation. However, other parameters may also be uncertain in real disassembly systems, such as battery condition, task feasibility, robot execution time, risk level, energy consumption, quality of recovered components and availability of product information.

Third, the stochastic model was tested using a limited number of scenarios in order to preserve computational tractability. A larger number of scenarios could provide a more detailed representation of uncertainty, but it would also increase the size of the mathematical model and the required computation time.

The main limitation of the proposed approach concerns the scalability of the exact MILP formulation. The results showed that the exact deterministic and stochastic formulations are suitable for small and medium-size instances, but they become computationally difficult for larger cases involving four and five battery types. This difficulty is due to the rapid increase in the number of tasks, assignment variables, precedence constraints, station-resource coupling constraints, non-overlap constraints and scenario-dependent variables. As a result, exact methods may require long execution times and may not provide exploitable solutions for larger industrial instances.

For this reason, a natural continuation of this work is the development of a metaheuristic solution approach for larger-scale instances. Such an approach would make it possible to search for good-quality solutions in reasonable computational time when the exact MILP model becomes too large. In particular, a metaheuristic based on Adaptive Large Neighborhood Search could be used to explore the solution space by progressively destroying and repairing parts of a solution. This type of method is well suited to the considered problem because the solution is composed of several interdependent decisions, including task assignment, station selection, execution mode choice, resource allocation and precedence feasibility.

A metaheuristic extension could also be combined with a simulated annealing acceptance criterion in order to avoid premature convergence and to allow the exploration of solutions that are temporarily worse but potentially useful for reaching better configurations later. This would be particularly relevant for large multi-product instances, where the search space is highly combinatorial and where exact optimization becomes

computationally expensive.

Future work could therefore focus on designing, implementing and testing such a metaheuristic approach for the larger instances that could not be solved effectively by the exact models. The objective would not be to replace the mathematical formulation, but to use it as a reference framework. The exact model defines the problem rigorously and provides optimal solutions for small instances, while the metaheuristic would extend the applicability of the approach to larger and more realistic cases.

Other perspectives may also be considered. The stochastic model could be enriched by integrating additional uncertainty sources, such as battery degradation level, component accessibility, task failure, robot execution variability or safety risk. The model could also include more detailed industrial constraints, such as tool changes, ergonomic limits, operator qualification, station layout, shared tools, transportation between stations and safety distances in collaborative workspaces. Finally, the proposed framework could be validated using data collected from a real battery dismantling or remanufacturing facility.

In conclusion, this thesis contributes to the modelling and analysis of multi-type human-robot collaborative disassembly lines for end-of-life electric vehicle batteries. It shows that battery disassembly should be considered not only as a technical dismantling operation, but also as an optimization problem involving product variability, precedence relations, resource allocation, execution modes, uncertainty and workload balancing. By combining deterministic and stochastic formulations, the work provides a structured basis for evaluating collaborative battery disassembly systems and opens the way for future metaheuristic developments capable of addressing larger industrial-scale instances.

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